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AUTOMATION IN AN OPEN, CATCHING-UP ECONOMY: AGGREGATE AND MICROECONOMETRIC EVIDENCE*

Amaresh K Tiwari†

Abstract

Using the universe of firms in Estonia, we study the implications of imports-led and FDI-facilitated automation for productivity and factor shares of tasks and value-added. First, in contrast to the findings for developed economies, we find that the aggregate labour share of value-added for automation adopting firms is higher than that for non-adopters, and has grown, among others, through the reallocation of economic activities towards adopting firms. Second, the aggregate total factor productivity of the adopters concurrently grew faster than that of the non-adopters. Third, from the micro-level study, we find that the estimated labour share of tasks has declined over time among the adopting firms and is lowest in firms that automate frequently, where the frequency of automation provides rich information on firm automation characteristics. The study emphasizes international spillovers and the creation of productive new jobs by multinational adopters among the reasons for the increase in the labour share of value-added for adopters, even as their labour share of tasks declined. Fourth, the productivity impact of automation is heterogeneous: (a) firms that automate regularly, (b) multinational adopters, and (c) firms that realize complementarities between automation and innovative management practices are among the most productive adopters. The latter establishes that the innovative management practices instituted by adopters are those that help discover and facilitate complementarities between automation and human labour.

Keywords: Imports-Led Automation, Foreign Direct Investment (FDI), Productivity, Labour Share, Factor Task Content of Production, Complementarities

JEL Classifications: D24, E23, J30, O3, L60, L70, L80

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1 Introduction

The past few decades have been marked by the diffusion of automation related technology, as well as an increase in the set of tasks that can be performed by machines. Automation, as argued by Autor and Salomons (2018) and Acemoglu and Restrepo (2018b), displaces labour from production in at least two ways: employment displacement, which reduces aggregate employment, and labour share displacement, which reduces labour's share of value-added in the economy. At the same time, as shown by Graetz and Michaels (2018), Acemoglu and Restrepo (2020), and Koch *et al*. (2021), automation increases the productivity of adopting firms and industries, and if the productivity effect is large enough, it could, as shown by Acemoglu and Restrepo (2018b), countervail the negative effect of employment and labour share displacement.

Although there are many studies that have used industry-level information to study the industry level, local labour market, and aggregate implications of automation – a partial list includes Graetz and Michaels (2018), Autor and Salomons (2018), Acemoglu and Restrepo (2020), Dauth *et al*. (2021), Acemoglu and Restrepo (2021b) – there are few studies that have provided micro evidence. Besides, with the exception of Cséfalvay (2020) and Jungmittag (2021), who compare robotisation in the manufacturing sector of Central and Eastern Europe (CEE) with that of the developed European countries, we do not know of any study that has studied automation and its implications for catching-up economies.

This study fills the research gap as the incentives for automation and its implications for the outcomes of interest can be different for the catching-up economies when compared to the same for developed economies. We provide both aggregate and microeconometric evidence, while also highlighting the role of trade in the adoption of automation and its implications.

Because labour shares in the CEE countries are lower than in the OECD and developed European countries, both at the aggregate and at all sectoral levels (Kónya *et al*., 2020), and unlike some of the recent papers that study the aggregate (or local labour market) employment implications of automation, we study the aggregate productivity and labour share implications of automation. As far as microeconometric evidence is concerned, we develop an empirical strategy to (a) study the impact of automation for the factor task content of production (or factor shares of tasks), and (b) provide evidence on sources of the heterogeneous total factor productivity (TFP) impact of automation.

What distinguishes our study from the papers referenced here is the scope and kind of data used for the empirical analysis. Because of the non-existent (or thin) domestic market for machinery for automation in Estonia, import data convey almost all information on automation for the universe of firms in Estonia starting from 1995. And so we are able to observe all the subsequent automation activities of all the firms from 1995 onwards. For a certain part of our empirical exercise, to be elaborated below, we complement census data with Estonian Community Innovation Survey (CIS) data, which has information on the innovative activities of a certain sample of firms.

Using firm-level census data, we begin by describing aggregate outcomes for automation adopting and non-adopting firms in three broad sectors: manufacturing, services, and the sector comprising construction, mining, and utilities. We find that in all three sectors, automation adopters' share in aggregate employment has declined to a modest level, but their market share and shares in the aggregate TFP and labour share of value-added, which have grown over the years, in recent years are larger than half. While the productivity of an average firm has increased over the years, on average, automation adopters are more productive than non-adopters. Moreover, the growth rate of the aggregate TFP of the adopters is higher than that of non-adopters.

Although the aggregate labour share of value-added in Estonia in 2018 was higher compared to the mid-1990s, (a) the share's trajectory has been uneven, falling in the years following the Financial-Crisis until about 2012 before rising again, and (b) it is yet to catch-up to the level of developed economies, where it has been falling during the last two decades (Karabarbounis and Neiman, 2014). The literature that seeks to understand the causes for the decline in the labour share in the aggregate income is extensive (see Grossman and Oberfield (2022) for an important review). Although there are potentially multiple causes for the decline in labour share because automation reduces the labour task content of production, it has been found that in the developed economies, labour share of value-added among automation adopting firms is lower than that for non-adopters: see Acemoglu *et al*. (2020) for France, Dauth *et al*. (2018) for Germany, Koch *et al*. (2021) for Spain, Humlum (2021) for Denmark, and Dinlersoz and Wolf (2019) and Acemoglu and Restrepo (2021b) for the US.

labour share in Estonia, though arguably lower than the same for the developed economies, has increased, especially in last decade. Besides, contrary to the finding for the developed economies, the aggregate labour share for the automation adopting firms is *higher* than that for the non-adopters; especially in the manufacturing. In the services sector, labour share for the adopting firms in a recent year surpassed that for the non-adopting firms. Moreover, the labour share gap between the two sets of firms has widened. A closer examination, which entailed decomposing changes in the aggregate labour share and the aggregate TFP during the last decade, showed that, strikingly, in all the three broad sectors, reallocation from less productive non-adopters towards more productive adopting firms, which increased in the aggregate TFP, also increased the aggregate labour share. These findings are in contrast to that in Acemoglu *et al.* (2020), who for the French manufacturing find that reallocation from non-adopters towards "robot" adopting firms resulted in a decrease in labour share. However, similar to Acemoglu *et al.* (2020), we find that reallocation of resources from less productive adopters to the more productive adopters, which increased aggregate TFP, also reduced labour share among the adopter. A similar phenomena, though less pronounced, was noted among the non-adopters.

These results suggest that (a) it is mainly the superstar effect, *à la* Autor *et al.* (2020), that exerts a downward pressure on labour share, especially for the adopting firms, and (b) the productivity effects, not limited to those due to automation, more than offset the negative effect of the decline in the labour task content of production due to automation. The latter claim is also supported by a set of reduced form regressions using both firm level as well aggregated NACE 2-digit industry level data, where we regress changes in labour share on measures of automation and labour productivity. We find a large productivity effect, which likely dominates the displacement effect of automation.

While the sources of productivity growth, as in all economies, include cost savings due to automation, domestic productivity deepening and factor augmenting efforts, the creation of productive new tasks and jobs, and reallocation, in catching-up economies such as the CEE countries, which lag behind the technological frontier and where automation is largely imports-led and facilitated by foreign direct investment (FDI), we argue that because of knowledge/technology spillovers thorough imports and technology transfers through FDI, investment specific capital goods for automation double as productivity deepening and factor augmenting technologies (see Keller (2010) for an important review on international spillover). Besides, it is likely that global companies investing in automated production through FDI, to take advantage of the relatively low cost of well skilled labour, created productive new (and likely complementary) jobs, even while production in such firms involves a higher share of automated tasks.

Motivated by the finding that productivity growth – including that due to automation – led the recent increase in aggregate labour share, we undertake a firm-level analysis of the impact of automation for (i) the labour task content of production and (ii) productivity. While the various sources of productivity growth inform the formulation of certain hypotheses regarding the productivity impact of automation, we do not attempt to delineate the contributions of various sources for productivity growth, either at the micro or at the aggregate level, and their subsequent impact on labour share. Instead, what we show is that there is heterogeneity in (a) the adoption of automation, and (b) its impact on the labour task content of production and productivity is heterogeneous.

Our measure of automation for firm-level analysis is the cumulative frequency with which firms have imported capital goods for automation during the years, 1995–2018. Based on the measure, we classify firms as those that automate *occasionally* and those that automate *regularly*. The cumulative frequency conveys information about (a) the kind of firms that automate, and (b) the type of automation they undertake. First, inarguably, firms that automate *regularly* are firms that operate in industries where production is more *suitable* for automation and for whom it is *easier* to replace workers and/or expand with more automated tasks, and are therefore, more *exposed* to automation (Acemoglu and Restrepo, 2020; Bonfiglioli *et al*., 2020). Second, judging from the amount expended on automation, we infer that firms that automate *occasionally* invest in automation technologies that are simpler with the ability to automate fewer tasks, whereas firms that automate *regularly* are larger and invest in technologies that can automate and integrate more tasks – like an automated production line – thus yielding an automated production process. Third, firms that automate *regularly* include firms that are more likely to invest in new vintages of machinery to replace older vintages, which "deepens" the automation (Acemoglu and Restrepo, 2018a, 2019a).

Given the above observations, we argue that the measure of automation is a sufficient statistic, conditional on which factor shares of tasks are independent of labour and capital stock in the model of production developed by Acemoglu and Restrepo (2018a,b, 2019b), where automation determines the factor task content of production. This key identifying assumption along with the assumption that shares of various tasks in the firm production process are fixed (i.e., assuming that the elasticity of substitution between tasks is one) helps us identify the labour and capital task content of production as a function of the proposed measure. We find that the labour task content of production (or labour share of tasks) declines with the frequency with which firms invest in automation. Second, among automation adopters, the labour task content of production has declined over the years, whereas it remains unchanged among non-adopting firms. We believe that the identification strategy is novel, and can benefit from generalization.

To elicit the productivity impact of automation, while estimating the factor shares of tasks for firms with varying frequency of automation, and in a manner similar to Doraszelski and Jaumandreu (2013), we let productivity evolve endogenously by allowing it to depend flexibly on the past decisions of firms. In our case, these decisions are: if and how to automate and whether to institute new/innovative organizational practices.

First, we find that firms that automate *regularly* are highly productive, whereas firms that automate *occasionally* are in certain sectors found to be less productive than the firms who do not automate. We attribute the higher TFP impact of automation for firms that automate *regularly* to (a) the deepening of automation, (b) to greater cost savings aided by expensive automation technologies that in all likelihood efficiently automate and integrate multiple routine tasks, and (c) to a larger accumulated stock of knowledge through technology spillovers and/or transfers. Second, multinational adopters are more productive than their domestic counterparts, which suggests that knowledge transfer and spillover effects accompanying FDI are important sources of productivity growth. Third, firms that realize complementarities between automation and innovative management practices, information about which is obtained from Estonian CIS data, are more productive than those that only automate. This establishes that the innovative management practices adopted by automating firms are investments in what we term "*automation enabling practices and complements*", and these help discover and facilitate synergies between automation and human labour.

These automation enabling practices and complements include – but are not limited to – costly adjustments such as re-training programmes and providing incentives to their workers to successfully adjust to the impact of automation. Brynjolfsson and McElheran (2016) argue that many of the adjustments required for the effective operation of certain new technologies may be difficult for firms to discover and implement. Finding efficient ways to work with new technology requires constant work from entrepreneurs, managers, and workers to reinvent the relevant processes and change the production process, by design or through luck (Brynjolfsson and Mitchell, 2017). In other words, to maximize the value of investments in automation, firms are likely to be required to improve upon automation enabling managerial practices.

Finally, we would like to mention that firms that automate *regularly* and those that institute new organizational practices are larger firms. Since it is these firms that benefit highly from automation, we argue that the aggregate implication of automation is to a considerable extent driven by these firms, which constitute a small fraction of the total. In addition, these results suggest that automation is likely to have implications for the widening productivity gap between frontier and laggard firms in the same industry (Syverson, 2011).

The remainder of this paper is structured as follows. In Section 2 we present some motivating empirical findings, where we discuss the aggregate implications of automation, and which also *serves as a literature review* of some of the papers on the aggregate implications of automation. In Section 3 we present a model of automation with scope for automation enabling management practices and complements. Section 4 describes the data used in our study, while in Section 5 we develop an empirical strategy to test the predictions of our model and to test for complementarities between automation and innovation in management practices. In Section 6, we present and discuss the empirical results, while Section 7 draws concluding remarks. Certain details of the econometric methodology are relegated to the Appendix.

2 Motivating Aggregate Empirical Findings

In this section, we begin by describing automation activities in Estonia. Information on automation is obtained from firm-level data on trade (customs data) for the universe of firms in Estonia. Since we find little evidence of exports of capital goods for automation, it can be assumed that the domestic market for capital goods for automation is thin or non-existent. This is likely to be true of catching-up economies, like Estonia, that mostly rely on imports for capital goods that embody technological change. In other words, it can be said that automation in Estonia is largely imports-led.

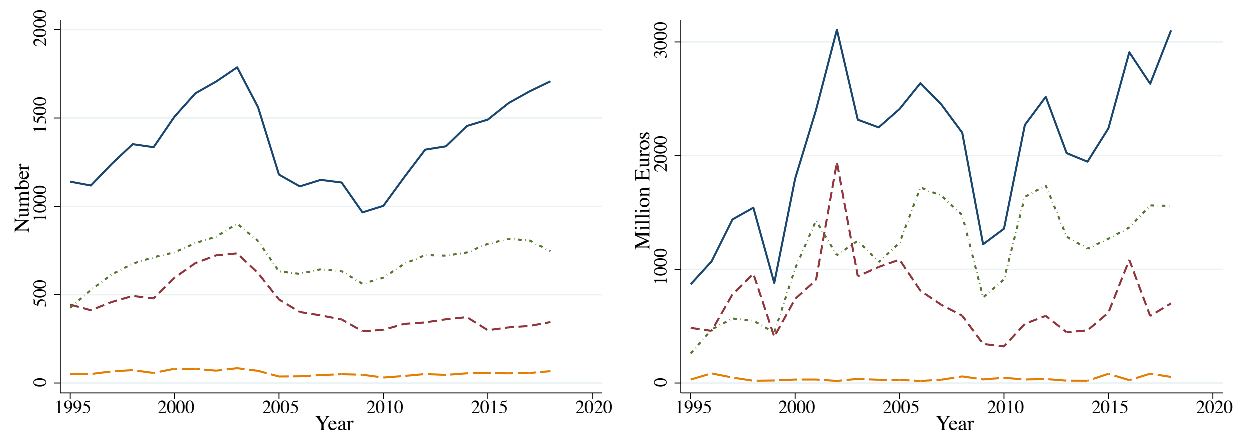
To begin with, based on list of 6-digit HS codes in Table 2 that identify goods for automation in the customs data, we in Figure 1 depict the incidence of imports of intermediate capital goods for automation. The number and the value of intermediate goods for automation while dipping during the Financial Crisis years, has generally increased since 1995. Furthermore, the service sector, which is the largest employer in Estonia, has the largest share of imports both in terms of the number and the value of goods for automation at 2015 prices.

In Figure 2a we plot the percentage of firms that has imported goods for automation in the current or previous periods, which can be interpreted as percentage that has adopted automation.[1][2] Now, even though the number of new automation adopters, as can be seen in Figure 1, has increased, the proportion of adopters, because of the addition of new non-adopting firms in a growing economy, has declined. Though the service sector has the largest share of adopters, within a given sector the proportion of firms that has adopted automation is highest in the manufacturing sector. Within manufacturing, the percentage of adopters has increased from about 10% in 1995 to about 20% in 2005, and since then been relatively constant. In the service sector, the

[1] All line graphs in Figures 2, Figure 3, Figure 4, Figure 6, Figure 7, Figure 8, and Figure 9 are smoothed using kernel-weighted local polynomial regression of the outcomes on year.

[2] While Figure 1 is based on all firms that imported capital goods for automation, the empirical analysis in the rest of the paper following Figure 2 excludes firms that we identify as likely retailers and/or service providers of automation services (see Section 4 for details regarding the data).

Figure 1. Number and Value of Imported Intermediate Capital Goods for Automation



(a) Number **(b)** Value

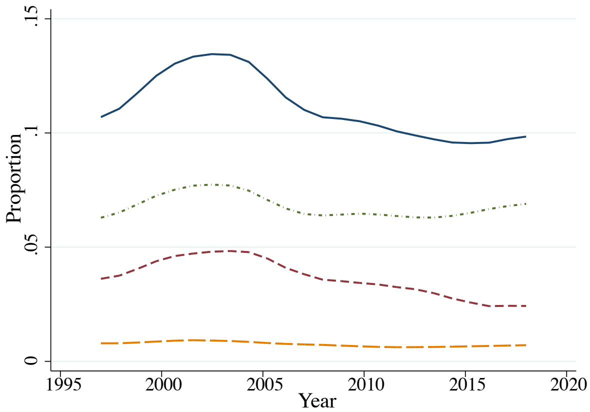
Total: ______ , Services: _ . _ . _ , Manufacturing: _ _ _ _ , Mining, Utilities, and Construction: __ __ __

percentage has varied between 2% to 6%. And in mining, utilities, and construction, it has varied between 3% to 5%. The employment share of the adopters (Figure 2b), which increased initially, has declined to a modest level. In absolute numbers, the total number employed by the adopting firms in the manufacturing sector has declined since its peak in 2005, whereas the number employed by the same in other two sectors increased. Notwithstanding the shift from manufacturing to the other sectors and the likely shift from routine worker towards technology workers, in the aggregate, employment level since 2005 in the adopting firms has stagnated.

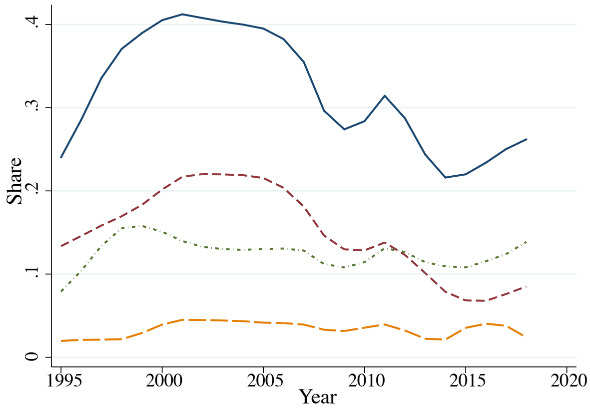
However, as Figure 2c shows, the market share, calculated as share of revenue, of the automation adopters has increased since 1995 to above 50% in recent years. This shows that even though the fraction of firms that has adopted automation is small, it commands a large market share. Among the adopters, though, in the recent years the market share of adopters in the service sector has increased while the market share of the adopters in the manufacturing sector has declined. Within manufacturing, the market share of the adopters increased from 50% to about 80% during the same period. In the service sector, the market share of such firms has increased from about 25% in 1995 to about 50% in 2018. These findings indicate that the market concentration of the adopting firms in the manufacturing and service sectors has increased. The same is true of firms in the sector comprising of mining, utilities, and construction.

In Figure 2d, we plot automation adopting firms' share in the aggregate total factor productivity (TFP). TFP for each firm is computed using the control function method for estimating produc-

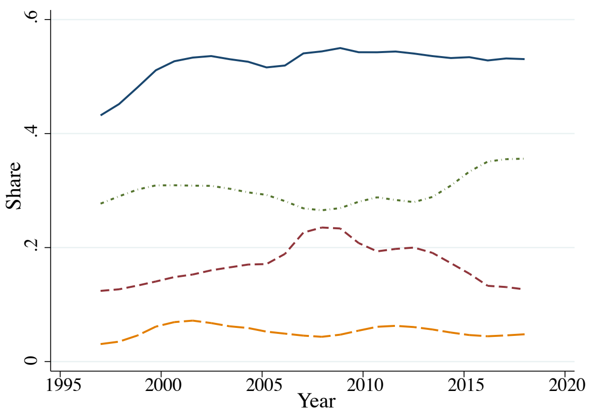
Figure 2. Description of Automation Adopting Firms



(a) Proportion of Adopters

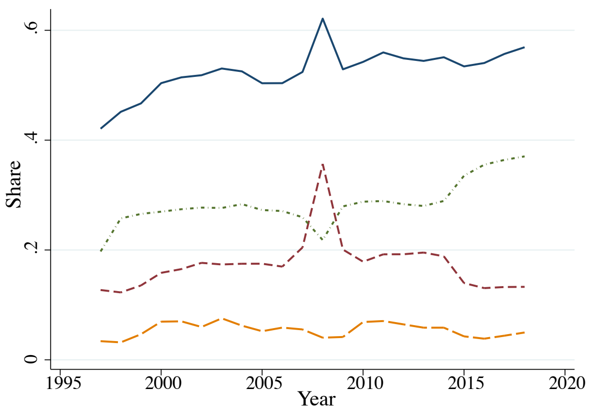


(b) Employment Share of Adopters



(c) Market Share of Adopters

(d) Adopters' Share of Aggregate Total Factor Productivity



(e) Adopters' Share of Aggregate labour Share of Value-Added

Total: ______ , Services: _ . _ . _ , Manufacturing: _ _ _ _ , Mining, Utilities, and Construction: __ __ __

tion function developed by Ackerberg *et al*. (2015).[3] For example, the share depicted by the solid blue line in Figure 2d is $\dfrac{\sum_{j\in\mathcal{A}_t} s_{jt}Z_{jt}}{\sum_j s_{jt}Z_{jt}}$, where $\mathcal{A}_t$ denotes the set of automation adopters in period, t. The weight, s_{jt}, is the revenue share in the entire economy of firm, j, in period, t, and Z_{jt} is the estimated TFP. The adopting firms' shares in the aggregate labour share of value added – ratio of compensation of employees (or employment costs) to gross value added – in Figure 2e are obtained analogously.

In Figure 2d, we find that in recent years the share of adopting firms' TFP in the aggregate increased to more than their market share. While this has been largely due increase in the TFP share of adopting firms in the service sector, adopting firms in all sectors, as can be see in Figure 3, recorded a higher growth in aggregate TFP than non-adopting firms. The higher growth rate of adopting firms' aggregate TFP could result from (a) reallocation of economic activities towards more productive adopting firms, and (b) due to faster growth of adopting firms' TFP compared to the non-adopters'. The latter, as can be seen in Figure 4, seems to be true of firms in the service sector and the sector comprising of mining, utilities, and construction. Also, in all the sectors, an average adopting firm is more productive than an average non-adopting firm.

To understand the growth in aggregate TFP, Z, we decompose changes in aggregate TFP between 2010 ($t = 0$) and 2017 ($t = 1$) for all sectors following the decomposition method in Melitz and Polanec (2015), which has been further extended by Acemoglu *et al*. (2020).[4] Aggregate TFP, as we know, is given by $Z = \sum_j Z_j s_j$, where Z_j is firm j's TFP and the weight, s_j, is firm j's share of revenue in the sector. Melitz and Polanec (2015) show that changes in aggregate TFP, ΔZ, can be decomposed as

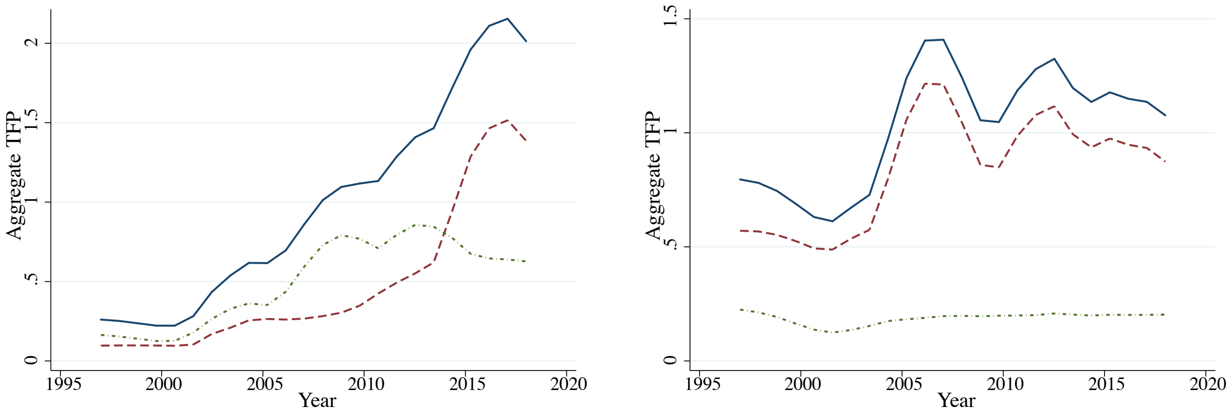
$$\Delta Z = \Delta \bar{Z}_S + \Delta\left[\sum_{j\in S}(Z_j - \bar{Z}_S)(s_j - \bar{s}_S)\right] + s_{X,0}(\bar{Z}_{S,0} - \bar{Z}_{X,0}) + s_{E,1}(\bar{Z}_{E,1} - \bar{Z}_{S,1}), \tag{2.1}$$

where $\bar{Z}_S$ and $\bar{s}_S$, are the unweighted averages of Z_j and s_j respectively of the set of surviving firms, S. Here, subscript S denotes survivors, subscript X denotes exiters and subscript E denotes entrants. The terms, $s_{G,t} = \sum_{j\in G} s_j$ and $\bar{Z}_{G,t} = \sum_{j\in G}(s_j/s_{G,t})Z_j$, respectively, represent

[3] TFP is computed as $\Omega_{jt} = \exp(y_{jt} - \beta_l l_{jt} - \beta_k k_{jt})$ where y_{jt}, l_{jt} and k_{jt} are natural logarithm of value-added, number of employees and replacement value of capital stock. We estimate separate coefficients for the four sets of years: 1997 to 2002, 2003 to 2007, 2008 to 2012, and 2012 to 2018; this allows the coefficients to have some variability over time. We obtain similar results when TFP is computed by Levinsohn and Petrin (2003) method, in which case TFP is computed as $\Omega_{jt} = \exp(y_{jt} - \beta_l l_{jt} - \beta_k k_{jt} - \beta_m m_{jt})$, where y_{jt} and m_{jt} are natural logarithm of gross output and material inputs.

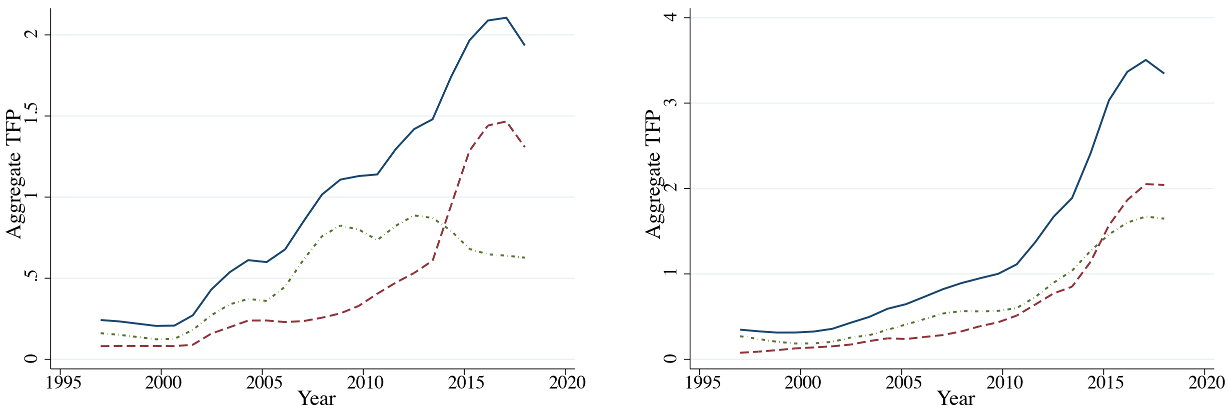
[4] We chose the period 2010-2017 because it overlaps the period chosen by Acemoglu *et al*. (2020), who study changes in labour share for the French manufacturing. It therefore allows us to compare some of our findings to those from a technologically advanced economy. Secondly, it avoids the Financial Crisis years.

Figure 3. Aggregate Total Factor Productivity



(a) Entire Economy

(b) Manufacturing



(c) Services

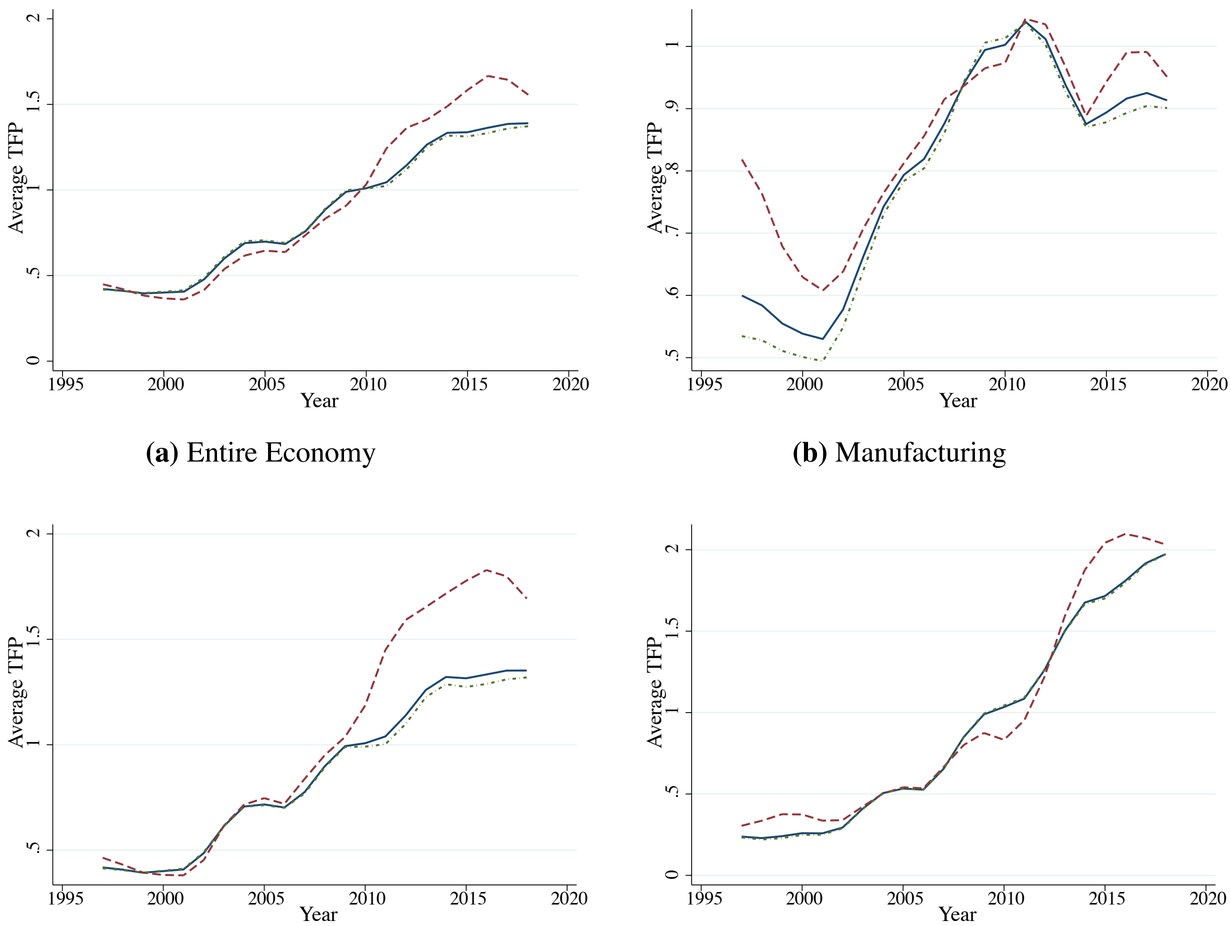
(d) Mining, Utilities, and Construction

All Firms: ______ , Automation Adopters: _ _ _ _ , Non-Adopters: _ . _ . _
Note: Aggregate TFP of 'All Firms' for the year 2010 has been assumed as 1.

the aggregate market share and the aggregate TFP of firms in group G and time period t, where $G \in \{S, X, E\}$ and $t \in \{0, 1\}$.

The first component in equation (2.1) is the change in mean TFP of surviving firms (the within effect), the second component captures resource reallocation between surviving firms (between effect), the third component is the entry effect, and the last term is the exit effect. Aggregate TFP growth for the industry is the sum of these four components. The within effect as shown in Figure 5, Panel A, is the sum of change in the mean TFP for automation adopting firms and the change in the same for non-adopters. Also, as in Acemoglu *et al*. (2020), the between/reallocation effect is further decomposed into (i) the effect due to the reallocation towards automating firms, and (ii) a residual reallocation effect (see Appendix C.3 for details). All figures in Figure 5 are

Figure 4. Unweighted Average Total Factor Productivity



(a) Entire Economy **(b)** Manufacturing

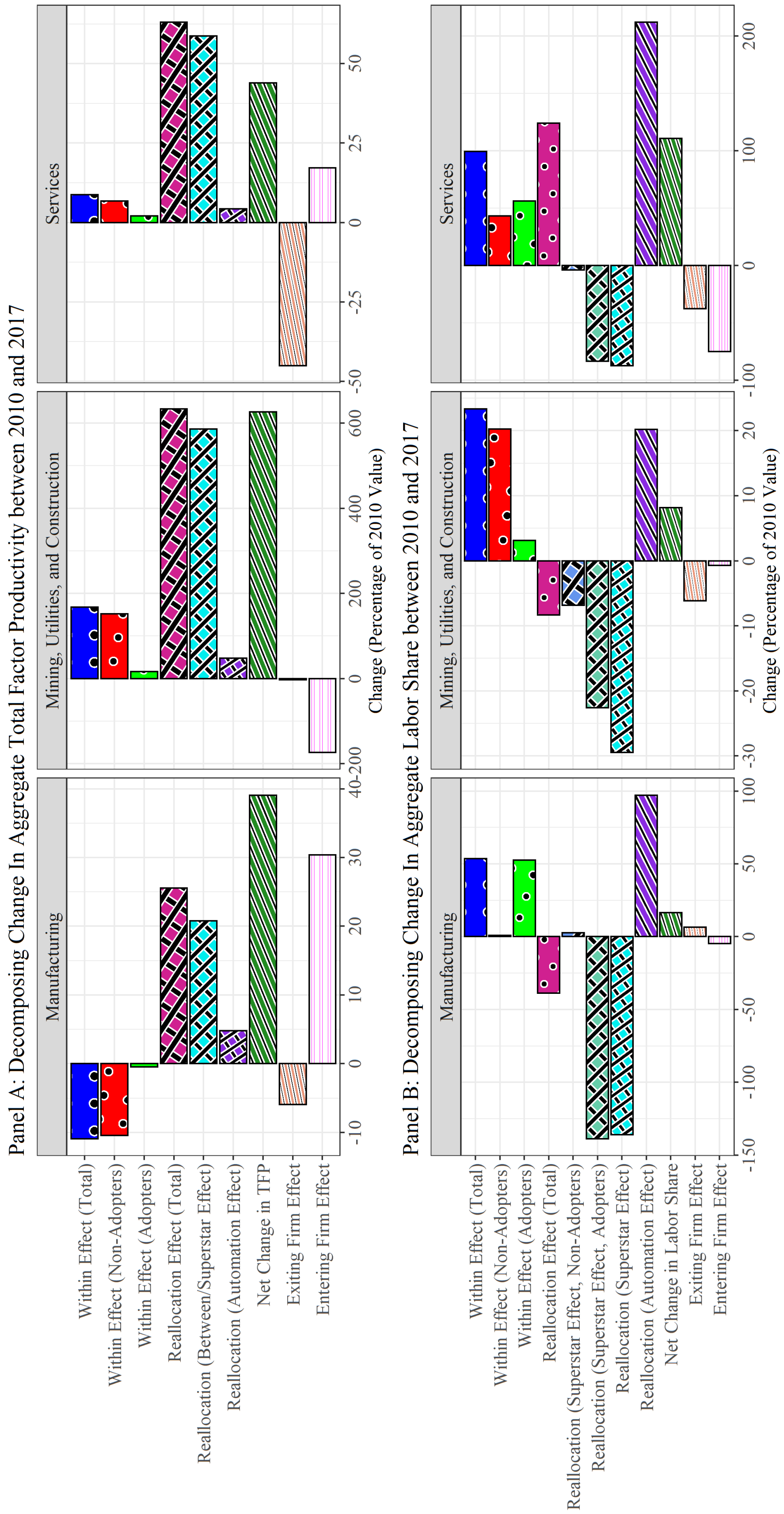
(c) Services **(d)** Mining, Utilities, and Construction

All Firms: ______ , Automation Adopters: _ _ _ _ , Non-Adopters: _ . _ . _
Note: Average unweighted TFP of 'All Firms' for the year 2010 has been assumed as 1.

expressed as a percentage of aggregate TFP in 2010 ($t = 0$).

Figure 5, Panel A, shows that in the service sector and the sector comprising mining, utilities, and construction, the average within-firm changes in TFP for both adopters and non-adopters among surviving firms are positive. In the manufacturing sector, the average within-firm TFP for both sets of surviving firms has declined; although the decline is much larger for the non-adopters.

Figure 5. Decomposition of Changes in Aggregate Labour Share and Aggregate Total Factor Productivity



However, the entry effect for the manufacturing sector is positive and large. A further decomposition of the entry effect[5] for the manufacturing sector shows that entry effect is large only because of the adopters among the entrants: the entry effect due to the adopters is 31% whereas the same due to non-adopters is -0.4%.[6]

We find that the reallocation effects are large and positive in all sectors. The residual reallocation effects are larger than the "Reallocation (Automation Effect)", which is the effect due to the reallocation of resources from the less productive non-adopters towards the more productive adopters. This suggests that TFP growth in each sector is largely due to resources being reallocated from low productivity firms to high productivity firms among the adopters and the same happening among the non-adopters. Still, a significant proportion of the reallocation effects are also due the "Automation Effect"; this, as we will see, is one of the prime reasons for the increase in labour share.

As far a labour share of value-added (LSVA) is concerned, in Figure 2e we also find that the share of adopting firms' labour share of value-added in the aggregate, mirroring the market/revenue share, has increased. In Figure 6, we plot the aggregate LSVA for automation adopting and non-adopting firms. The weights used when plotting for the individual sectors are the revenue shares for the firms within that sector, and the weights when we plot for the entire economy are revenue shares for the firms in the entire economy. In Figure 7, we plot the unweighted aggregate LSVA for automation adopting and non-adopting firms.

First, notwithstanding the decline following the Global Financial Crisis, in Figure 6 we find that the aggregate LSVA has been rising, especially in recent years. However, compared to the other developed economies, the LSVA is arguably still low (Kónya *et al*., 2020). The increase can therefore be thought of as "catching-up" to the levels observed in the OECD countries. Second, contrary to the findings for the developed economies; for example Koch *et al*. (2021), who estimate for Spanish manufacturing, we find that aggregate (weighted and unweighted) LSVA for adopting firms in the manufacturing sector is higher than that for non-adopting firms. In the services sector, aggregate (weighted and unweighted) LSVA for adopting firms in recent

[5]The entry effect, $s_{E,1}(\bar{Z}_{E,1} - \bar{Z}_{S,1})$, can be further decomposes as

$$s_{E,1}(\bar{Z}_{E,1} - \bar{Z}_{S,1}) = s^{\text{A}}_{E,1}(\bar{Z}^{\text{A}}_{E,1} - \bar{Z}_{S,1}) + s^{\text{N}}_{E,1}(\bar{Z}^{\text{N}}_{E,1} - \bar{Z}_{S,1}),$$

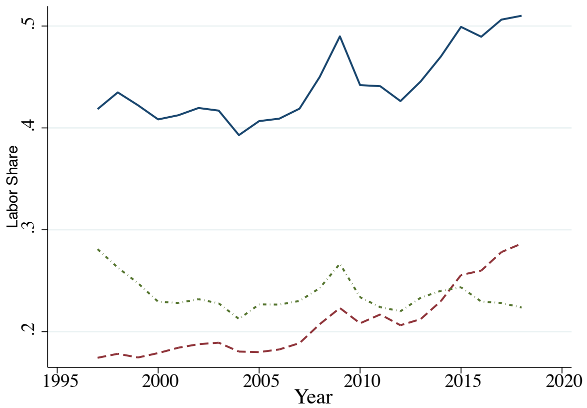
where the first component is the entry effect due to adopters and the second is the same due to non-adopters. $s^{\text{A}}_{E,1} = \sum_{j \in E^{\text{A}}} s_j$ and $s^{\text{N}}_{E,1} = \sum_{j \in E^{\text{N}}} s_j$, where E^{A} is the set of automation adopting entrants and E^{N}, the set of non-adopting entrants. And $\bar{Z}^{\text{A}}_{E,1}$ and $\bar{Z}^{\text{N}}_{E,1}$ are $\sum_{j \in E^{\text{A}}}(s_j/s^{\text{A}}_{E,1})Z_j$ and $\sum_{j \in E^{\text{N}}}(s_j/s^{\text{N}}_{E,1})Z_j$ respectively.

[6]The results should be interpreted with caution, as entry and exit can occur because of merger and acquisition and spin-off activities rather than de novo start-ups or closing down of establishments.

Figure 6. Aggregate Labour Share of Value-Added

(a) Entire Economy

(b) Manufacturing



(c) Services

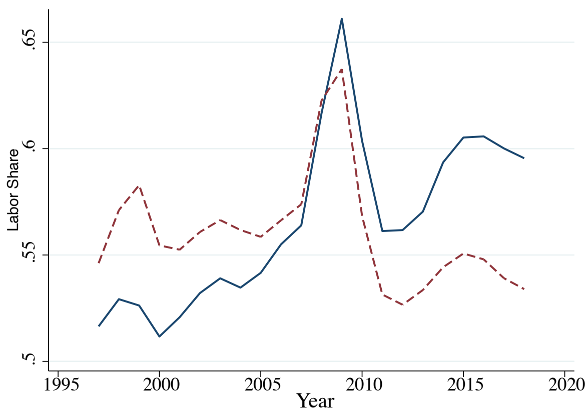
(d) Mining, Utilities, and Construction

All Firms: ______ , Automation Adopters: _ _ _ _ , Non-Adopters: _ . _ . _

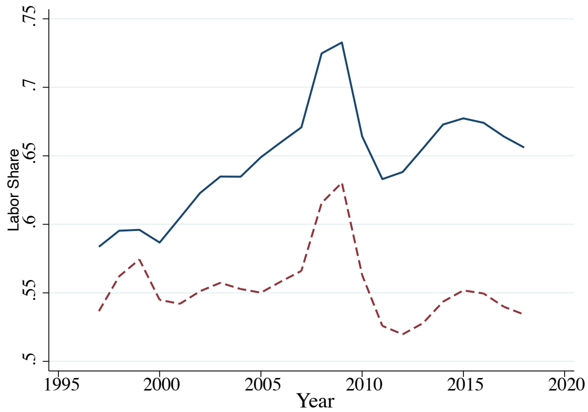
years surpassed that of non-adopting firms. This is also the reason why in Figure 2c, apart from the fact that their market share is higher, adopting firms, which constitute a small fraction, command a majority share in aggregate LSVA.

To understand the recent increase in the aggregate LSVA, we decompose the changes in it – as for the changes in aggregate TFP – between 2010 and 2017. First, as can be seen from Figure 5, Panel B, the aggregate LSVA increased in all sectors. This is because, both the within effect – for both the adopters and the non-adopters – and, strikingly, the reallocation effects due to reallocation from less productive non-adopters to more productive adopters (Automation Effect) are positive. While LSVA increased *within* all surviving firms, in the manufacturing and the services sectors, the within effect is higher for adopters compared to non-adopters.

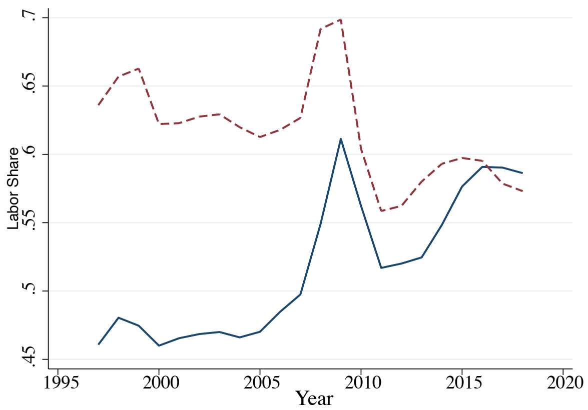
Figure 7. Unweighted Aggregate Labour Share of Value-Added



(a) Entire Economy



(b) Manufacturing



(c) Services

(d) Mining, Utilities, and Construction

Automation Adopters: ______ , Non-Adopters: _ _ _ _ .

What is striking is that the reallocation effects due to reallocation from less productive non-adopters towards more productive adopters are large and positive. Given that adopters have a higher market share, which has increased over time, this can happen if the *unweighted (or within)* aggregate LSVA for the adopters is larger than or surpasses the same for the non-adopters (see Figure 7). This positive effect is complemented if the *unweighted* aggregate LSVA for the non-adopters is smaller than or refuses to fall below the same for the adopters. The steep rise in the unweighted LSVA among automation adopters in the service sector since 2011 (see Figure 7c) is therefore likely to be the primary reason why the "Reallocation (Automation Effect)" for the service sector is large. These results are contrary to the findings in Acemoglu *et al*. (2020), who decompose change in the aggregate LSVA for the manufacturing sector in France.

What is common with Acemoglu *et al*. (2020) is that the residual reallocation effects (or "Superstar Effect") are negative. That is, the reallocation of resources from less productive adopting firms towards the more productive adopting firms with larger market shares, which increased the aggregate TFP, reduced the aggregate LSVA. A similar phenomenon, though much less pronounced, is found for the non-adopting firms. These results suggest that the "Superstar Effect" (Autor *et al*., 2020) – whereby highly productive firms with above-average mark-ups and below-average labour share of value-added are able to expand at the expense of their competitors, thereby resulting in higher market concentration – is underway in all sectors, but more so among adopters.

To understand why the aggregate LSVA in Estonia increased (a) due to increased LSVA within all firms, and (b) in contrast to the findings for the developed economies, due to the reallocation of resources from non-adopters towards adopters, consider the task-based framework developed in Acemoglu and Restrepo (2018a,b, 2019b,a), where the aggregate output of an industry is produced by combining the services of a unit measure of tasks $i \in [N-1, N]$ according to the following aggregator:

$$Y = \left(\int_{N-1}^{N} y(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}, \tag{2.2}$$

where $y(i)$ denotes the output of task, i, and $\sigma \in (0, \infty)$ is the elasticity of substitution between tasks. All tasks are produced competitively. The creation of new tasks is modelled as an increase in N. Assuming that the final output, Y, is competitively produced and assuming its price as the numéraire, it can be shown that the demand for task i is given as

$$y(i) = Y\big(p(i)\big)^{-\sigma}, \tag{2.3}$$

where $p(i)$ is the unit cost incurred in producing task i.

For industry Φ, which lies between $N-1$ and N, the threshold task is such that all tasks i in (2.2) that are greater than Φ are technologically non-automated and have to be produced by labour with the production function,

$$y(i) = A^L \gamma(i) l(i), \tag{2.4}$$

where $\gamma(i)$ denotes the productivity of labour in task i. On the other hand, for tasks $i \leq \Phi$, which are technologically automated, capital and labour are perfect substitutes, that is,

$$y(i) = A^K \eta(i) k(i) + A^L \gamma(i) l(i), \tag{2.5}$$

where $\eta(i)$ is the productivity of capital in task i. The labour-augmenting technology term A^L and the capital-augmenting term A^K increase the productivity of labour and capital in all tasks they currently produce. The threshold Φ denotes the frontier of automation possibilities. This threshold can rise over time due to advancements in automation, artificial intelligence, industrial robotics, etc.

As in Acemoglu and Restrepo (2019b,a), it is assumed that it is cost-minimising to use capital in all tasks that can be automated[7] and labour is more productive in a newly created task; that is,

$$\frac{R}{\eta(i)A^K} < \frac{W}{\gamma(i)A^L} \text{ for all } i \in [N-1, \Phi] \text{ and } \frac{R}{\eta(N)A^K} > \frac{W}{\gamma(N)A^L}, \tag{2.6}$$

where $\frac{R}{\eta(i)A^K}$ is the effective price of capital used in task i and $\frac{W}{\gamma(i)A^l}$ is the effective price of labour used in task i. From equations (2.3), (2.4) and (2.5) it, therefore, follows that the total demand for capital and labour respectively are:

$$Y\int_{N-1}^{\Phi}\frac{1}{A^K\eta(i)}\left(\frac{R}{A^K\eta(i)}\right)^{-\sigma}di \text{ and } Y\int_{\Phi}^{N}\frac{1}{A^L\gamma(i)}\left(\frac{W}{A^L\gamma(i)}\right)^{-\sigma}di. \tag{2.7}$$

For exposition, as in Acemoglu and Restrepo (2019b), we assume that the supply of labour, L, and the supply of machines, K, are fixed and that they are supplied inelastically.[8] Equating the total demand for factors in (2.7) to their supply, we obtain the market clearing conditions:

$$R = \left(\frac{Y}{K}\int_{N-1}^{\Phi}(A^K\eta(i))^{\sigma-1}di\right)^{\frac{1}{\sigma}} \text{ and } W = \left(\frac{Y}{L}\int_{\Phi}^{N}(A^L\gamma(i))^{\sigma-1}di\right)^{\frac{1}{\sigma}}. \tag{2.8}$$

Following the steps in Section 3, it can be shown that the equilibrium output of the sector is produced using the following CES production function:

$$Y = \left(\left(\int_{N-1}^{\Phi}\eta(i)^{\sigma-1}di\right)^{\frac{1}{\sigma}}(A^K K)^{\frac{\sigma-1}{\sigma}} + \left(\int_{\Phi}^{N}\gamma(i)^{\sigma-1}di\right)^{\frac{1}{\sigma}}(A^L L)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{2.9}$$

From equation (2.8) it follows that the shares of capital and labour are given by

$$\begin{aligned} S_K &= \frac{RK}{Y} = \left(\frac{Y}{K}\right)^{\frac{1-\sigma}{\sigma}}\left(\int_{N-1}^{\Phi}(A^K\eta(i))^{\sigma-1}di\right)^{\frac{1}{\sigma}} \text{ and} \\ S_L &= \frac{WL}{Y} = \left(\frac{Y}{L}\right)^{\frac{1-\sigma}{\sigma}}\left(\int_{\Phi}^{N}(A^L\gamma(i))^{\sigma-1}di\right)^{\frac{1}{\sigma}}. \end{aligned} \tag{2.10}$$

[7] See Acemoglu and Restrepo (2019a) for a discussion regarding this assumption.

[8] These assumptions are relaxed in Acemoglu and Restrepo (2018b), where a representative household with a certain preference over consumption, C, and labour, L, implies a labour supply function that increases in $\frac{W}{C}$. They show that automation reduces employment because it raises aggregate output (or consumption) per worker more than it raises wages (as shown below, automation may even reduce wages). Therefore, the negative income effect on the labour supply resulting from greater aggregate output dominates any substitution effect that might follow from the higher wages. On the other hand, the creation of new tasks always increases employment: new tasks raise wages more than aggregate output, increasing the labour supply.

From the above, it is clear that LSVA and wages (equation (2.8)) depend on labour productivity, $\frac{Y}{L}$,[9] and the labour task content of production, $\int_{\Phi}^{N}(A^{L}\gamma(i))^{\sigma-1}di \equiv \tau(\Phi, N)$, which is the measure of the set of tasks allocated to labour weighted by the "importance" of the tasks (Acemoglu and Restrepo, 2021b).

Table 1. Reduced Form Regressions

Panel A: Using Firm Level Data.			
Regressors	Manufacturing	Services	Mining, Utilities, and Construction
Dependent Variable: Change in LSVA between 2011 and 2017. Method: OLS.			
Dummy for Automation	-0.021	-0.001	-0.020
	(0.023)	(0.011)	(0.033)
Lag of ln(Labour Productivity)	0.095***	0.090***	0.119***
	(0.012)	(0.004)	(0.010)
Number of Observations	1895	11476	2119
Dependent Variable: Annual Changes in LSVA. Time Period: 2010 to 2017. Method: Fixed Effects.			
Dummy for Automation	-0.043*	-0.030**	0.023
	(0.023)	(0.015)	(0.055)
Lag of ln(labour Productivity)	0.281***	0.208***	0.303***
	(0.005)	(0.002)	(0.005)
Number of Firms	5394	33994	7956
Number of Observations	22605	137488	27248

Note: The control variables are (i) lag of log of number of employees, (ii) dummy for North Estonia, (iii) age of the firm, (iv) dummies for NACE 2-digit industry classification, (v) time dummies, and (vi) interactions of time and industry dummies.

Panel B: Using Industry Wise Aggregated Data.			
Dependent Variable: Annual Changes in Industry Wise Aggregate LSVA. Time Period: 2010 to 2017. Method: OLS.			
$\sum_j s_{jt}D_{jt}^{A}$	-0.264***	-0.095***	-0.017
	(0.083)	(0.035)	(0.095)
$\sum_j s_{jt}Z_{jt}$	0.042**	0.032***	0.053**
	(0.019)	(0.009)	(0.021)
Number of Observations	161	308	60

Significance levels : $*$: 10% $**$: 5% $***$: 1%. Standard Error in Parenthesis

Note: s_{jt}: Revenue Shares. D_{jt}^{A}: Dummy for Automation. Z_{jt}: logarithm of labour Productivity. The control variables are (i) lag of weighted average of logarithm of number of employees, (ii) proportion of firms in North Estonia (iii) dummies for NACE 2-digit industry classification, and (iv) time dummies.

[9] We are not aware of studies that have estimated the aggregate elasticity of substitution for Estonia, or for that matter the same for the various industries in Estonia. However, we can rely on the meta-analysis by Gechert *et al.* (2021), who find that the mean estimates for the developed European countries and for the developing countries are below 1. And, therefore, for realistic values of σ, the exponent of $\frac{Y}{L}$, $\frac{1-\sigma}{\sigma}$, in equation (2.10) is positive.

Automation, which is modelled as an increase in Φ, reduces aggregate LSVA by reducing the share of tasks performed by labour. However, from equations (2.8) and (2.10) it is clear that wages and LSVA will increase if productivity – including that due to automation – increases. To see this, consider Table 1, where Panel A, which uses firm level data, illustrates the results of reduced form regressions of changes in LSVA on value-added labour productivity in the base period and the dummy for automation, a firm level indicator of task displacement (we will return to the issue of measuring task displacement at the end of this section). Panel B of Table 1 illustrates the regression of changes in aggregate LSVA on the aggregate measures of automation and labour productivity. The aggregation is at the level of NACE 2-digit industry classification and the weights used for the aggregation are the revenue shares of the firms. The results in Panel A show that compared to automation, which negatively affects LSVA by reducing the share of tasks performed by labour, the effect of labour productivity on changes in LSVA is significant and even larger than an order of magnitude. The results for the aggregated data show a large negative influence of the aggregate measure of automation. However, since the weights used for aggregating are the market shares of the firms, the relatively large negative coefficients of the aggregate measure of automation likely reflect the confounding influence of the Superstar Effect.

Since, as shown in Figure 8, the value-added labour productivity of the adopting firms is higher than that of non-adopters, partly due to their higher TFP (see Figure 4), the reduced form regressions imply that aggregate LSVA increased due productivity effects: first, productivity increased LSVA among adopters, and second, the reallocation of economic activities from non-adopters towards the more productive adopters, which increased the market share of the adopters, further increased aggregate LSVA.

To understand how labour share of value-added (LSVA) is affected by automation, productive new jobs, and the various channels that affect productivity, $\frac{Y}{L}$, using equations (2.8) and (2.9), we can write the change in LSVA as

$$
\begin{aligned}
d\ln(S_L) =& \frac{1-\sigma}{\sigma} d\ln\left(\frac{Y}{L}\right) + \frac{1}{\sigma} d\ln(\tau(\Phi, N)) \\
=& \underbrace{-\frac{1}{\sigma}\left[\frac{(A^L\gamma(\Phi))^{\sigma-1}}{\tau(\Phi,N)}\right] d\Phi}_{\substack{\text{Decline in LSVA due to} \\ \text{Task Displacement}}} + \underbrace{\frac{1}{\sigma}\left[\frac{(A^L\gamma(N))^{\sigma-1}}{\tau(\Phi,N)}\right] dN}_{\substack{\text{Increase in LSVA due to} \\ \text{Creation of Highly Productive New Jobs}}} \\
& + \underbrace{\frac{1}{\sigma}\left[\left(\frac{W}{A^L\gamma(\Phi)}\right)^{1-\sigma} - \left(\frac{R}{A^K\eta(\Phi)}\right)^{1-\sigma}\right] d\Phi}_{\substack{\text{Increase in LSVA due to} \\ \text{Productivity impact of Cost Saving from Task Displacement}}} \\
& + \underbrace{\frac{1}{\sigma}\left[\left(\frac{R}{A^K\eta(N-1)}\right)^{1-\sigma} - \left(\frac{W}{A^L\gamma(N)}\right)^{1-\sigma}\right] dN}_{\substack{\text{Increase in LSVA due to} \\ \text{Productivity impact of Creation of Highly Productive New Jobs}}} \\
& + \underbrace{(1-S_L)d\ln\left(\int_{\Phi}^{N}(A^L\gamma(i))^{\sigma-1}di\right)^{\frac{1}{\sigma}}\Bigg|_{\Phi,N} - S_K d\ln\left(\int_{N-1}^{\Phi}(A^K\eta(i))^{\sigma-1}di\right)^{\frac{1}{\sigma}}\Bigg|_{\Phi,N}}_{\substack{\text{Productivity impact of (i) Knowledge Spillovers and/or Transfer from (a) Imports} \\ \text{Led Automation, (b) FDI, and (c) becoming a part of the Global Value Chain;} \\ \text{(ii) Firm Level Productivity enhancement measures (see equation (3.8)); and} \\ \text{(iii) Other Factor Augmenting and Productivity Deepening Efforts}}}.
\end{aligned}
\tag{2.11}
$$

Automation, while reducing labour share of task, which reduces LSVA, also raises output and productivity because capital is more cost-effective than labour in the newly automated tasks (see equation (2.6)), a share of which goes to labour. The creation of new jobs increases LSVA (a) because it increases the labour share of task, and (b) because according to the assumption in equation (2.6), the new tasks are labour intensive and highly productive.

Since $\ln(S_L) = (1-\sigma)\ln(W) + \ln\tau(\Phi, N)$, the reduction in LSVA due to automation in (2.11) encapsulates the direct effect of the reduction in labour task content of production as well as the effect of this reduction on wages. It can verified that $\frac{d\ln(W)}{d\Phi} = -\frac{1}{\sigma}\left[\frac{(A^L\gamma(\Phi))^{\sigma-1}}{\tau(\Phi,N)}\right]$. The reduction in the share of tasks worked by labour bunches workers into fewer tasks. To compensate, workers produce more $y(i)$ in each of the remaining tasks, i, still worked by labour. However, because there is diminishing returns to $y(i)$ in the aggregate production function, (2.2), this bunching puts downward pressure on wages (see Acemoglu and Restrepo, 2018b). The same argument "in reverse" applies to the LSVA impact of the creation of productive new jobs, dN, which increases the labour task content of production.

The last expression in equation (2.11) represents changes in factor augmenting and productivity terms for the given values of Φ and N. Now, improvements in factor augmenting and productivity terms, while improving the productivity of the respective factors, reduces the price of the tasks the respective factors produce (see equation (2.6)). Consequently, improvements in A^L and $\gamma(i)$ reduce the price of the labour task content of production, $\int_{\Phi}^{N}(A^L\gamma(i))^{\sigma-1}di \equiv \tau(\Phi, N)$. However, at the same time, improvements in A^L and $\gamma(i)$ raise output and the productivity of labour. If $\sigma < 1$, the price effect dominates to potentially reduce wages and LSVA in a static economy.[10]

The above formalism, however, makes it clear that automation by reducing the task content of production reduces LSVA, but the creation of productive new jobs, cost saving due to automation and other technological changes, raise productivity. The increase in productivity raises labour demand and wages,[11] which in turn increase LSVA. Below we discuss the various channels through which technological changes are affected.

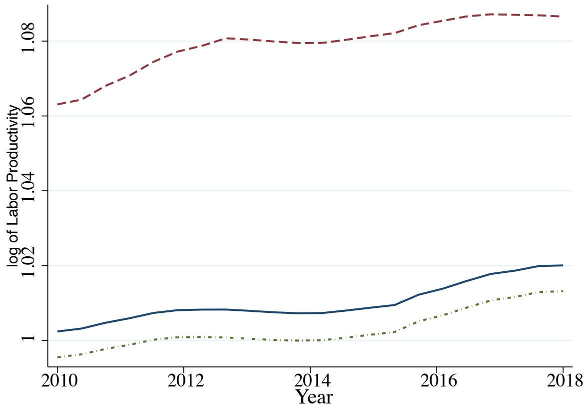
Now, Acemoglu and Restrepo (2021b), calibrating their general equilibrium model, which links changes in wages of demographic groups to task displacements for the US, find that the productivity impact from cost savings accounts for a modest 3.8%, at best 6.3%, of the TFP growth. The rest of the TFP growth, which grew by 35% during 1980 to 2016, is attributable to "productivity deepening, factor augmenting, sectoral TFP, or even new tasks".

In catching-up economies, however, which lag behind the technological frontier and where automation is primarily imports-led and FDI-facilitated, automation in addition to saving costs leads to technology spillovers and transfers. The idea dates back to Grossman and Helpman (1991), who identified trade and FDI as channels through which a country's R&D affects the TFP of its trade partners. Keller (2010) argues that since there are fixed costs of foreign market entry, it is the highly productive firms that are internationally active in most of the foreign markets. Given their higher productivity, the potential for technological learning from foreign firms is higher than from interacting with an average domestic firm. Empirically, Coe and Helpman

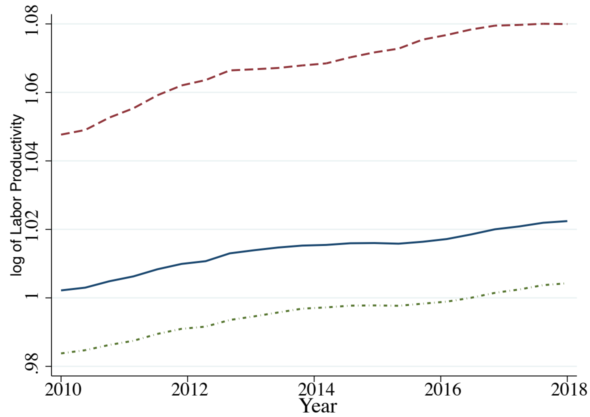
[10] Acemoglu and Restrepo (2018b), as in much of the growth literature, consider only labour-augmenting technological changes in addition to the two main technological changes – automation and the creation of new jobs/tasks – to investigate the conditions under which such an economy admits a balanced growth path. They show that along the balanced growth path, where factor shares are constant, output, consumption and capital grow at the rate of $g = \Delta A$, where Δ is the rate of the creation of new jobs, which is equal to the rate of job displacement due to new automation technologies, and A is the growth rate of labour-augmenting technology. Grossman *et al.* (2017) emphasize other mechanisms to account for phenomena such as the declining price of investment goods, which is symptomatic of investment-specific technical change, but which is inconsistent with the Uzawa Growth Theorem. In Grossman *et al.* (2017), capital-augmenting technological progress and endogenous schooling in the presence of "capital-skill complementarity" achieves balanced growth in the presence of falling investment-good prices.

[11] Although all sources of technological change – increases in Φ, N, $(A^L, \gamma(i))$ and $(A^K, \eta(i))$ – increase labour productivity, Y/L, because $\ln(W) = \frac{1}{\sigma}\ln(Y/L) + \frac{1}{\sigma}\ln(\tau(\Phi, N))$, automation, which reduces the labour task content of production, $\tau(\Phi, N)$, and labour augmenting technical changes, which reduce the price of the labour task content of production, exerts downward pressure on wages when $\sigma < 1$.

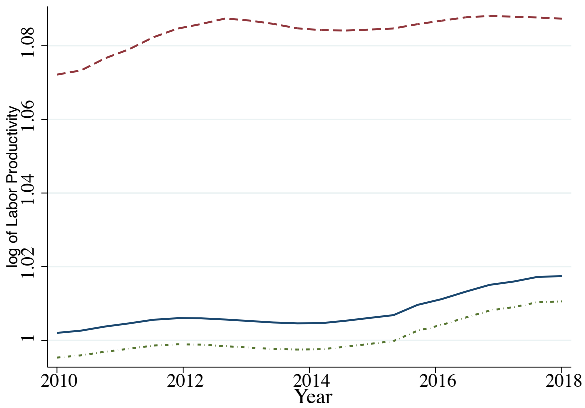
Figure 8. Unweighted Average log of Labour Productivity



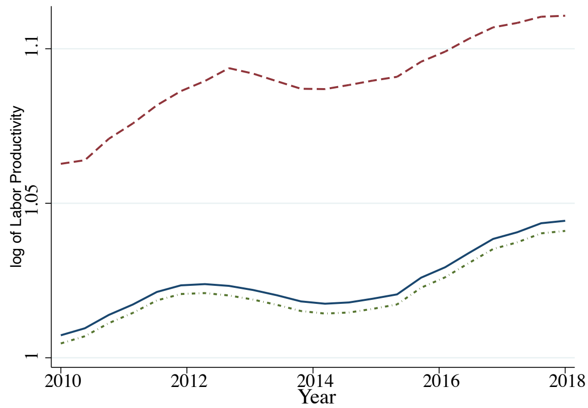
(a) Entire Economy



(b) Manufacturing



(c) Services



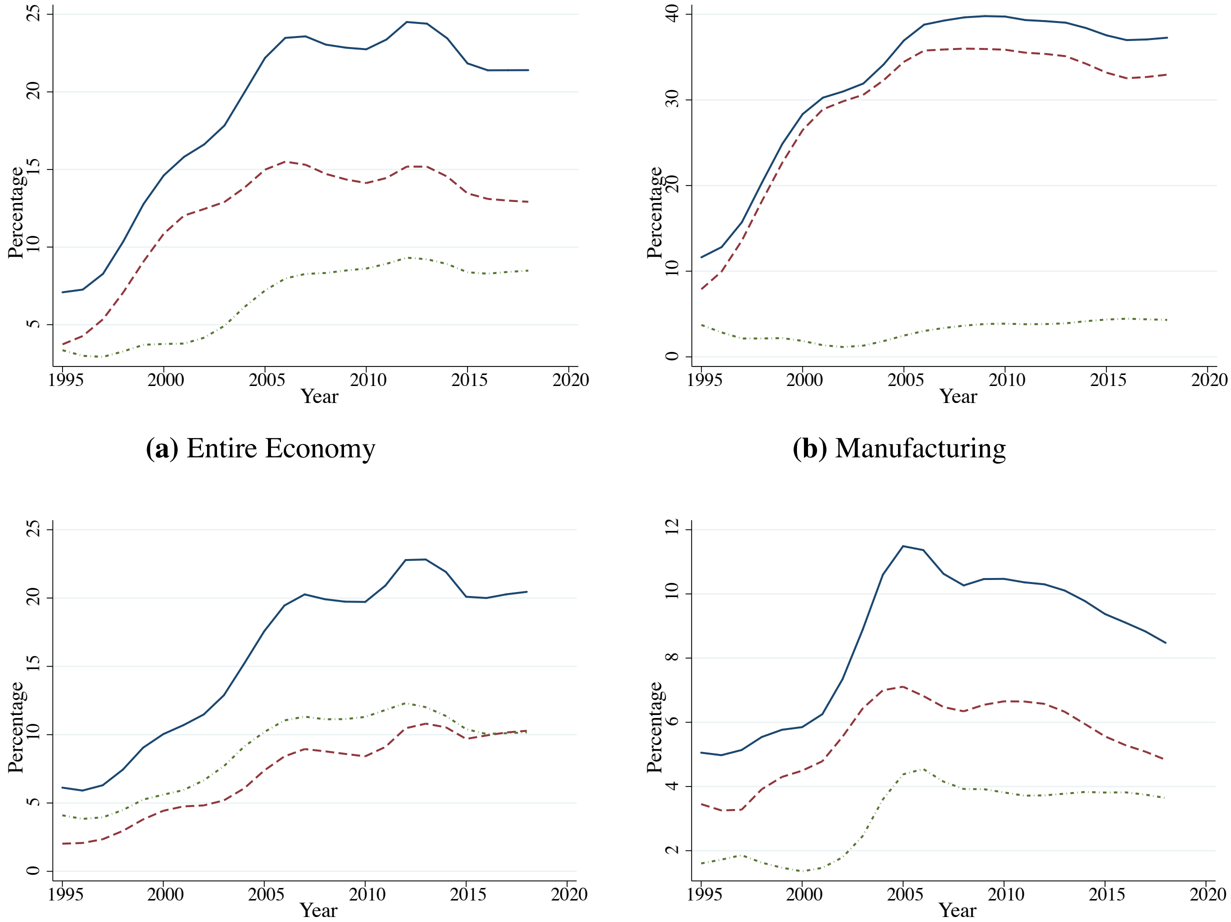
(d) Mining, Utilities, and Construction

All Firms: ______ , Automation Adopters: _ _ _ _ , Non-Adopters: _ . _ . _
Note: Labour Productivity of 'All Firms' for the year 2010 has been assumed as 1.

(1995), Madsen (2007), and Coe *et al*. (2009) have shown that the international transmission of R&D knowledge through the channel of trade is a significant contributor to TFP growth.

Cséfalvay (2020) studying the growing stock of robots in Central and Eastern Europe (CEE), argues that one of the main drivers of the integration of CEE countries into the European Single Market after their accession to the European Union in 2004 was the large-scale FDI flow into the region. This has partly been in search of new consumer markets, but mostly in search of relatively well-skilled labour at low cost. European global companies working in industries with middle or higher skills demands, therefore, 'nearshored' their activities to CEE countries by deploying industrial robots for routine and automatable tasks while employing well-skilled labour at low cost for other complementary and supplementary activities.

Figure 9. Aggregate of the Percentage of Shares of Firms Owned by Multinationals



(a) Entire Economy

(b) Manufacturing

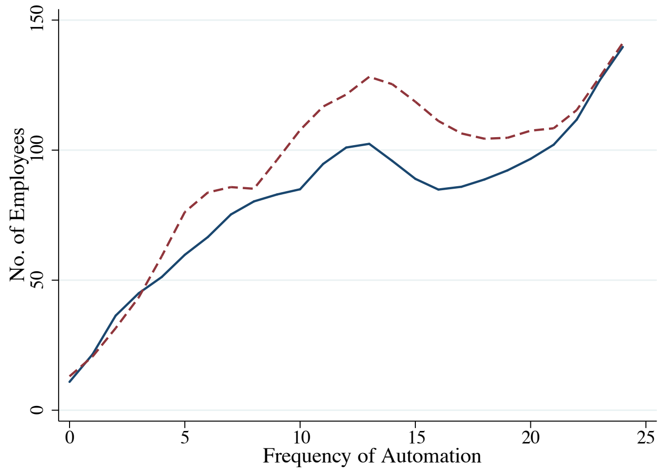
(c) Services

(d) Mining, Utilities, and Construction

All Firms: ______ , Automation Adopters: _ _ _ _ , Non-Adopters: _ . _ . _
Note: The weights used for aggregation are the employment shares of firms.

Between 1995 and 2018, 12.5% of the firm-years are those in which multinationals had some ownership, and of these, a large percentage ($\sim$ 77%) are those where multinationals held the majority of shares. The corresponding percentages for the population of automation adopters are 34% and 74%. In Figure 9 we plot the aggregate of the percentage of shares of firms owned by multinational enterprises. The figure suggests that FDI by multinationals is more likely for financing investments in automation activities, and almost all FDI by multinational companies in the manufacturing sector has been to finance investments in automation. This, as suggested by Céfalvay (2020), is likely to be true of other CEE countries. Such investments are accompanied by knowledge transfers and other spillover effects that have likely contributed to increase the aggregate TFP and LSVA. Besides, instead of displacing labour from task, the FDI in automation is likely to have created productive new jobs, which were previously unknown in the host

Figure 10. Firm Size by Automation Frequency



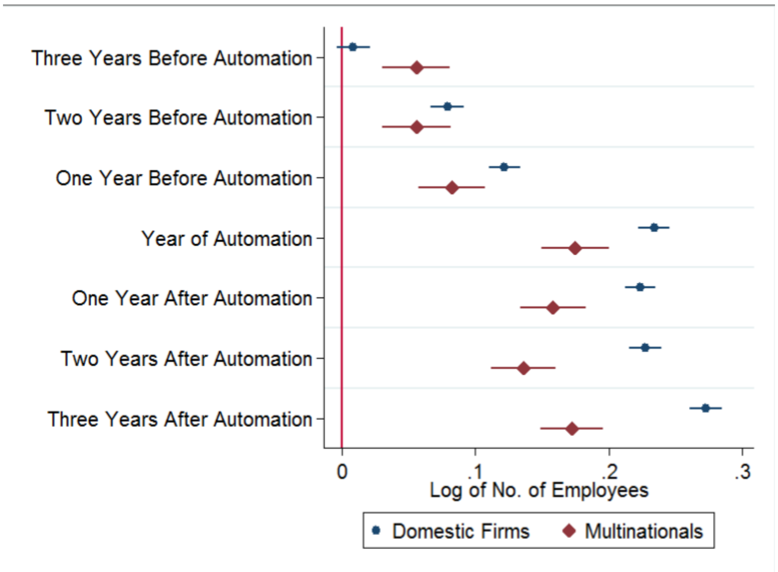
Domestic Adopters: ______ , Multinational Adopters: _ _ _ _ ,

(Estonian) economy. So, in the aggregate, while these automation adopting global companies may have helped increase Φ, the share of tasks preformed by capital, they are also likely to have contributed to increasing N.

While we do have information on the skill distribution of employees pre and post automation, some evidence that multinationals investing in automation have created productive new jobs can be found in Figure 10, which plots firm size as measured by number of employees against frequency of importing capital goods for automation, and in Figure 11, which plots the coefficients from the fixed effect regression of the log of number of employees on dummies that denote time before and after the import of capital goods for automation. Figure 10 shows that firms that automate frequently are larger and that, on average, multinationals employ more people. Figure 11 shows that both multinationals and domestic adopters increase employment in the year automation is adopted and in the years following the adoption.

In other papers, Barro and Sala-I-Martin (1997) argue that follower countries tend to catch up to leaders because imitation and implementation of discoveries are cheaper than innovation. The equilibrium rate of growth in a catching-up economy depends on the cost of imitation and on its initial stock of knowledge. If the cost of imitation is lower than the cost of innovation, the catching-up economy grows faster than the advanced one, which results in convergence. Similar ideas are discussed in Aghion and Jaravel (2015), where it is argued that the process of diffusion, or technology spillover, is an important factor behind cross-country convergence. However, in line with the theory of absorptive capacity by Cohen and Levinthal (1989), the

Figure 11. Employment Response (in Logs) to Automation



Note: A firm is classified as a multinational if a positive fraction of its shares is owned by a foreign enterprise. All firms from 1995 to 2018 are included in the regression. The data comprises of 211586 domestic firms with 1201320 observations, while the corresponding numbers for multinationals are 24471 and 112756. The specification includes year and time dummies and their interactions.[a]

[a]The total number of operating enterprises, which has been rapidly increasing, in Estonia as of 2019 is about 85K. The very large number of firms in the regression is due the fact that the data consists of firms that for various reasons no longer exist.

process of catching-up depends on the current stock of skilled workers: the more backward the country, the more skilled workers are required for the country to catch up with the technological frontier.

The factor-augmenting terms, A^K and A^L, which denote disembodied technical knowledge, increase through investments in R&D and innovation.[12] In catching-up economies, because of knowledge spillovers and transfers of new technological know-how in imports-led and FDI-facilitated automation, capital goods for automation, which embody investment specific knowledge, help factor-augmenting technical change. However, knowledge spillovers are not the only source of technological change. In our data, firms that adopt automation are larger and older, and Estonian incumbents, as Masso and Tiwari (2021) document, are the primary carriers of 'scientific and technologically-based innovative' (STI) activities.

The formalism above assumes a single sector economy. Autor and Salomons (2018) empirically show that in addition to the *direct* effect of industry-specific technological changes on various outcomes of interest, such as employment and LSVA, there are *indirect* effects, which are the general equilibrium effects of the same technological forces.[13] The *direct* effect, as discussed above in the case of automation, is the net of the displacement effect and productivity effect. The *indirect* effects they identify are the effects due to (i) input–output linkages, (ii) changes in final demand, and (iii) between-industry compositional shifts. They argue that the effect of productivity growth occurring in an industry is unlikely to be confined to the sector in which it originates. The input–output linkage effect refers to various positive upstream and downstream spillover effects on outcomes related to labour. Second, productivity growth in each industry augments aggregate income, and hence it indirectly raises the final demand for the outputs of all industries, which in turn affects wages and employment in all industries. Finally, compositional shifts refer to the effect of uneven productivity growth across industries, which shifts the industries' shares of value-added, which in turn alter aggregate labour share of value-added (see also Acemoglu and Restrepo, 2019b). They find that for developed economies the direct effect decreases both employment and LSVA. However, the indirect effects are sizeable and are countervailing for employment, but not so for LSVA. For LSVA, the indirect effects complement the direct effect, which dominates, to further lower the LSVA. In a similar vein, Gregory *et al.* (2021) argue that declining capital costs of routine-replacing technologies by reducing the prices of final goods increases the demand for the goods, which induces additional employment. This also has a spillover effect because the increase in product demand raises incomes, which is par-

[12] See Acemoglu (2003) on ways to model factor-augmenting technical progress.

[13] These technological changes, as Autor and Salomons (2018) argue, are primarily but not limited to developments in artificial intelligence and automation.

tially spent on goods and services from other more labour intensive sectors, further raising local employment.

Grossman and Oberfield (2022) and Acemoglu and Restrepo (2021b) point to yet another kind of general equilibrium effect. They argue that because automation is concentrated in few industries, it affects the sectoral composition of the economy, which can in turn shift the demand for different types of workers. Grossman and Oberfield (2022) argue that "a spurt of automation even if it is felt in some industries more than others, may induce an economy-wide increase in the skill premium if there is a capital-skill complementarity. This could induce a change in the relative supply of skilled workers, which could alter factor shares in all industries." Acemoglu and Restrepo (2021b), on the other hand, argue that certain workers displaced due to automation compete against others for non-automated tasks, bidding down their wages and spreading negative wage effects of automation more broadly in the population. Humlum (2021), considering various general equilibrium effects in a multi-sector economy, finds evidence of both for Denmark: due to industrial robots in manufacturing, wages of production workers declined by 6% but that of tech workers increased by 2.3%; the remaining occupations gained between 0.3 and 1.2%. Because production workers constitute only 3% of total employment, robots in fact increased the aggregate wages by 0.8%. However, since revenues due to robots increased more than wages, LSVA declined.

Finally, as Grossman and Oberfield (2022) highlight and Acemoglu and Restrepo (2021b) show, there could be confounding influences of other mechanisms that impact LSVA. To state very briefly, apart from automation, alternative explanations for the reduction in LSVA include: increase in capital accumulation (Piketty, 2014; Karabarbounis and Neiman, 2014),[14] globalization and offshoring (Elsby *et al*., 2013); the emergence of "Superstar" firms (Autor *et al*., 2020); and rising mark-ups and the consequent rents (De Loecker *et al*., 2020). Oberfield and Raval (2021) find that the decline in the labour share in the US stems from factors that affect technology, which includes automation and offshoring rather than mechanisms that work solely through factor prices.

It is beyond the scope of this paper to undertake a similar quantitative exercise as in Acemoglu and Restrepo (2021b) to study the implications of automation for the wage struc-

[14]While Piketty (2014) and Karabarbounis and Neiman (2014) differ in the underlying reasons for capital accumulation, the reason why capital accumulation leads to a decline in labour share is common to both: because the rising quantity of capital is not fully offset by a fall in the returns per unit of capital, capital accumulation leads to growth in capital income. Whereas Karabarbounis and Neiman (2014) emphasize the role of the decreasing cost of capital relative to labour, Piketty (2014) argues that several factors that drive up aggregate savings relative to income as reasons for capital accumulation.

ture, or the counter-factual exercise of the kind in Autor and Salomons (2018) to delineate the quantitative implications of the direct and the indirect effects on LSVA. Neither do we attempt to delineate the implications of various factors in equation (2.11) for the evolution of productivity or labour share in Estonia. However,

- since the aggregate (weighted and unweighted) TFP of automation adopters grew faster than the same for non-adopting firms (Figure 3 and Figure 4),
- and since the growing TFP and labour productivity of adopters are higher than those of non-adopters (Figure 4 and Figure 8),
- the decomposition exercise in Figure 5, and
- the reduced form estimates in Table 1

strongly suggest that because of the productivity impact of automation, its *direct effect* has contributed to increase the aggregate LSVA in Estonia in the last decade. In addition, due to spillover effects through the various channels discussed above, it is likely to have also *indirectly* increased the aggregate LSVA. This motivates us to study, among others, *the total factor productivity implications of automation*, which we do minutely at the level of the firm. We show that the productivity impact of automation is not uniform across firms even after exploring the sources of its heterogeneous impact.

We conclude this section by discussing the issue of measuring task displacement, $d\Phi$, to which we had alluded earlier. Based on an equation analogous to equation (2.11) and armed with an estimate of cost savings due to automation and estimates of σ, Acemoglu and Restrepo (2021b) construct *aggregate* measures of task displacement between 1980 and 2016 for each of the 500 demographic groups as a function of the *net/unexplained* decline in labour shares of value-added in various industries, where the net decline is net of the effects of changes in factor prices and mark-ups (see footnote 15 of their paper). For $\sigma = 1$, however, which defines their baseline measure, it is easy to see in equation (2.11) that task displacement, $d\Phi$, is equal to $-d\ln(S_L)$; that is, when $\sigma = 1$, aggregate task displacement in an industry can be measured by the decline in LSVA in that industry.

Now, in the last decade, of the 88 2-digit NACE industries in Estonia, 59 experienced automation, and only 11 of these registered a not-so-steady decline in LSVA; in the rest of the industries, it increased rather consistently. Evidence of which can be seen in figures 2e, 6, and 7, which show that the aggregate LSVA increased in the last decade, especially among adopters. Therefore, for Estonia, a measure based simply on changes in LSVA will not reflect the extent of task displacement.[15] Acemoglu and Restrepo (2021b) clarify that their expression of the measure of task displacement is an "approximation because it ignores the effects of augmenting technologies or productivity deepening." According to the authors, "the contribution of such terms to changes in the LSVA [for the US] is small, and that the approximation is accurate." In our context, however, as we have argued, automation technologies, brought in through imports and FDI, help factor-augmenting and productivity deepening technical change. Moreover, FDI in automation is likely to have directly created new jobs. And therefore its role as augmenting technology – and more generally the role of the acquisition of productivity deepening knowledge, through trade or otherwise, in a rapidly catching-up economy – cannot be ignored.

Since we do not study the wage and inequality implications of task displacement, we do not attempt to quantify/estimate the effects of various factors that impact labour share of value-added to distil out aggregate measures of task displacement. Instead, we provide micro evidence of the impact of automation for factor shares of tasks. For this, we adapt the task-based framework for the aggregate economy developed by Acemoglu and Restrepo (2018a,b, 2019b,a) to model firm j's output in period t, Y_{jt}, as a function of Φ_{jt}, the fraction of tasks that have been automated. After assuming that the elasticity of substitution, $\sigma = 1$, which is equivalent to assuming that the share of each task in output is fixed, we estimate the expected value of $1 - \Phi_{jt}$ (share of tasks worked by labour) and Φ_{jt} (share of tasks worked by capital) for firms that differ by the frequency with which they automate. In Section 5, we empirically show that labour task content of production, $1 - \Phi_{jt}$, (a) decreases with the frequency with which automation is increased and/or deepened, and (b) that the same has decreased over time among adopting firms.

3 A Simple Model of Automation with Scope for Management Innovation

3.1 Model Specification and Derivation of the Production Function

In this section, borrowing from the task based framework developed in Acemoglu and Restrepo (2018a,b, 2019b), we write a simple model of the automation undertaken by firms with scope for innovations in complementary organizational practices. In Section 5, we use the model to devise

[15] Acemoglu and Restrepo (2021b), however, complement the measure of task displacement with an index of automation, which they construct as predicted value of LSVA from a regression of LSVA on industry level robot adoption and utilization of software and specialist equipment.

an empirical strategy for studying the productivity implications of automation and the adoption of (and/or improvements in) complementary practices.

We assume that firm, j, in time period, t, produces the final good Y_{jt} by combining a unit measure of tasks, $y_{jt}(i)$, with an elasticity of substitution $\sigma \in (0, \infty)$:

$$Y_{jt} = \left(\int_0^1 y_{jt}(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}}. \tag{3.1}$$

All tasks are produced competitively. The final goods market, however, is monopolistically competitive. The limits of integration, which run between 0 and 1, assumes that the measure of tasks used in production always remains at 1. For firm j, Φ_{jt}, which lies between 0 and 1, is the threshold task such that all tasks i in (3.1) that are greater than Φ_{jt} are technologically non-automated and have to be produced by labour with the production function,

$$y_{jt}(i) = A^L_{jt} \gamma_{jt}(i) l(i), \tag{3.2}$$

where $\gamma_{jt}(i)$ denotes the productivity of labour in task i. On the other hand, tasks $i \leq \Phi_{jt}$ are technologically automated and can be produced by either labour or capital, that is,

$$y_{jt}(i) = A^K_{jt} \eta_{jt}(i) k_{jt}(i) + A^L_{jt} \gamma_{jt}(i) l(i), \tag{3.3}$$

where $\eta_{jt}(i)$ is the productivity of capital in task i. That in technologically automated tasks, capital and labour are perfect substitutes reflects the key aspect of this approach.[16] The labour-augmenting technology term A^L_{jt} and the capital-augmenting term A^K_{jt} increase the productivity of labour and capital in all tasks they currently produce.

As discussed in the previous section, Acemoglu and Restrepo (2018b) model at the aggregate level to consider two types of technological changes: (a) automation, which allows firms to substitute capital for tasks previously performed by labour, and (b) creation of new tasks, which enables the replacement of old tasks by new variants in which labour has a higher productivity. The creation of new tasks is modelled by letting the limits of integration in (3.1) run from $N - 1$ to N, where the creation of new tasks increases N. Since we focus only on automation, the limits of integration run from 0 to 1.[17] Automation, which is modelled as an increase in Φ_{jt}, then corresponds to expanding the fraction of tasks where machines can substitute for labour.

[16]Because the likely novel non-routine tasks – which require (a) physical flexibility and adaptability in the manual tasks (e.g. in the service industry), and (b) abstract reasoning, creativity, and problem-solving skills in abstract, analytical and managerial tasks – in firms that automate are labour intensive (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2019b), equations (3.2) and (3.3) serve as a reasonable approximation of the production process.

[17]Acemoglu and Restrepo (2018b) consider a dynamic economy in which capital accumulation is endogenous, and they characterize the restrictions under which their model delivers balanced growth with automation and the

The automation possibility for industry k is represented by Φ_t^k. For a firm, the unit cost, $p_{jt}(i)$, of producing each task i is a function of factor prices and the automation possibility represented by Φ_t^k, and is given by:

$$p_{jt}(i) = \begin{cases} \min\left\{ \dfrac{R_t}{A_{jt}^K \eta_{jt}(i)}, \dfrac{W_t}{A_{jt}^L \gamma_{jt}(i)} \right\} & \text{if } i \leq \Phi_t^k \\ \dfrac{W_t}{A_{jt}^L \gamma_{jt}(i)} & \text{if } i > \Phi_t^k \,, \end{cases} \tag{3.4}$$

where W_t is the wage rate and R_t is the user cost or the rental price of capital. In equation (3.4), the unit cost of production for tasks $i > \Phi_t^k$ is given by the effective cost of labour, $\dfrac{W_t}{A_{jt}^L \gamma_{jt}(i)}$. The effective cost takes into account that the productivity of labour in task i for firm j is $A_{jt}^L \gamma_{jt}(i)$. The unit cost of production for tasks $i \leq \Phi_t^k$ is given by $\min\left\{ \dfrac{R_t}{A_{jt}^K \eta_{jt}(i)}, \dfrac{W_t}{A_{jt}^L \gamma_{jt}(i)} \right\}$, which reflects the fact that capital and labour are perfect substitutes in the production of automated tasks. In these tasks, firms will choose whichever factor has a lower effective cost: $\dfrac{R_t}{A_{jt}^K \eta_{jt}(i)}$ or $\dfrac{W_t}{A_{jt}^L \gamma_{jt}(i)}$. Therefore, depending on whether it is cheaper to produce with capital as compared to producing with labour, the extent of automation in firm j is Φ_{jt}, where $0 \leq \Phi_{jt} \leq \Phi_t^k$. Also, it goes without saying that even if it is cheaper to produce higher indexed task, $i > \Phi_t^k$, with capital, technologically it would not be feasible.

Assumption 1

(i) As in Acemoglu and Restrepo (2018a,b), it is assumed that for all firms labour has a comparative advantage in higher-indexed tasks; that is, $\dfrac{A_{jt}^L \gamma_{jt}(i)}{A_{jt}^K \eta_{jt}(i)}$ *is strictly increasing in* i.

The above assumption ensures that labour is employed for tasks that have not been automated.

In tasks that have been automated, $i \in [0, \Phi_{jt}]$, it must be that it is cheaper to produce with capital than labour. Since we have assumed that labour has a comparative advantage in higher-indexed tasks, it implies that for automatable tasks that have not been automated, $i \in (\Phi_{jt}, \Phi_t^k]$, and the *relative* price of capital is not low enough.

Now, in our data we find that not all firms in the same industry adopt automation. Besides, our estimates show that the labour task content of production is not uniform among automation

creation of new tasks; that is, they take this to be a good approximation of economic growth in the United States and the United Kingdom over the last two centuries. While it would be worthwhile to study the productivity and labour share implications of new tasks and new job titles, we limit ourselves to studying only automation partly because we lack yearly firm level data on the share of new job titles within each occupational category.

adopters. In the following subsection, we discuss how financing frictions, future uncertainty, adjustment costs for automation to take effect, and the irreversibility of the decision to automate, which increases the user cost of capital, could give rise to such heterogeneity in the threshold, Φ_{jt}. Before that, taking Φ_{jt} as given, we derive the production function and factor shares of value-added as a function of Φ_{jt}.

As shown in Appendix A.1, for elasticity of substitution $\sigma = 1$; that is, when the share of each task in value-added is fixed, we get the following Cobb-Douglas production function,

$$Y_{jt} = A_{jt}\left(\frac{A^K_{jt}K_{jt}}{\Phi_{jt}}\right)^{\Phi_{jt}}\left(\frac{A^L_{jt}L_{jt}}{1-\Phi_{jt}}\right)^{1-\Phi_{jt}} = \Omega_{jt} f(\Phi_{jt}) K^{\Phi_{jt}}_{jt} L^{1-\Phi_{jt}}_{jt}, \tag{3.5}$$

where $\Omega_{jt} = A_{jt}(A^K_{jt})^{\Phi_{jt}}(A^L_{jt})^{1-\Phi_{jt}}$ is the total factor productivity (TFP). The term $A_{jt} = \exp\left[\int_0^{\Phi_{jt}} \ln(\eta_{jt}(i))di + \int_{\Phi_{jt}}^1 \ln(\gamma_{jt}(i))di\right]$ consists of the sum of the productivity of capital employed in tasks $i \leq \Phi_{jt}$ and the sum of the productivity of labour employed for tasks $i > \Phi_{jt}$. The term, $f(\Phi_{jt})$, is bounded between 1 and 2.

Suppressing the subscript, jt, from the factors demand in equation (A.1.4) in Appendix A.1, we can obtain the shares of labour's and capital's cost in revenue. The shares of labour and capital receptively are

$$S^L = \frac{WL}{PY} = \frac{P^{\sigma-1}}{\mu^\sigma}\int_\Phi^1\left(\frac{W_t}{A^L\gamma(i)}\right)^{1-\sigma}di = \frac{1}{\mu}\left(\frac{Y}{L}\right)^{\frac{1-\sigma}{\sigma}}\left(\int_\Phi^1 (A^L\gamma(i))^{\sigma-1}di\right)^{\frac{1}{\sigma}} \text{ and}$$

$$S^K = \frac{RK}{PY} = \frac{P^{\sigma-1}}{\mu^\sigma}\int_0^\Phi\left(\frac{R}{A^K\eta(i)}\right)^{1-\sigma}di = \frac{1}{\mu}\left(\frac{Y}{K}\right)^{\frac{1-\sigma}{\sigma}}\left(\int_0^\Phi (A^K\eta(i))^{\sigma-1}di\right)^{\frac{1}{\sigma}}, \tag{3.6}$$

where $\mu = \dfrac{1}{1+1/\varepsilon}$ is the mark-up and ε the price elasticity of demand. For elasticity of substitution, $\sigma = 1$, the shares are given by $S^L = \dfrac{1-\Phi}{\mu}$ and $S^K = \dfrac{\Phi}{\mu}$.

Since a monopolistic firm chooses an output in the elastic range of the market demand, $|\varepsilon| \geq 1$, it implies that the mark-up, $\mu = \dfrac{1}{1+1/\varepsilon} \geq 1$. In other words, a higher mark-up reduces the shares of labour and capital and increases the economic rent of the firm's owners. Since automation – increase in Φ – has implications for employment, especially that of low-skilled workers in routine jobs, and, given wages for labour share, we, as shown in the next section, based on the production function in (3.5), estimate the averages of the share of tasks between labour, $1-\Phi$, and capital, Φ, for firms that differ by frequency of automation.

Now, in the canonical CES models of the production function, if the elasticity of substitution between capital and labour is $\sigma = 1$, then we get a Cobb-Douglas production function and technological change, be it labour augmenting or capital augmenting, does not change the factor shares of the firm's output. And if the relative price of inputs do not change, the mix of inputs remains unchanged. In the task-based approach, however, where labour and capital are perfect substitutes in automatable tasks ($i \leq \Phi_t^k$), any technical change that improves the productivity of capital in automatable tasks makes capital relatively cheaper, and can increase automation (that is, increase Φ), which can decrease the labour share of income regardless of the value of σ.

3.2 Why Do Some Firms Adopt Automation?

We now come to the question of why some firms in industries amenable to automation adopt automation and some not, and among adopters, why certain firms automate some but not all automatable tasks. We attribute the heterogeneity in the share of automated tasks, Φ_{jt}, to (a) *irreversibility* (if partial) of the decision to automate, (b) the presence of *adjustment costs*, (c) *uncertainty about future demand*, and (d) *financing frictions*, which can be firm specific, and which can also increase the investment costs of certain firms.

Since all automation requires plant restructuring, worker retraining and organizational restructuring, the adjustment costs will likely have a fixed cost component. The adjustment costs could also depend on the size of the firm and of the investment, and thus have a convex component as well (Abel and Eberly, 1994; Cooper and Haltiwanger, 2006; Bond *et al*., 2011). These costly adjustments are part of what we term, *automation enabling practices and complements*, about which we elaborate below.

Consider demand uncertainty. Since in the absence of adjustment frictions and costly reversibility, investment does not depend on uncertainty; the effects of uncertainty for investment are attributable to different forms of adjustment costs and to irreversibility. To understand how automation policy, which maximizes firm value, depends on these costs, it would be required – subject to such costs – to solve a dynamic optimization problem, where the investment to automate in period t is chosen to maximise the present discounted value of current and expected future net revenues, where the expectation is taken over the distribution of future demand shocks, $P_{js}, s > t$. Since it is not the objective of this paper to estimate these costs, we do not write and solve such a problem. Nonetheless, to understand how adjustment costs, uncertainty, and irreversibility can affect decisions to invest in automation, we briefly discuss some of the results in the "real options" literature that seeks to understand the implications of these factors for investments in general.

When an investment is irreversible and when there are adjustment costs, the optimal investment policy is to purchase capital only as needed to prevent the marginal revenue product of capital from rising above an optimally-derived hurdle. This hurdle, which is the user cost of capital, R_{jt},[18] appropriately defined to take account of irreversibility and/or adjustment costs in the presence of uncertainty, is higher than the Jorgensonian user cost (Abel and Eberly, 1994, 1996). Bond *et al*. (2011), studying the impact of uncertainty on long-run capital accumulation, find a negative relationship between uncertainty and average capital stock levels, which is stronger in the case of the model with quadratic adjustment costs. They reason that firms anticipate that future fluctuations in demand will require them to adjust their capital stocks, and since adjustment is costly or irreversible, the expected level of this cost is reduced by substituting away from capital towards flexible inputs, such as labour.[19]

Now, Bond *et al*. (2011) find that with a general specification for adjustment costs, which involves both fixed and convex components and a specification for irreversibility, the dynamic optimization problem has no analytical solution that describes the optimal level of investment as a function of the state variables. They, therefore, solve the problem numerically. They show that – as in Abel and Eberly (1994), who solve for the investment policy analytically under a different specification, and as in Abel and Eberly (1996), who consider only costly reversibility – the optimal investment policy under uncertainty and fixed costs and irreversibility is a barrier control policy, according to which it is optimal not to purchase capital when the marginal revenue product of capital is lower than the user cost of capital. Only when the marginal revenue product of capital equals the user cost is it optimal to purchase capital; this prevents the marginal revenue product of capital from rising above the user cost.

Automation policy, therefore, will be a barrier control policy: assuming that the effective user cost of capital, $\frac{R_{jt}}{\eta_{jt}(i)A_{jt}^K}$, is lower the effective wage rate, $\frac{W_t}{\gamma_{jt}(i)A_{jt}^L}$, only those firms will automate for whom the marginal revenue product of capital equals the user cost, R_{jt}. Since the marginal revenue product of capital is a function of price, P_{jt}, put simply, a firm will invest in costly automation if the demand for its output is high. However, since for automatable tasks, labour and capital are perfect substitutes, if the effective wage rate is lower than the effective user cost of capital, firms will keep on employing labour in automatable tasks.

[18]Since the user cost depends on the adjustment costs, irreversibility, and financing frictions, all of which are firm specific, we have introduced the firm subscript, j.

[19]Under fixed costs and irreversibility, even in the absence of uncertainty, investments (here, in automation) will be infrequent and lumpy. Even for very low values of the uncertainty parameter, Bond *et al*. (2011), in their numerical exercise, find that average capital stock levels are about 3.5 per cent lower than the level obtained without adjustment costs.

The costly adjustments – such as retraining the work force, providing incentives to workers to successfully adjust to the impact of automation, adopting necessary organizational practices, and investing in potential complements – are, as mentioned above, a part of automation enabling practices and complements. When there are complementarities among practices that may be necessary to adopt for automation to take effect, but the new practices conflict with the old system of practices, then it is likely that the transition will be difficult, especially if decisions are decentralized. Because of the complementarities, changing only one practice, or a small set of practices, is likely to reduce overall performance. However, changing all of the practices in the new system simultaneously can be difficult (Brynjolfsson and Milgrom, 2012). Shifting capital investment into new automation technologies takes time, as does changing organizational processes and practices – such as inventory management, or coordination on the factory floor – to adapt to new technologies. Brynjolfsson *et al.* (2019) provides examples of costly and time-consuming inventions and implementations (which entail adjustment costs, organizational changes, and new skills) of complementary processes and products related to many general purpose technologies, which are relevant for automation as well. Raisch and Krakowski (2021), while reviewing three recent influential books on the use of artificial intelligence (AI) in organization, discuss the scope of management for facilitating complementarities between automation/AI and human capabilities.

Financing frictions or borrowing constraint manifest themselves by raising investors' required rate of return, which also increase the user cost of capital, R_{jt}. Hadlock and Pierce (2010) propose an index of financial constraint that is only based on firm size and age. They point out that literature on financial frictions reveals that firm size, and to a lesser extent firm age, are both related to the presence of financing constraints. Hennessy and Whited (2007) find that the estimated external financing costs are most closely related to firm size, and that the costs decrease as firms grow. The higher external financing costs faced by small and young firms could, therefore, be a reason why the incidence of automation is seen mostly among the larger and older firms (see Table 5). Furthermore, low productivity firms with little internal resources who wish to invest in response to higher expected profitability are more likely to face borrowing constrains.

Humlum (2021) mentions that of the total cost of an average robotic system, which includes fixed adjustment costs and expenditure on machines, accounts for just a third. Humlum (2021) estimates that for robot adopters in Denmark, which are large firms, the sunk costs of adoption amount to 10% of their average sales. He argues that it is because of these costs that "only 31% of manufacturing firms [in Denmark] have adopted industrial robots almost 30 years after their arrival." Firms for whom the adjustment costs are too high are unable to adopt automation or automate few of the automatable tasks. That is, financing frictions interact with adjustment costs leading to underinvestment in automation, which also manifests in non-adopting firms selecting themselves into more labour intensive, and probably less profitable, activities as SMEs.

Other obstacles, such as a lack of certain skills complementary to new technologies and other complements, such as information technology and/or educated workforce with the necessary skills, could also hamper the introduction of automation.[20] Autor (2015) presents examples where skilled professionals radically simplify the environment in which machines work to enable autonomous operation. Using data from a survey of Japanese firms, Morikawa (2017) present evidence that the adoption of recent automation technologies is positively associated with the skill level of the firms' employees.

3.3 Productivity Impact of Automation and Complementary Practices

We finally discuss how (I) automation, and (II) and investments in automation enabling practices and complements can affect labour productivity and total factor productivity (TFP), Ω_{jt}, which has been defined in equation (3.5). Since,

$$d\ln(\Omega) = \ln\left(\frac{\eta(\Phi)A^K}{\gamma(\Phi)A^L}\right)d\Phi + \Phi d\ln(A^K) + (1-\Phi)d\ln(A^L) + \int_0^{\Phi} d\ln(\eta(i))di + \int_{\Phi}^{1} d\ln(\gamma(i))di, \tag{3.7}$$

TFP can increase if (i) productivity of capital in the newly automated tasks is higher than that of labour, $\ln\left(\frac{\eta(\Phi)A^K}{\gamma(\Phi)A^L}\right) > 0$, and/or (ii) if automation is accompanied by factor augmenting, and/or (iii) productivity deepening technological changes. Since technological changes that improve the productivity of capital relative to that of labour in routine tasks lead to automation and the reallocation of tasks away from workers toward capital, Acemoglu and Restrepo (2021b) label such technological changes as "task displacing" technological change, whereas technological changes that improve the productivity of capital, $\eta(i)$, and/or that of labour, $\gamma(i)$, in their respective tasks is termed productivity deepening. Factor augmenting technological changes that increase the augmenting terms, A^L and A^K, increase the productivity of labour and capital in all tasks they produce. Productivity deepening or factor augmenting technological changes, however, do not displace labour from the tasks they are performing.

[20]For example, Brynjolfsson and McElheran (2016) have found that data-driven decision-making is concentrated in plants with three key advantages: size, high levels of potential complements (particularly information technology and educated workers), and awareness.

Papers that study the productivity implications of automation in developed economies, Acemoglu and Restrepo (2021b) for example, focus on the productivity impact of task displacement. However, in catching-up economies that invest in absorptive capacity, imports-led and FDI driven automation, through technology spillovers and transfers, is likely to increase A^L and A^K as well. Besides, automation could be productivity deepening if (a) automation is accompanied by organizational changes and investment in complements that facilitate machine augmentation of human capabilities, and (b) automation is done at the intensive margin.

Investments in automation enabling practices and complements, to summarize the discussion in the last subsection, are efforts to economize on expensive inputs. Further investments in these may well raise the TFP by increasing both $\int_0^{\Phi_{jt}} \ln(\eta_{jt}(i))di$ and $\int_{\Phi_{jt}}^1 \ln(\gamma_{jt}(i))di$, but in particular such investments are given to raise the productivity, $\gamma(i)$, of their remaining employees employed in tasks, $i \in (\Phi, 1]$.[21] In other words, automation along with the adoption of and improvements in complementary practices create complementarities between automated tasks and labour employed in tasks that cannot be substituted by automation. Using examples, Autor (2015) discusses such complementaries between automation/computerization, that largely substitute for routine tasks, and human labour which perform abstract, analytical, and managerial tasks that require problem-solving capabilities, intuition, creativity, and persuasion. These practices and complements could also potentially pave the way for further productivity enhancing automation.[22] We take the managerial efficiency view (Bloom and Van Reenen, 2007) of automation enabling practices and complements; in models of managerial efficiency, TFP increases in the quality of management practices.

Automating at the intensive margin or by deepening automation, increases the productivity of capital, $\eta(i)$, for the tasks that are already automated, and is, therefore, equivalent to capital-augmenting technological change for the tasks that have been automated (Acemoglu and Restrepo, 2019a, 2018a). Possible ways in which automation could be deepened include investing in (a) artificial intelligence (AI), and (b) new vintages of machinery for replac-

[21] Dinlersoz and Wolf (2019) and Humlum (2021) distinguish between tech workers – engineers, researchers, and skilled technicians – and production workers. Humlum (2021) finds that in years subsequent to the adoption of robots by Danish firms in manufacturing, the proportion of tech workers and their relative productivity increase, while the proportion and the relative productivity of production workers decrease. Since we do not have information on occupations and tasks, we do not distinguish between worker type, and $\int_{\Phi_{jt}}^1 \ln(\gamma_{jt}(i))di$ in the TFP aggregates over tasks worked by different occupations.

[22] Acemoglu and Autor (2011) write that "substitution of machines for tasks previously performed by semi-skilled workers, or outsourcing and offshoring of their tasks, may necessitate significant organizational changes. One might reinterpret the changes in equilibrium threshold tasks [thresholds that determine the amount of tasks to be allocated to machines or to different kinds of skills] in our model as corresponding to a form of organizational change."

ing older vintages, which are being used in already automated tasks (Acemoglu and Restrepo, 2019a).

We finally look at how automation impacts labour productivity. With output, Y, defined in equation (3.5), using the factor demand equation (A.1.4) defined at $\sigma = 1$, the change in labour productivity can be expressed as:

$$d\ln\left(\frac{Y}{L}\right) = \underbrace{\left[\ln\left(\frac{W}{A^L\gamma(\Phi)}\right) - \ln\left(\frac{R}{A^K\eta(\Phi)}\right)\right]d\Phi}_{\text{Cost Saving due to Task Displacement}} + \underbrace{\Phi d\ln\left(\frac{K}{L}\right)}_{\substack{\text{Impact of Capital}\\ \text{Accumulation}}}$$
$$+ \underbrace{\Phi d\ln(A^K) + (1-\Phi)d\ln(A^L) + \int_0^{\Phi} d\ln(\eta(i))di + \int_{\Phi}^{1} d\ln(\gamma(i))di}_{\substack{\text{Productivity impacts of (a) Investments in Automation Enabling Practices \& Complements,}\\ \text{(b) Automation Deepening, (c) Knowledge Spillovers \& Transfers from Imports \& FDI}\\ \text{driven Automation, and (d) Other Factor Augmenting \& Productivity Deepening Efforts.}}} \tag{3.8}$$

Now, if the wages of production workers are high (e.g. due to the scarcity of middle-aged workers induced by demographic changes) and the rental price of capital is sufficiently low (e.g. due to falling prices of machinery for automation or the absence of financial constraints in large productive firms) then firms can automate all the way up to Φ_t^k to substitute cheaper capital for expensive labour, and raise labour productivity. That is, by automating more tasks or capturing automation at the extensive margin (Acemoglu and Restrepo, 2018a), which is likely to increase the capital-labour ratio, $\frac{K}{L}$, firms can increase the productivity of their remaining labour. However, if (i) the efficiency of capital in the newly automated tasks is lower than that of labour, i.e. $\eta(\Phi)A^K - \gamma(\Phi)A^L \leq 0$, and (ii) automation does not improve the productivity of the factors, then any gain from automation is reduced. The former case is usually the result of the adoption of automation technologies that are "so-so" – just productive enough to be adopted but not much more productive or cost-saving than the production techniques that they are replacing; such technologies reduce labour demand but are not "brilliant" enough to substantially improve TFP (Acemoglu and Restrepo, 2018a). The latter is often the result of a lack of complementary skills and/or the necessary organizational changes, which could reduce the efficiency with which newly automated tasks are operated. So, depending on how TFP is affected, labour productivity may or may not increase with automation.

4 Data and Variables: Definitions and Description

For our study, we use Estonian Business Registry data, which is a census data and has firm balance sheet information comprising profit and loss statements. Wherever possible, the missing information in the Business Registry data was obtained from the EKOMAR data, which is survey data and has more detailed information from firm balance sheets. While the Business Registry data has been maintained since 1993, two years after Estonia's independence, the EKOMAR survey was launched in 2003.

The data on firm-level imports and exports, which is used to obtain information on automation, are taken from the International Goods trade dataset of Statistics Estonia (Eesti Statistika) and Services trade dataset (Bank of Estonia). The trade data also contains information for the universe of firms in Estonia. As in Acemoglu and Restrepo (2021a), we consider imports of intermediate capital goods for automation, defined as products whose 2-digit HS code is given by 84 (Mechanical machinery and appliances), 85 (Electrical machinery and equipment), and 90 (Instruments and apparatus). In Table 2, we list 6-digit HS codes that identify if the goods imported are for automation. The various 6-digit HS codes that identify goods for automation are categorized into 10 categories. The listed 6-digit HS codes allow one to track the categories consistently over time and compute the total value of imports of intermediates for each year between 1995 and 2018. In Table 2 The import distribution of the various categories of intermediate goods for automation is shown in Table 3.

One concern is that some of the firms who report importing capital goods for automation are retailers and/or service providers of automation and related services, and not necessarily users of capital goods for automation. Such firms can be identified by looking at their import and export patterns. Firms that are found to have exported the goods for automation are removed from the data. Now, it is likely that firms that repeatedly import the same — of the 10 categories — category of capital goods for automation are retailers and/or service providers. Firms that imported the same category of capital goods for automation in all the years constitute less than 3% of the firms that imported capital goods for automation. Removing exporters of capital goods for automation from the data incidentally removes most of the firms that are found to have repeatedly imported the same category of machines for automation; any such remaining firms were removed from the estimating sample. In the remaining sample, the maximum number of times a category of goods is imported by any firm is 5.

[Table 2 about here]

[Table 3 about here]

Information on the adoption of newly innovated or improved organizational practices is obtained from the Estonian Community Innovation Survey (CIS), which is a biennial survey about innovation activities in Estonian enterprises.[23] We use eight waves of CIS data: CIS2004 to CIS2018. A combination of a census and a stratified random sampling is used to collect the CIS data. A census of large enterprises, and a stratified random sample for small and medium sized enterprises from the population is used to construct the data set for every survey. The stratum variables are the economic activity classification (NACE) and the size of an enterprise. The target population includes all firms that have ten or more employees.

After removing firms for whom the required information was missing, the data for the period, 2003 to 2018, comprised of an unbalanced panel of 85,305 firms with 498,971 firm-year observations. After merging the data on balance sheets and trade with CIS data, our CIS sample comprised an unbalanced panel of 3,752 firms with 21,161 firm-year observations. The minimum number of observations per firm is 2, the maximum 16, and the average number is about 6 years.

Our main outcome variables are revenue and value-added, where value-added is the difference between revenues and the value of intermediate inputs. As far as capital is concerned, in order to convert the book value of the gross capital stock into its replacement value, we use the perpetual inventory method described in Salinger and Summers (1983) whenever data in the Business Registry and EKOMAR data is continuous between 2003 and 2018. According to this method, the replacement value of the capital stock is equal to the book value of fixed assets for the first year the firm appears in the data. For the subsequent years, first, the useful life of capital goods, L_t, at time t is calculated as:

$$L_t = \frac{GK_{t-1} + I_t}{DEPR_t},$$

where GK_{t-1} is the reported value of gross property, plant, and equipment at time $t-1$, I_t is the investment in the same in period t, and $DEPR_t$ is the reported depreciation. Then L_t is averaged over time to obtain L, which is then used in the following formula to obtain the replacement value of the capital stock of a firm in industry k:

$$K_t = \left(K_{t-1} \frac{p_t^k}{p_{t-1}^k} + I_t \right) (1 - 2/L),$$

[23] The survey adheres to the Oslo Manual, which provides guidelines for the definition, classification, and measurement of innovation (OECD, 1992; 1997; 2005).

where p_t^k is the deflator for industry, k. The second term represents the amount of capital stock that depreciates each year and is based on the assumption that economic depreciation is double declining balance. For new firms and for existing firms that appear again after a gap at later time periods in the data, the book value of the capital stock in the first year is taken as the replacement value. However, for firms that reappear after gaps, this method will not yield as good an estimate of the replacement value as for firms for whom a long, continuous time-series is available.

In our analysis we include a dummy for north Estonia, which takes the value 1 if the company is located in Harju county. Harju county is the biggest of all Estonian counties in terms of population and economic activity, and includes the national capital city, Tallinn. The rationale for including this dummy is that firms located in Harju county, which qualifies as the economic hub of Estonia, are likely to be better networked with implications for productivity due to agglomeration.

In Table 4, we find that among the firms that adopted automation, about 56% imported/invested only once and about 14% imported/invested twice. Even among the firms that are present in the data in 19 to 24 years out of the maximum of 24 years, a majority did not invest in more than 3 years. This suggests that investment in automation does not happen frequently and is not smoothed across periods. In other words, investment in automation is scarce across firms and infrequent within. To assess whether, among firms that have invested in automation more than once, the different occasions on which they invested are similar, or if most of the investments were concentrated in few of the occasions, we compute for each firm the share of investment in year t relative to the cumulative sum invested in automation. For each firm we then rank these yearly shares from largest to lowest in Figure 3. We find that the mean concentration of investment in a single year is close to 80% and the median is almost 100%. That is, from Table 4 and Figure 3 we can conclude that investments in goods for automation is lumpy. However, we know that indivisibilities and adjustment costs can generate lumpiness in firm investment (Doms and Dunne, 1998).

[Table 4 about here]

[Figure 3 about here]

The information on organizational or management change/innovation, as mentioned above, is obtain from the CIS data. The survey asks firms: "During [the last three years], did your enterprise introduce any of the following types of new processes or improved processes that differ significantly from your previous processes?"

- Methods of organising work responsibility, decision-making or human resource management, which includes (i) personnel recruitment and payroll management, (ii) training, and (iii) workplace organisation, such as new employee responsibility systems, teamwork, decentralization, or integration or de-integration of departments.
- Business practices for organising procedures or external relations, which includes strategic decisions regarding (i) alliances, (ii) partnerships, and (iii) outsourcing or subcontracting.

The binary variable, $\mathcal{M}^{\mathcal{I}}_{j,t}$, which denotes innovation/changes in management practices, takes the value 1 if the firm answered in the affirmative to any of the above and 0 otherwise. Since the CIS survey is biennial and certain questions, like the one on management innovation, pertain to all the years the survey covers, $\mathcal{M}^{\mathcal{I}}_{j,t} = \mathcal{M}^{\mathcal{I}}_{j,t-1}$.

[Table 5 about here]

[Table 6 about here]

The descriptive statistics of some of the variables in 5 are based on the *CIS sample*. As can be seen from the table, measured in terms of number of employees and capital stock, automation adopters are larger than non-adopters. Also, in all sectors, younger firms are more likely to introduce new organizational practices. This is in line with studies that have found younger firms to be lacking the structural inertia for reorganisation that beset older firms; the inertia is attributed to the hierarchical structures among older firms. This leads to faster decision-making processes, streamlined operations, and timely responses to changing industry environments among younger firms. Among other observations, we find that a significantly higher percentage of firms in the services sector are based in north Estonia. This suggests that for firms in the services sector there are agglomeration effects from being located in what is the economic hub of Estonia.

In Table 6, we describe the automation and management activities of CIS firms. As is evident, in the CIS sample, compared to firms in other sectors, a higher percentage of firms in the manufacturing sector import capital goods for automation: about two thirds of the firms in the manufacturing sector engage in automation, whereas about only a third of firms in the sector comprising mining, utilities, and construction engage in automation. In the CIS sample, the manufacturing sector is overrepresented.

In Table 6, judging from the row percentages in parenthesis, we find that compared to the firms in the full sample, firms that instituted new organizational practices are more likely to adopt automation. This is true of all sectors. Also, although the column percentages have not been reported, one can calculate them to see that in all sectors, automation adopting firms, as compared to non-adopters, are more likely to institute new organizational practice.

5 Empirical Strategy

For estimation, we assume that the production function for producing the final output is Leontief in material input, where material input is proportional to output. In which case, value-added is proportional to output, which is given by the Cobb-Douglas production function in equation (3.5):

$$Y_{jt} = \Omega_{jt} f(\Phi_{jt}) L_{jt}^{1-\Phi_{jt}} K_{jt}^{\Phi_{jt}}, \tag{5.1}$$

where L_{jt} is labour, and K_{jt} is capital. The total factor productivity (TFP), Ω_{jt}, and the faction of task, Φ_{jt}, that have been automated are unobserved to the econometrician but known to the firm. The objective, among others, is to (i) estimate the factor shares of tasks, Φ_{jt} and $1 - \Phi_{jt}$, as a function of the proposed measure of automation, and (ii) to estimate the TFP implications of the same measure.

Unlike in a textbook treatment of the Cobb-Douglas technology, where the exponents of L_{jt} and K_{jt} are assumed to be uncorrelated with L_{jt} and K_{jt} and interpreted as output elasticities of L_{jt} and K_{jt}, here the exponents, Φ_{jt} and $1 - \Phi_{jt}$, are random and correlated with L_{jt} and K_{jt}. The strategy developed below accounts for the correlation between Φ_{jt} and (L_{jt}, K_{jt}).

For firm, j, $j \in \{1, \ldots, J\}$ in time period t, $t \in \{1, \ldots, T\}$, we observe its deflated revenues, which with a slight abuse of notation we denote by Y_{jt}, the deflated value of material inputs, M_{jt}, the number of employees, L_{jt}, and capital, K_{jt}, computed using the perpetual inventory method. The log form of the production function in (5.1) is

$$y_{jt} = \varphi_{jt} + \alpha_{jt} l_{jt} + \beta_{jt} k_{jt} + \omega_{jt} + \epsilon_{jt}, \tag{5.2}$$

where the lower-case symbols, y_{jt}, k_{jt}, l_{jt}, represent natural logs of Y_{jt}, K_{jt}, and L_{jt} respectively. The term, ω_{jt}, is the log of TFP, Ω_{jt}, $\varphi_{jt} = f(\Phi_{jt})$, $\alpha_{jt} = 1 - \Phi_{jt}$ is the fraction of tasks worked by labour, and $\beta_{jt} = \Phi_{jt}$ the fraction of tasks that are automated. Finally, the term, ϵ_{jt} is the measurement error in value-added or ex-post shocks.

5.1 Implications of Automation for Productivity and Share of Tasks between Factors

In this section, we adopt an empirical strategy to estimate whether and how task shares of capital and labour and firm level productivity depend on the extent of automation. Our measure of automation is based on the cumulative frequency with which firms have imported intermediate capital goods for automation during the years, 1995-2018; formally, on $\mathcal{N}_{jt}^{A}$, the number of times a firm since 1995 has imported equipment and machinery for automation. We believe that $\mathcal{N}_{jt}^{A}$ serves as a good proxy for the extent of automation within firms. First, because, as we have argued in Section 2, the market for capital goods for automation in Estonia is thin or non-existent, and therefore nearly all the information on automation can be obtained from imports data. Second, as we argue below, firms that import capital goods for automation over several periods are firms that are (a) automating extensively by automating more tasks, and/or (b) by investing in new vintages of machinery to replace the older vintages automating intensively, which deepens automation.

Some of the papers that have used imports of capital goods for automation to construct measures of adoption and of robots and other automation technologies are Acemoglu *et al*. (2020), Acemoglu and Restrepo (2021a,b), Bonfiglioli *et al*. (2020) and Bonfiglioli *et al*. (2021). Acemoglu and Restrepo (2021a) note that for countries that are net importers of industrial robots, yearly change in the stock of robots (at the industry-level) per thousand (industry) workers is highly correlated with the change in the value of imports of industrial robots, where the data on stock of robots are obtained from the International Federation of Robotics (IFR).

Based on $\mathcal{N}_{jt}^{A}$, we group firms in year $t = 2018$ into (a) firms that automate *occasionally*, which are firms that have imported in at most 25% of the years they are observed in the data, and (b) firms that automate *regularly*, which are firms that have imported in 25% to 100% of the years they are observed. Firms that did not import intermediate goods for automation in any of the years ($\mathcal{N}_{jt}^{A} = 0$) are assumed to be *Non-Adopters*. The threshold that distinguishes firms that automate *occasionally* and firms that automate *regularly* has been set at 25% because, as discussed in Section 4, investment in automation is infrequent across and within firms. While less then 20% of the firms have adopted automation, about 70% invested only once or twice in automation, and even among the firms that are observed in the data in 19 to 24 years out of the maximum of 24 years, the majority did not import in more than 3 years (see Table 4). We, therefore, believe that setting the threshold higher to, say, 50% or higher will lead to a misclassification of firms that automate *occasionally* and those that do *regularly*, and as a result some of the firms that automate extensively and/or intensively may risk being classified as firms that automate *occasionally*. Nevertheless, our results are *robust* to (a) increases in the threshold that distinguishes firms that automate *occasionally* and those that automate *regularly*, and (b) changing the classification of firms based on the proportion of times that they have imported equipment and machinery for automation since 1995 to that based on the number of times.

Let D^{N}_{jt} be the indicator variable that takes the value 1 if the firm is a *non-adopter*. Let D^{O}_{jt} be the indicator variable that indicates if the firm automates *occasionally*, and let D^{R}_{jt} indicate if firm j automates *regularly*. Here we would like to note that we use 2017-2018 census data for the estimation because (a) a short panel of two years suffices to estimate how the share of tasks between factors varies with automation, and (b) it is in the final years, 2017 and 2018, that $\mathcal{N}^{\mathcal{A}}_{jt}$ is most informative about the extent and intensity of automation.

Now, the random coefficients φ_{jt}, α_{jt} and β_{jt} in (5.2), which depend on the labour task content of production, Φ_{jt}, are correlated with capital, k_{jt} and labour, l_{jt}. For identification we assume that:

Assumption 2 *In a given sector, conditional on $D_{jt} \equiv \{D^{N}_{jt}, D^{O}_{jt}, D^{R}_{jt}\}$, the random coefficients, φ_{jt}, α_{jt}, and β_{jt}, are mean independent of k_{jt} and l_{jt}.*

According to the above assumption, there is no information about the mean of the labour task content of production, Φ_{jt}, contained in capital stock and labour employed over and above that which is contained in $D_{jt} \equiv \{D^{\mathrm{N}}_{jt}, D^{\mathrm{O}}_{jt}, D^{\mathrm{R}}_{jt}\}$. This assumption, we believe, is valid because, as argued above and in the arguments leading to the hypothesis 1 below, $\mathcal{N}^{\mathcal{A}}_{jt}$ serves as a good proxy for the extent of automation. And, therefore, given the coarsened version of $\mathcal{N}^{\mathcal{A}}_{jt}$, D_{jt}, changes in a firm's capital stock and labour, for whatever reason, are not changing the factor shares of tasks. We use $D_{jt} \equiv \{D^{\mathrm{N}}_{jt}, D^{\mathrm{O}}_{jt}, D^{\mathrm{R}}_{jt}\}$, the coarsened version of $\mathcal{N}^{\mathcal{A}}_{jt}$, because even though it helps to considerably reduce the number of parameters for estimation, it does not obstruct us from empirically establishing heterogeneity in task displacement. Below, we discuss the various information regarding automation that the frequency with which firms invest in automation reveals, which makes it clear why and how factor shares of tasks depend on D_{jt}.

According to Assumption 2, for a given time period, $t = 2018$, and a sector, the conditional expectation of α_{jt} in equation (5.2) is given by:

$$\mathrm{E}(\alpha_{jt}|k_{jt}, l_{jt}, D_{jt}) = \mathrm{E}(1 - \Phi_{jt}|k_{jt}, l_{jt}, D_{jt}) = \mathrm{E}(1 - \Phi_{jt}|D_{jt}).$$

Since $D_{jt} \equiv \{D^{\mathrm{N}}_{jt}, D^{\mathrm{O}}_{jt}, D^{\mathrm{R}}_{jt}\}$ consists of three indicator variables, where each one indicates one of the three mutually exclusive groups, we have

$\bar{\alpha}^{\mathrm{N}}_t \equiv \mathrm{E}(\alpha_{jt}|D_{jt} = (1,0,0))$ for firms with *No Automation,*

$\bar{\alpha}^{\mathrm{O}}_t \equiv \mathrm{E}(\alpha_{jt}|D_{jt} = (0,1,0))$ for firms that have *Automated Occasionally,* and

$\bar{\alpha}^{\mathrm{R}}_t \equiv \mathrm{E}(\alpha_{jt}|D_{jt} = (0,0,1))$ for firms that have *Automated Regularly*.

Analogously, for the three groups of firms, let $\bar{\beta}^{\mathrm{N}}_t$, $\bar{\beta}^{\mathrm{O}}_t$, and $\bar{\beta}^{\mathrm{R}}_t$ be the expectation of β_{jt} in equation (5.2) in time period, t, and let $\bar{\varphi}^{\mathrm{N}}_t$, $\bar{\varphi}^{\mathrm{O}}_t$, and $\bar{\varphi}^{\mathrm{R}}_t$ be the same for φ_{jt}. From the above, it is clear that, given Assumption 2, the expectation terms are the unconditional expectations of $\varphi_{jt} = f(\Phi_{jt})$, $\alpha_{jt} = 1 - \Phi_{jt}$, and $\beta_{jt} = \Phi_{jt}$ for each of the three groups of firms.[24]

We expect that the fraction of tasks that are automated, Φ_{jt}, to be higher for the group of firms who imported equipment and machinery for automation a higher proportion of times for the following reasons. First, clearly, firms that automate *regularly* are more *exposed* to automation; that is, they operate in industries where production is more *suitable* for automation and where it is *easier* to replace workers and/or expand with more automated tasks (Acemoglu and Restrepo, 2020; Bonfiglioli *et al*., 2020).

Second, as shown in Table 7, while the distribution of investment expenditure on automation in each year is skewed to the right for both groups of producers, compared to firms that automate *occasionally*, the expenditure for firms that automate *regularly* is larger by an order of magnitude. The median expenditure on automation – median taken over the firm-years – is about €27 K and the mean is €332 K for firms that automate *occasionally*, while for those that automate *regularly*, which are large firms with large market share, the same figures are €133 K and €1730 K, respectively. The median and mean expenditure on automation per employee are €3.1 K and €48.5 K respectively for firms that automate *occasionally*, and €6.6 K and €185 K for those that automate *regularly*. These figures suggest that firms that automate *occasionally* invest in automation technologies that are simpler with the ability to automate a few tasks, whereas larger firms that are given to automating *regularly* invest in technologies that can integrate more tasks and yield entirely automated production processes (e.g., an automated production line).

Third, as argued below in the context of Hypothesis 2, firms that automate *regularly* are more likely to import the same category of automation goods more than once, which suggests that

[24] If the conditioning in Assumption 2 were to be on $\mathcal{N}^{\mathcal{A}}_{jt}$, then, because it is mainly through the imports of capital goods for automation that firms automate in Estonia, factor shares of task would be statistically independent of factors by the very definition of $\mathcal{N}^{\mathcal{A}}_{jt}$. Another way to interpret Assumption 2 is to assume that for each sector and time period, factor shares of tasks take only three values: $(\bar{\beta}^{\mathrm{N}}_t, \bar{\alpha}^{\mathrm{N}}_t)$ for the *non-adopters*, $(\bar{\beta}^{\mathrm{O}}_t, \bar{\alpha}^{\mathrm{O}}_t)$ for the *occasional* adopters, and $(\bar{\beta}^{\mathrm{R}}_t, \bar{\alpha}^{\mathrm{R}}_t)$ for the *regular* adopters.

regular adopters are more likely to invest in new vintages of machinery to replace older vintages, which deepens automation.

Given the above considerations, we hypothesize that

$$\text{Hypothesis 1: } \bar{\alpha}_t^{\mathrm{N}} > \bar{\alpha}_t^{\mathrm{O}} > \bar{\alpha}_t^{\mathrm{R}} \text{ and } \bar{\beta}_t^{\mathrm{N}} < \bar{\beta}_t^{\mathrm{O}} < \bar{\beta}_t^{\mathrm{R}}.$$

If the above hypothesis is true, it would also be a test of Assumption 2 that the extent of automation among firms in certain economies, such as Estonia, mainly depends on the import of intermediate goods for automation.

Before proceeding further, we would like to note that since $\varphi_{jt} = f(\Phi_{jt})$ is not monotonic in Φ_{jt}, it is difficult to predict how its expected value behaves for the three groups of firms. Since the expected values, $\bar{\varphi}_t^{\mathrm{N}}$, $\bar{\varphi}_t^{\mathrm{O}}$, and $\bar{\varphi}_t^{\mathrm{R}}$, are uninformative about the share of tasks, they are treated as nuisance parameters that must be estimated in order to obtain consistent estimates of the parameters of interest.

While the coefficients, φ_{jt}, α_{jt}, and β_{jt}, in equation (5.2) are heterogeneous across firms, to establish Hypothesis 1 we only need the estimates of the averages of α_{jt} and β_{jt}, for the three groups of firms. Now, we can write φ_{jt}, α_{jt}, and β_{jt} as

$$\varphi_{jt} = \bar{\varphi}_t^l + \widetilde{\varphi}_{jt}, \alpha_{jt} = \bar{\alpha}_t^l + \widetilde{\alpha}_{jt}, \text{ and } \beta_{jt} = \bar{\beta}_t^l + \widetilde{\beta}_{jt}, l \in \{\mathrm{N}, \mathrm{O}, \mathrm{R}\} \tag{5.3}$$

where $\widetilde{\varphi}_{jt}$, $\widetilde{\alpha}_{jt}$ and $\widetilde{\beta}_{jt}$, respectively, are individual deviations from the common means, $\bar{\varphi}_t^l$, $\bar{\alpha}_t^l$, and $\bar{\beta}_t^l$. We can, therefore, write equation (5.2) as

$$\begin{aligned} y_{jt} =& (\bar{\varphi}_t^{\mathrm{N}} + \bar{\alpha}_t^{\mathrm{N}} l_{jt} + \bar{\beta}_t^{\mathrm{N}} k_{jt}) D_{jt}^{\mathrm{N}} + (\bar{\varphi}_t^{\mathrm{O}} + \bar{\alpha}_t^{\mathrm{O}} l_{jt} + \bar{\beta}_t^{\mathrm{O}} k_{jt}) D_{jt}^{\mathrm{O}} + (\bar{\varphi}_t^{\mathrm{R}} + \bar{\alpha}_t^{\mathrm{R}} l_{jt} + \bar{\beta}_t^{\mathrm{R}} k_{jt}) D_{jt}^{\mathrm{R}} \\ &+ \omega_{jt} + \tilde{\varphi}_{jt} + \tilde{\alpha}_{jt} l_{jt} + \tilde{\beta}_{jt} k_{jt} + \epsilon_{jt}. \end{aligned} \tag{5.4}$$

Because according to Assumption 2, the residual random coefficients – $\tilde{\varphi}_{jt}$, $\tilde{\alpha}_{jt}$, and $\tilde{\beta}_{jt}$ – are uncorrelated with k_{jt}, l_{jt}, and D_{jt}, as shown in Appendix B.2, canonical control function methods, such as those by Ackerberg *et al*. (2015) (ACF) for estimating production functions that account for correlation between productivity, ω_{jt}, and the inputs can be adapted to estimate the coefficients of interest in equation (5.4).[25] By adapting the control function methodology due

[25] As shown by Ackerberg *et al*. (2015), a value-added production function, which is what we have assumed the production function in (5.1) to be, can be derived from a gross-output production function that is Leontief in material inputs. Since material input is proportional to gross-output in a Leontief production function, value-added, is also proportional to gross-output. Our results are ***robust*** to using either measure – gross-output or value-added – as the outcome variable. Due to lack of space, we report only the results that used value-added as the outcome variable.

to ACF, we estimate the averages of α_{jt} and β_{jt} – $(\bar{\alpha}_t^{\mathrm{N}}, \bar{\alpha}_t^{\mathrm{O}}, \bar{\alpha}_t^{\mathrm{R}})$ and $(\bar{\beta}_t^{\mathrm{N}}, \bar{\beta}_t^{\mathrm{O}}, \bar{\beta}_t^{\mathrm{R}})$ – for the three groups of firms for time period, $t = 2018$, using 2017-2018 census data.[26]

The method by ACF accounts for the correlation of the input choices, l_{jt} and k_{jt}, and the indicator variable for automation, D_{jt}, with the unobserved productivity, ω_{jt} in equation (5.4) (and the endogenous variables in equation (5.12) below). The method involves the use of economic theory to derive a proxy for the anticipated shock productivity, ω_{jt}, by assuming that they can be inverted out from certain firm inputs if the firm has adjusted these optimally in response to the ω_{jt} it observed. Below we state some of the identifying assumptions, most of which are from ACF, that are relevant for the discussion of the identification and estimation of the model parameters in equations (5.4) and (5.12) and for estimating the productivity impact of automation.

Assumption 3 *(Scalar Unobservable) Firms' demand for material inputs is given by given by:*

$$m_{jt} = f_t(l_{jt}, k_{jt}, D_{jt}, x_{jt}, \omega_{jt}), \tag{5.5}$$

where m_{jt} is the logarithm of the value of material inputs and x_{jt} is the set of other state variables such as the location of the firms.

Assumption 4 *(strict monotonicity) Intermediate inputs in (5.5) is strictly increasing in ω_{jt}.*

Given the above assumptions, a proxy for ω_{jt} in equation (5.4) (and in equation (5.5) below) is obtained by inverting the intermediate input demand in equation (5.5),

$$\omega_{jt} = f_t^{-1}(l_{jt}, k_{jt}, D_{jt}, x_{jt}, m_{jt}). \tag{5.6}$$

Assumption 5 *(Information Set) The firm's information set at t, $\mathcal{I}_{jt}$, includes current and past productivity shocks $\{\omega_{j\tau}\}_{\tau=0}^{t}$ but does not include future productivity shocks $\{\omega_{j\tau}\}_{\tau=t+1}^{\infty}$. The transitory shocks ϵ_{jt} satisfy $\mathrm{E}\{\epsilon_{jt}|\mathcal{I}_{jt}\} = 0$.*

[26]The coefficients – $(\bar{\alpha}_t^{\mathrm{N}}, \bar{\alpha}_t^{\mathrm{O}}, \bar{\alpha}_t^{\mathrm{R}})$ and $(\bar{\beta}_t^{\mathrm{N}}, \bar{\beta}_t^{\mathrm{O}}, \bar{\beta}_t^{\mathrm{R}})$ – are traditionally interpreted as elasticities of output with respect to the inputs, labour and capital. De Loecker and Goldberg (2014) and Bond *et al*. (2021) have pointed out that the production functions such as the one in (5.2) is written in terms of physical quantities of inputs and outputs, but in practice deflated values of monetary variables (sales, material inputs, capital stocks) are used for the estimation. If due to market imperfections there are variations in output and/or input prices across firms, such practices could lead to a price bias in the estimated elasticities. We, however, do not have the information employed by De Loecker and Goldberg (2014) to account for the price bias(es).

Mairesse and Jaumandreu (2005), meanwhile, find that it makes very little difference whether deflated sales or actual quantities of output are used for the estimation. They conclude that their results are reassuring since they validate the customary practice of using deflated output and input measures for the estimation. Because input and output price biases tend to act in opposite directions (De Loecker and Goldberg, 2014), the magnitude of the bias, if any, will likely be small. Inferences regarding Hypotheses 1 and 3 are, therefore, unlikely to be affected even if revenue production functions instead of the ideal quantity production functions are estimated.

While automation in all likelihood increases future output, the decision to automate is determined both by past output and expectations regarding future output. And thus, even as the expectation of future productivity, $\omega_{j,t+1}$, affects the endogenous choice of automation and capital inputs in the current period, the effect on the output of past instances of automation affects the evolution of productivity, ω_{jt}. We therefore, in a manner similar to De Loecker (2013) and Doraszelski and Jaumandreu (2013), endogenize productivity evolution by making ω_{jt} depend on $\omega_{j,t-1}$, $\mathcal{N}^{\mathcal{A}}_{jt}$ and $\mathcal{M}^{\mathcal{I}}_{j,t-1}$. $\mathcal{N}^{\mathcal{A}}_{jt}$ depends on the extent of automation undertaken in the past; formally, $\mathcal{N}^{\mathcal{A}}_{jt} = D^{\mathcal{A}}_{j,t-1} + \mathcal{N}^{\mathcal{A}}_{j,t-1}$, where $D^{\mathcal{A}}_{j,t-1}$ is a binary variable that takes value 1 if the firm invests in automation in period $t-1$. $\mathcal{M}^{\mathcal{I}}_{jt}$ is a binary variable, which takes the value 1 if firm j introduces new or improved management practices or undertakes organizational innovation and 0 otherwise. Now, if investments in automation are accompanied by investments in automation enabling practices and complements, which help firms realize complementaries between automation and human labour, and which often occur without leaving a paper trail, then productivities of all factors will increase. While assessing complementarities between automation and organizational innovation is the topic of the following subsection, here it suffices to state that we control for $\mathcal{M}^{\mathcal{I}}_{jt}$ so that the estimated productivity effects of $\mathcal{N}^{\mathcal{A}}_{jt}$ is not confounded by the effects of changes in organizational practices.[27] To assess if FDI is accompanied by knowledge transfer and spillover effects with implications for productivity, we let ω_{jt} depend on $\mathcal{O}^{\mathcal{F}}_{j,t-1}$, which is the percentage of the shares of a firm (share of firm for brevity) held by a multinational.

In view of the above discussion, suppressing the firm script, j, we assume that:

Assumption 6 *(Productivity Evolution) Productivity shocks, ω_t evolve according to the first order controlled Markov Process, i.e., $p(\omega_t|\mathcal{I}_{t-1}) = p(\omega_t|\omega_{t-1}, \mathcal{N}^{\mathcal{A}}_t, \mathcal{M}^{\mathcal{I}}_{t-1}, \mathcal{O}^{\mathcal{F}}_{t-1},)$, where the distribution, $p(\omega_t|\omega_{t-1}, \mathcal{N}^{\mathcal{A}}_t, \mathcal{M}^{\mathcal{I}}_{t-1}, \mathcal{O}^{\mathcal{F}}_{t-1})$, which is stochastically increasing in ω_{t-1}, $\mathcal{O}^{\mathcal{F}}_{t-1}$, $\mathcal{N}^{\mathcal{A}}_t$, and $\mathcal{M}^{\mathcal{I}}_{t-1}$, is known to the firm.*

Because of the adjustment costs inherent in the process of automation, like capital, $\mathcal{N}^{\mathcal{A}}_t$, which is determined by past decisions to automate, is a state variable that is quasi-fixed. Therefore, $\mathcal{N}^{\mathcal{A}}_t$, along with $\mathcal{M}^{\mathcal{I}}_{t-1}$, and $\mathcal{O}^{\mathcal{F}}_{t-1}$ belong to the information set, $\mathcal{I}_{t-1}$, and are therefore among the set of instruments used in the second stage of the two stage method proposed by ACF.

[27] Now, it is only for the CIS firms that we know if they have made organizational changes by instituting novel or improved processes that differ significantly from their previous processes. For the non-CIS firms, $\mathcal{M}^{\mathcal{I}}_{jt}$ takes the value of probability of instituting novel or improved organizational practices that depends on (i) firm size as measured by a logarithm of the number of employees, (ii) age of the firm, (iii) market/revenue share, (iv) export intensity as measured by the ratio of export revenue to total revenue, and (v) industry dummies (Sapprasert and Clausen, 2012). However, Estonian CIS samples include a large majority of potentially innovative – innovating in organizational practices or otherwise – firms.

The Markovian assumption implies that

$$\omega_t = \mathrm{E}(\omega_t|\omega_{t-1}, \mathcal{N}_t^{\mathcal{A}}, \mathcal{M}_{t-1}^{\mathcal{I}}, \mathcal{O}_{t-1}^{\mathcal{F}}) + \xi_t = g(\omega_{t-1}, \mathcal{N}_t^{\mathcal{A}}, \mathcal{M}_{t-1}^{\mathcal{I}}, \mathcal{O}_{t-1}^{\mathcal{F}}) + \xi_t. \tag{5.7}$$

In the above, productivity, ω_t, in period t has been decomposed into expected productivity, $g(\omega_{t-1}, \mathcal{N}_t^{\mathcal{A}}, \mathcal{M}_{t-1}^{\mathcal{I}}, \mathcal{O}_{t-1}^{\mathcal{F}})$, and a random shock, ξ_t.[28] The residual, ξ_t, by construction is orthogonal to ω_{t-1}, $\mathcal{N}_t^{\mathcal{A}}$, $\mathcal{M}_{t-1}^{\mathcal{I}}$, and $\mathcal{O}_{t-1}^{\mathcal{F}}$. The productivity innovation, ξ_t represents the unanticipated shocks that are naturally linked to productivity and the uncertainties inherent in the automation process, such as the degree of applicability and success in implementation.

The two stage control function procedure proposed by ACF that we adapt to estimate the parameters of the production function also estimates the conditional expectation function, $g(\omega_{t-1}, \mathcal{N}_t^{\mathcal{A}}, \mathcal{M}_{t-1}^{\mathcal{I}}, \mathcal{O}_{t-1}^{\mathcal{F}})$, non-parametrically by approximating it using a polynomial function (see Appendix B.2, equation (B.2.3), for estimation details).

Now, as stated earlier, $\mathcal{N}_t^{\mathcal{A}}$ can increase over the years if firm j automates at (a) the extensive margin, and/or (b) the intensive margin. As we have discussed in subsection 3.3, automating at either margin can increase productivity. Automating at the extensive margin increases TFP, ω_t, because (i) capital goods for automation, which substitute for expensive labour, saves costs and is likely to be more efficient than labour in newly automated tasks,[29] and (ii) technology spillovers from importing such capital goods increases the labour and capital augmenting terms, A^L and A^K. The latter, as argued in Section 2, is likely to be true of firms in catching-up economies, like Estonia. Automating at the intensive margin, which is akin to capital-augmenting technological change, improves capital productivity and TFP consequently.

The above arguments also imply that depending on how firms automate, its impact on productivity will vary. For firms that automate *occasionally*, the expected productivity, $\mathrm{E}[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}}]$, will reflect *mostly* the productivity impact of cost savings due to

[28] De Loecker (2013) and De Loecker and Goldberg (2014) emphasize that if instead of a quantity production function, a revenue production function is estimated, which is what we do, then ω_t captures differences in both firm-level cost and demand factors. However, unless there are improvements in the quality of the output produced, it is unlikely that investments in automation, as captured by $\mathcal{N}_t^{\mathcal{A}}$, and the instituting of novel or improved organizational practices, and FDI will affect the demand for the firm's output. As we argue in the text, it is by enhancing the productivity – by reducing the costs of production, some of which could be passed on to the consumers – that these variables effect ω_t.

[29] Note that in subsection 3.3, where we discuss the productivity impact of automation, cost saving from substituting cheaper capital for expensive labour improves labour productivity (see equation (3.8)). But unless capital is more productive than labour in newly automated tasks, TFP does not increase or could even decline (see equation (3.7)). However, unless cost saving can be measured and controlled for, the impact of $\mathcal{N}_t^{\mathcal{A}}$ on TFP, ω_t, is likely to reflect the confounding effects of cost saving as well as of the efficiency of capital vis-à-vis labour in newly automated tasks. This is because the two effects are not independent: the higher the efficiency of capital in newly automated tasks, the larger the cost saving.

task displacement resulting from the adoption of simpler or "so-so" automation technologies, which are capable of automating few tasks (see the arguments while positing Hypothesis 1). On the other hand, for firms that automate *regularly*, $\mathrm{E}[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}}]$, will capture the productivity implications of deepening automation *as well as* of cost savings due to task displacement.

This is evidently because it is mainly the firms that automate *regularly* that import the same category of intermediate capital goods for automation more than once. For example, of all the firms that imported dedicated machinery more than once, 84% belonged to the group that automates *regularly* and the rest to the group that automates *occasionally*; the figures for industrial robots and numerically controlled machines are 86% and 93% respectively. In addition, it goes without saying that the number of times that a particular category is imported when it is imported more than once is much larger for firms that automate *regularly*. These findings suggests that it is the firms that automate *regularly* that are more likely to deepen automation by importing new vintages of machinery for replacing older, less efficient vintages. In addition, as we have discussed in the arguments leading to Hypothesis 1, firms that automate *regularly* employ technologies that can automate large proportions of the production processes. Such technologies (e.g. a production line) are likely to be more efficient. Finally, the accumulated stock of knowledge earned through technology spillovers is also likely to be higher in firms that automate *regularly*.

We, therefore, conjecture that the expected productivity, $\mathrm{E}[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}}]$, for firms that automate *regularly* is likely to be higher than the same for firms that automate *occasionally*, while the expected productivity for firms that automate *occasionally* is expected to be higher than the same for *non-adopters*. That is,

$$\text{Hypothesis 2: } \mathrm{E}[g_{\mathrm{R}}(.)] > \mathrm{E}[g_{\mathrm{O}}(.)] \geq \mathrm{E}[g_{\mathrm{N}}(.)],$$

where

$$\begin{aligned} &g_{\mathrm{R}}(.) \equiv g(\omega_t, \mathcal{N}^{\mathcal{A}}, \mathcal{M}_t^{\mathcal{I}}, \mathcal{O}_t^{\mathcal{F}}) \text{ such that } \mathcal{N}^{\mathcal{A}} \in \{7, \ldots, 24\}, \\ &g_{\mathrm{O}}(.) \equiv g(\omega_t, \mathcal{N}^{\mathcal{A}}, \mathcal{M}_t^{\mathcal{I}}, \mathcal{O}_t^{\mathcal{F}}) \text{ such that } \mathcal{N}^{\mathcal{A}} \in \{1, \ldots, 6\}, \text{ and} \\ &g_{\mathrm{N}}(.) \equiv g(\omega_t, \mathcal{N}^{\mathcal{A}}, \mathcal{M}_t^{\mathcal{I}}, \mathcal{O}_t^{\mathcal{F}}) \text{ such that } \mathcal{N}^{\mathcal{A}} = 0. \end{aligned}$$

$\mathrm{E}[g_{\mathrm{R}}(.)]$, for example, is given by

$$\mathrm{E}[g_{\mathrm{R}}(.)] = \sum_{i=7}^{24} \mathrm{E}[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} = i]\mathrm{Pr}(\mathcal{N}^{\mathcal{A}} = i), \tag{5.8}$$

where the expectation is taken over the distribution of $(\omega, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})$. Now, firms that imported in at most 25% of the years they are observed in the data are categorized as *occasionally* automating, and those that imported in 25% to 100% of the years as *regularly* automating. For a firm that has been observed in all years, 1995-2018, if it invested in automation 7 or more times in 2018, it would be classified as *regularly* automating. That is why the summation in equation (5.8) runs from 7 to 24. Therefore, the expectation in (5.8) is the expected productivity of *regular* adopters in 2018.

Since (i) the function, $g(.)$, is estimated, (ii) ω_{jt} is computed for every firm-year, and (iii) we know $\mathcal{M}^{\mathcal{I}}_{jt}$ and $\mathcal{O}^{\mathcal{F}}_{jt}$ for every firm-year, we can estimate $\mathrm{E}[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} = i]$ in (5.8) for any given value of $\mathcal{N}^{\mathcal{A}} = i$ as

$$\frac{1}{2N}\sum_{j=i}^{N}\sum_{t=1}^{2}\hat{g}(\hat{\omega}_{jt}, \mathcal{N}^{\mathcal{A}} = i, \mathcal{M}^{\mathcal{I}}_{jt}, \mathcal{O}^{\mathcal{F}}_{jt}),$$

where $\hat{g}(.)$ is the estimate of $g(.)$ and $\hat{\omega}_{jt}$ that of ω_{jt}. Since we use only two years of data, 2017-2018, t takes the value 1 and 2. The probabilities, $\Pr(\mathcal{N}^{\mathcal{A}} = i)$, in equation (5.8) are estimated as the empirical probability of observing $\mathcal{N}^{\mathcal{A}} = i$ in 2018. This is given by the weighted sum:

$$\Pr(\mathcal{N}^{\mathcal{A}} = i) = \sum_{T_i=i}^{24}\Pr(\mathcal{N}^{\mathcal{A}} = i|T_i)\Pr(T_i), \tag{5.9}$$

where the weights are the probability of showing up in T_i number of years for firms that have invested in automation in i number of years.

Alternatively, Hypothesis 2 can be written as

$$\underbrace{\mathrm{E}[g_{\mathrm{R}}(.)] - \mathrm{E}[g_{\mathrm{N}}(.)]}_{\Delta_{\mathrm{RN}}} > \mathrm{E}\,\underbrace{[g_{\mathrm{O}}(.)] - \mathrm{E}[g_{\mathrm{N}}(.)]}_{\Delta_{\mathrm{ON}}} \geq 0, \tag{5.10}$$

where Δ_{RN} is the average treatment effect (ATE) of automating *regularly*, and Δ_{ON} is the ATE of automating *occasionally*.

5.2 Temporal Implications of Automation for Factor Share of Tasks, and Testing for (I) the Productivity Impact of FDI in Automation, and (II) Complementarities Between Automation and Management Innovation

In this subsection, we outline the empirical strategy for assessing (i) how factor shares of tasks have changed overtime among adopters and non-adopters, (ii) if there are complementarities between automation and organizational changes and/or innovation, and (iii) if, because of knowledge transfers and/or spillovers accompanying FDI in automation, multinational adopters are more productive. To assess how factor shares of tasks have changed overtime, we use census data from 2004 to 2018. Panel data over a longer period also allows us to exploit both cross-section and time-series variations in $\mathcal{M}^{\mathcal{I}}_{jt}$ and $\mathcal{O}^{\mathcal{F}}_{jt}$ to test for complementarities and for knowledge transfers/spillovers.

To assess how factor shares of tasks have changed overtime among adopters and non-adopters, we assume that:

ASSUMPTION $2'$ *In a given sector, conditional on D^A_{jt}, the random coefficients, φ_{jt}, α_{jt}, and β_{jt}, are mean independent of k_{jt} and l_{jt}, where D^A_{jt} indicates whether firm j at time t or before had adopted automation.*

Assumption $2'$ is similar to Assumption 2, except that we have further coarsened the conditioning variable, $\mathcal{N}^A_{jt}$, by assuming that given its binary version, $D^A_{jt} = 1\{\mathcal{N}^A_{jt} > 0\}$, capital stock and labour are uninformative about the fraction of tasks that the firms have automated. Since (a) we are estimating additional time dependent coefficients, and (b) testing for complementarity between automation and instituting new or improved management practices requires estimating additional parameters with a reduced sample size, the additional coarsening has been done to reduce the number of parameters for estimation.

According to Assumption $2'$, for a given sector, the conditional expectation of α_{jt} in equation (5.2) is given by: $\mathrm{E}(\alpha_{jt}|k_{jt}, l_{jt}, D^A_{jt}) = \mathrm{E}(1 - \Phi_{jt}|k_{jt}, l_{jt}, D^A_{jt}) = \mathrm{E}(1 - \Phi_{jt}|D_{jt})$. Let

$\bar{\alpha}^{\mathrm{A}}_t \equiv \mathrm{E}(1 - \Phi_{jt}|D^A_{jt} = 1)$ for firms that have *Automated* and
$\bar{\alpha}^{\mathrm{N}}_t \equiv \mathrm{E}(1 - \Phi_{jt}|D^A_{jt} = 0)$ for firms that have *Not Automated*.

Analogously, let the averages of β_{jt} be $\bar{\beta}^{\mathrm{A}}_t$ and $\bar{\beta}^{\mathrm{N}}_t$, and the averages of φ_{jt} be $\bar{\varphi}^{\mathrm{A}}_t$ and $\bar{\varphi}^{\mathrm{N}}_t$. As in the previous subsection, we write φ_{jt}, α_{jt}, and β_{jt} as

$$\varphi_{jt} = \bar{\varphi}^l_t + \widetilde{\varphi}_{jt}, \alpha_{jt} = \bar{\alpha}^l_t + \widetilde{\alpha}_{jt}, \text{ and } \beta_{jt} = \bar{\beta}^l_t + \widetilde{\beta}_{jt}, l \in \{\mathrm{A}, \mathrm{N}\} \tag{5.11}$$

where $\widetilde{\varphi}_{jt}$, $\widetilde{\alpha}_{jt}$ and $\widetilde{\beta}_{jt}$, respectively, are individual deviations from the common means, $\bar{\varphi}^l_t$, $\bar{\alpha}^l_t$, and $\bar{\beta}^l_t$. We can thus write the production function as

$$\begin{aligned} y_{jt} =& D^A_{jt}(\bar{\varphi}^{\mathrm{A}}_t + \bar{\alpha}^{\mathrm{A}}_t l_{jt} + \bar{\beta}^{\mathrm{A}}_t k_{jt}) + (1 - D^A_{jt})(\bar{\varphi}^{\mathrm{N}}_t + \bar{\alpha}^{\mathrm{N}}_t l_{jt} + \bar{\beta}^{\mathrm{N}}_t k_{jt}) \\ &+ \omega_{jt} + \tilde{\varphi}_{jt} + \tilde{\alpha}_{jt} l_{jt} + \tilde{\beta}_{jt} k_{jt} + \epsilon_{jt}, \end{aligned} \tag{5.12}$$

where the residual random coefficients – $\tilde{\varphi}_{jt}$, $\tilde{\alpha}_{jt}$, and $\tilde{\beta}_{jt}$ – are uncorrelated with k_{jt}, l_{jt}, and D^A_{jt}.

Though we have allowed the means – $(\bar{\varphi}^{\mathrm{A}}_t, \bar{\alpha}^{\mathrm{A}}_t, \bar{\beta}^{\mathrm{A}}_t)$ and $(\bar{\varphi}^{\mathrm{N}}_t, \bar{\alpha}^{\mathrm{N}}_t, \bar{\beta}^{\mathrm{N}}_t)$ – to be time dependent, estimating these means for every year between 2003 and 2018 is computationally challenging. Therefore, we estimate separate means for three different periods: the first period, T_1, covers the years 2003 to 2007; the second period, T_2, covers the years 2008 to 2012; and the third period, T_3, covers the years 2013 to 2018. That is, we estimate the following set of coefficients:

$(\bar{\varphi}^{\mathrm{A}}_{T_1}, \bar{\alpha}^{\mathrm{A}}_{T_1}, \bar{\beta}^{\mathrm{A}}_{T_1})$ and $(\bar{\varphi}^{\mathrm{N}}_{T_1}, \bar{\alpha}^{\mathrm{N}}_{T_1}, \bar{\beta}^{\mathrm{N}}_{T_1})$ for the period T_1,
$(\bar{\varphi}^{\mathrm{A}}_{T_2}, \bar{\alpha}^{\mathrm{A}}_{T_2}, \bar{\beta}^{\mathrm{A}}_{T_2})$ and $(\bar{\varphi}^{\mathrm{N}}_{T_2}, \bar{\alpha}^{\mathrm{N}}_{T_2}, \bar{\beta}^{\mathrm{N}}_{T_2})$ for the period T_2 and
$(\bar{\varphi}^{\mathrm{A}}_{T_3}, \bar{\alpha}^{\mathrm{A}}_{T_3}, \bar{\beta}^{\mathrm{A}}_{T_3})$ and $(\bar{\varphi}^{\mathrm{N}}_{T_3}, \bar{\alpha}^{\mathrm{N}}_{T_3}, \bar{\beta}^{\mathrm{N}}_{T_3})$ for the period T_3.

Again, since the labour task content of production, $1 - \Phi_{jt}$, is likely to be lower for the group of firms who imported equipment and machinery for automation compared to the same for the group of firms who did not, we can expect that for all $t \in \{T_1, T_2, T_3\}$,

$$\bar{\alpha}^{\mathrm{A}}_t < \bar{\alpha}^{\mathrm{N}}_t \text{ and } \bar{\beta}^{\mathrm{A}}_t > \bar{\beta}^{\mathrm{N}}_t.$$

Since over time (a) the number of firms that have adopted and/or extended automation increases, and (b) automation is deepened in certain firms, we expect that

$$\begin{aligned} \text{Hypothesis 3: } & \bar{\alpha}^{\mathrm{A}}_{T_1} > \bar{\alpha}^{\mathrm{A}}_{T_2} > \bar{\alpha}^{\mathrm{A}}_{T_3} \text{ and } \bar{\beta}^{\mathrm{A}}_{T_1} < \bar{\beta}^{\mathrm{A}}_{T_2} < \bar{\beta}^{\mathrm{A}}_{T_3} \\ & \bar{\alpha}^{\mathrm{N}}_{T_1} = \bar{\alpha}^{\mathrm{N}}_{T_2} = \bar{\alpha}^{\mathrm{N}}_{T_3} \text{ and } \bar{\beta}^{\mathrm{N}}_{T_1} = \bar{\beta}^{\mathrm{N}}_{T_2} = \bar{\beta}^{\mathrm{N}}_{T_3}. \end{aligned}$$

In other words, overtime, we expect the labour share of tasks to decline and capital's task share to increase among automation adopters. Among the non-adopters, we expect the shares to be stable or differ marginally over time.

As stated earlier, the information on organizational changes and/or innovation in management practices is obtain from the community innovation survey (CIS). It takes the form of a binary variable, $\mathcal{M}^{\mathcal{I}}_{jt}$, which takes the value 1 if firm j introduced new or improved management practices and 0 otherwise. As in models of managerial efficiency (Bloom and Van Reenen, 2007), productivity is likely to increase with the introduction of new or improved management practices – with or without automation. To capture the productivity effects of the introduction of new or improved management practices, we let TFP, ω_{jt}, in **Assumption 6** depend on the past instances of (a) automation, which is captured by $\mathcal{N}^{\mathcal{A}}_{jt}$, and (b) innovation/changes in management practices, $\mathcal{M}^{\mathcal{I}}_{j,t-1}$.

Brynjolfsson and McElheran (2016) mention that the many margins of adjustment required for the effective operation of certain new technologies, such as Data Driven Decision-Making, may be difficult for firms to discover and implement. When faced with new technologies, in order to find efficient ways to produce output, entrepreneurs, managers, and workers constantly work to reinvent the relevant processes and change the production process by design or through luck (Brynjolfsson and Mitchell, 2017). In other words, to maximize the value of investment in automation, firms may be required to improve upon automation enabling management practices. This would entail making organizational changes and investing in assets that are complementary to automation. See subsections 3.2 and 3.3 for a discussion on investments in automation enabling practices and complements, which include various costly adjustments that firms may have to undertake and their potential impact on productivity.

Now, the CIS data from which the information on the introduction of newly innovated or improved management practices are obtained does not mention that the practices are in response to automation (see Section 4 for the exact question asked of the firms). However, for adopters, the new or improved management practices, if instituted, are likely to be complementary processes that are automation enabling. These processes, to summarize earlier discussions, (a) ensure that the complementary non-routine tasks are executed efficiently, and (b) help discover newer complementarities between automation and the skilled workforce. In other words, it is likely that there are complementarities between automation, $\mathcal{N}^{\mathcal{A}}_{jt}$, and management innovation, $\mathcal{M}^{\mathcal{I}}_{jt}$; a test to assess this claim is developed below.

The estimation of equation (5.12) with specification for the controlled Markov process in equation (5.7) allows us to test for complementarities between management innovation and automation. Let

$$
\begin{aligned}
g_{11}(.) &\equiv g(\omega_{jt}, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}}_{jt}) \text{ such that } 1\{\mathcal{N}^{\mathcal{A}} > 0\} = 1, \mathcal{M}^{\mathcal{I}} = 1 \\
g_{10}(.) &\equiv g(\omega_{jt}, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}}_{jt}) \text{ such that } 1\{\mathcal{N}^{\mathcal{A}} > 0\} = 1, \mathcal{M}^{\mathcal{I}} = 0 \\
g_{01}(.) &\equiv g(\omega_{jt}, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}}_{jt}) \text{ such that } 1\{\mathcal{N}^{\mathcal{A}} > 0\} = 0, \mathcal{M}^{\mathcal{I}} = 1 \\
g_{00}(.) &\equiv g(\omega_{jt}, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}}_{jt}) \text{ such that } 1\{\mathcal{N}^{\mathcal{A}} > 0\} = 0, \mathcal{M}^{\mathcal{I}} = 0,
\end{aligned}
$$

where $1\{\mathcal{N}^{\mathcal{A}}_{jt} > 0\}$ is an indicator function that takes the value 1 if the argument inside the parenthesis is true and 0 otherwise.

The study of complementarities between activities (or practices) can be traced back to the theory of supermodularity (Milgrom and Roberts, 1995; Brynjolfsson and Milgrom, 2012). According to this theory, the necessary condition for innovation in management and automation to be complementary is that the expectation, $\mathrm{E}[g(\omega_{jt}, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}}_{jt})]$, be supermodular in $\mathcal{M}^{\mathcal{I}}$ and $1\{\mathcal{N}^{\mathcal{A}} > 0\}$:

$$\mathrm{E}[g_{11}(.)] - \mathrm{E}[g_{10}(.)] \geq \mathrm{E}[g_{01}(.)] - \mathrm{E}[g_{00}(.)]. \tag{5.13}$$

where, for example, $\mathrm{E}[g_{11}(.)]$ is the expectation of $g(\omega_{jt}, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}}_{jt})$ with respect to the marginal distribution of $(\omega_{jt}, \mathcal{O}^{\mathcal{F}}_{jt})$ when $\mathcal{N}^{\mathcal{A}} > 0$ and $\mathcal{M}^{\mathcal{I}} = 1$. The above inequalities can be interpreted as follows: on average, discovering and/or instituting novel management practices, which are likely to be those that facilitate synergies between machines and human labour, in firms that are automating has a higher incremental effect on productivity than discovering and/or instituting efficiency improving management practices in firms that do not automate. However, there are no reasons why the new or improved management practices instituted by firms that *do not* automate should be automation enabling; they are likely to be complementary to other technological changes that are not the objects of this study.[30] While certain automation enabling practices are likely to be instituted when capital goods for automation are installed, the discovering/instituting of novel management practices that are complementary with automation is more likely in line with the concept of dynamic complementarities (Love *et al*., 2014), whereby adding one activity increases the returns from an already existing strategy (automation in this case).

The complementarity condition in equation (5.13) can therefore be expressed as

$$\mathrm{E}[g_{11}(.)] - \mathrm{E}[g_{10}(.)] \geq 0 \Leftrightarrow \underbrace{\mathrm{E}[g_{11}(.)] - \mathrm{E}[g_{00}(.)]}_{\Delta_{11}} \geq \underbrace{\mathrm{E}[g_{10}(.)] - \mathrm{E}[g_{00}(.)]}_{\Delta_{10}}, \tag{5.14}$$

where Δ_{11} is the average treatment effect (ATE) of automating *and* implementing newly innovated management practices on productivity, and Δ_{10}, the ATE of *only* automating on productivity. To test if complementarities do exist between automation and new and improved organization practices we hypothesise:

Hypothesis 4: $\Delta_{11} \geq \Delta_{10} > 0$.

[30] If, however, the diffusion of new technologies – including automation – is accompanied by the diffusion of new organizational practices that are more conducive to automation and if non-automating firms adopt these practices, then equation (5.13) will hold, and Hypothesis 4 would be written as $\Delta_{11} \geq \Delta_{10} + \Delta_{01} \geq 0$, where Δ_{01} if the ATE of *only* instituting new management practices. Since only about 10% of the firms are found to have automated, the likelihood of such a scenario seems low.

Because the information on organizational changes and/or innovation in management practices, $\mathcal{M}^{\mathcal{I}}_{jt}$, is obtained from the community innovation survey (CIS) data, to test Hypothesis 4, we do not impute, as explained in the last subsection, $\Pr(\mathcal{M}^{\mathcal{I}}_{jt} = 1)$ for the non-CIS firms in the census data, which is the data used for testing all the other Hypotheses, but restrict the estimation sample to those firms that are present only in the CIS data.

Finally, to assess if FDI in automation is accompanied by transfers of productivity enhancing knowledge and spillover effects, we hypothesize that

$$\text{Hypothesis 5: } \Delta_{\mathcal{N}^{\mathcal{A}}>0, \mathcal{O}^{\mathcal{F}}=1} \geq \Delta_{\mathcal{N}^{\mathcal{A}}>0, \mathcal{O}^{\mathcal{F}}=0} > 0,$$

where $\Delta_{\mathcal{N}^{\mathcal{A}}>0, \mathcal{O}^{\mathcal{F}}=1}$ is the ATE of automation for the foreign-owned/multinational adopters and $\Delta_{\mathcal{N}^{\mathcal{A}}>0, \mathcal{O}^{\mathcal{F}}=0}$ is the ATE of automation for the domestic adopters. Because the highest frequencies of $\mathcal{O}^{\mathcal{F}}_{jt}$, the share of firm owned by a multinational, are at 0 and 1, we evaluate the ATEs at $\mathcal{O}^{\mathcal{F}} = 1$ and $\mathcal{O}^{\mathcal{F}} = 0$.[31]

6 Results

We discuss the results in two subsections. In the first subsection we discuss the results related to the hypotheses developed in subsection 5.1, and in the second subsection, results related to those that were developed in subsection 5.2.

6.1 Results: Implications of Automation for Productivity and Share of Tasks between Factors

The results in this subsection correspond to the empirical strategy outlined in subsection 5.1. Table 8, Panel A, illustrates the estimates for equation (5.4). The estimation yields the average of the share of tasks between capital and labour for (a) firms *without* automation, (b) firms that automate *occasionally*, and (c) firms that automate *regularly*. The shares have been estimated for each of the broad sectors, (i) manufacturing, (ii) services, and (iii) the 'other' sector comprising mining, utilities, and construction.

[31] In the population during the period 2003-2018, about 3% of the firm-years are partially owned by multinationals, whereas about 9% are fully controlled by the multinationals; and the rest are domestically owned. The corresponding percentages for the population of automation adopters are 16 and 21.

[Table 8 about here]

For the estimation, we first interact capital and labour with dummy variables for (a) the *non-adopters*, (b) firms that automate *occasionally*, and (c) those that automate *regularly*, and estimate the coefficients of equation (5.4) for all the groups simultaneously while treating the dummy variables as state variables. Now, since the classification of firms – which depends on the number of times a firm has imported capital goods for automation – is not exogenous, the dummy variables will be correlated with the unobserved productivity, ω_{jt}. By treating them as 'state' variables when using the control function method from ACF for the estimation, we account for their endogeneity. In addition, since there could be agglomeration effects of locating in what is the economic hub of Estonia, the choice of location is not a random but a deliberate choice made by the firms. The endogenous choice of location is accounted for by treating the dummy for north Estonia as a state variable.[32]

In Table 8, we can see that the fraction of tasks performed by labour in all the sectors is decreasing with the frequency (or degree) of automation: $\bar{\alpha}_t^{\mathrm{N}} > \bar{\alpha}_t^{\mathrm{O}} > \bar{\alpha}_t^{\mathrm{R}}$. The decrease is more pronounced in the manufacturing sector and the 'other' sector. At the same time, average task share of capital increases with the frequency of automation: $\bar{\beta}_t^{\mathrm{N}} < \bar{\beta}_t^{\mathrm{O}} < \bar{\beta}_t^{\mathrm{R}}$. So, as the results lend support to Hypothesis 1, we can conclude that automation does shift the task content of production against labour. Furthermore, it should be noted that for manufacturing and the 'other' sector, the labour share of tasks for the firms that automate *regularly* is disproportionately smaller than it is for the firms that automate *occasionally*. This is because, as argued while positing Hypothesis 1, firms that automate *regularly* are large, have large market shares, and can amortize investments in costly automation technologies that can automate large proportions of the production processes. Finally, in the service sector, however, because it is more labour-intensive, we see that even among firms that automate *regularly*, the task share of labour is relatively high.

Since, given wages, rental rate, and mark-ups, labour share of value-added (LSVA) in firm j decreases with Φ_{jt} and capital share increases (see equation (3.6)), we can conclude that automation exerts a downward pressure on LSVA as the theory predicts. However, as can be seen in Table 8, LSVA does not vary systemically with the frequency of automation in any of the

[32]In the control function methods for estimating the production functions, such as the one by ACF, decisions regarding the 'state' variables, which include fixed inputs, such as capital, are taken prior to the choice of flexible inputs, such as labour and material inputs. The timing of decisions allows one to construct control variables, which can account for the correlation of state variables with the unobserved productivity, ω_{jt}. Here the assumption is that the decision on whether to automate, the degree of automation, and the choice of location are taken prior to the choice of flexible inputs.

sectors. Moreover, as we have seen in Section 2, contrary to the findings in studies on LSVA implication of automation for developed economies, (a) LSVA is either higher among the automation adopters or increased to surpass the level observed for the non-adopters (see Figure 2e, Figure 6, and Figure 7), and (b) the recent increase in aggregate LSVA is partly explained by reallocation towards adopters.

Now, in each of the broad sectors, the fraction of firms that adopt automation is small, and the fraction that automate *regularly* is even smaller. But those that automate *regularly* have a much higher market share and, as the ATEs of automation in Table 8 suggest, are among the most productive firms. This suggests that due to productivity effects, as discussed in Section 2, wages for all or certain employees in firms with increasing automation have increased to compensate for the negative effects of task displacement on LSVA. The productivity effect could, as shown by Dauth *et al*. (2021) for Germany, manifest itself in extant workers taking over new roles within their original plants. So, even though workers are displaced from certain tasks, the swift transition of incumbent workers to higher quality new jobs that pay higher wages offset the effect of displacement from certain tasks. It is also possible that in certain firms no labour was displaced from routine tasks, but multinationals through FDI, to take advantage of the relatively low cost of well-skilled labour, set up operations – which created productive new jobs that paid wages higher than average local firms in the same industry – where the share of tasks worked by labour is low.

We now discuss the productivity implications of automation. Now, $g(\omega_{jt}, \mathcal{N}_{jt}^{\mathcal{A}}, \mathcal{M}_{jt}^{\mathcal{I}}, \mathcal{O}_{jt}^{\mathcal{F}})$ could be higher for firms that automate *regularly* because ω_{jt} is higher for such firms and not necessarily because the impact of $\mathcal{N}_{jt}^{\mathcal{A}}$ on $g(.)$ is higher. To rule out such a selection in quantitatively assessing the productivity impact of automation, as shown in subsection 5.1 (see equation (5.10)), we compute the ATE of automating *regularly* (Δ_{RN}) and the ATE of automating *occasionally* (Δ_{ON}). As can be seen in Table 8, $\Delta_{\text{RN}} > \Delta_{\text{ON}} \geq 0$ for all the sectors. These results, then, suggest that the productivity impact of automation increases with the frequency of automation. The reasons for the differential productivity impact has been discussed in the arguments that lead to the formulation of Hypothesis 2, and are not repeated here. However, we would like to point out that since the ATE, Δ_{ON}, for the service sector is not significant, it seems that preferred automation technologies of the *occasional* adopters are those that are not more efficient than the labour they displace.

Before ending our discussion on the productivity implications of automation, we would like to draw attention to its possible aggregate impact. First, while the productivity impact for those that automate *regularly* is substantial, those that automate *regularly* are a small number of large firms with higher market shares. That is, such productivity improvements accrue mostly to those who are able to incur the substantial fixed costs imposed by the large-scale automation they undertake. This is likely to have implications for the widening productivity gap between frontier and laggard firms in the same industry.

However, since firms that automate *regularly* have a larger market share and are more productive, their share in the aggregate productivity is large. For $t = 2018$, the share of estimated TFP, $g(\omega_j, \mathcal{N}_j^{\mathcal{A}}, \mathcal{M}_{jt}^{\mathcal{I}}, \mathcal{O}_{jt}^{\mathcal{F}})$, which is in logarithmic scale, of the firms that automate *regularly* is 0.38. On the other hand, even though *occasional* adopters have a reasonable market share, because the estimated TFP is small, their share in aggregate productivity is 0.16, which is comparatively small. In conclusion, it seems that the aggregate productivity implications of automation are largely due to the small number of firms that automate *regularly*.

In other results, we find robust evidence of firms located in north Estonia, which is the economic hub of the nation, being more productive; this suggests that firms in north Estonia benefit from a positive agglomeration effect.

6.2 Results: Temporal Implications of Automation for Factor Share of Tasks, and Testing for (I) the Productivity Impact of FDI in Automation and (II) Complementarities Between Automation and Management Innovation

Table 9 illustrates the estimates for equation (5.12), which allows for different labour and capital coefficients for (a) firms that adopted automation, and (b) for the non-adopters. These coefficients, as we have discussed, are the expected value of labour and capital task shares. To assess if the share of tasks between factors among automation adopters has changed over the years, we estimate separate coefficients for labour and capital for three different periods: the first period, T_1, covers the years 2003 to 2007; the second period, T_2, covers the years 2008 to 2012; and the third period, T_3, covers the years 2013 to 2018. The various labour and capital coefficients are estimated by pooling together adopting and non-adopting firms and the three time periods. The estimation details are presented in Appendix B.2.

As can be seen in Table 9, for all sectors, we find that the coefficient of labour for firms that have automated has decreased over the years and the coefficient of capital has increased. But the coefficients for firms that have not automated has stayed more-or-less unchanged. Besides, the coefficients of labour (capital) for firms that have automated are lower (higher) than firms that have not automated. Our results, which shows Hypothesis 3 to be true, follows because over time (a) the number of firms that have adopted and/or extended automation has increased, and (b) automation has deepened in certain firms. In other results, as before, we find that firms located in north Estonia produce more and are likely more productive.

[Table 9 about here]

[Table 10 about here]

To gauge the extent to which automation and/or the introduction of new or improved management practices improves productivity, as discussed in Section 5.2 and detailed in Appendix B.2, we estimate the average treatment effect (ATE) of (a) *only* automation (Δ_{10}), and (b) of automation *and* the introduction of new or improved management practices (Δ_{11}). The ATEs are reported in Table 10. We find that Δ_{10} is significantly positive for firms in all sectors, implying that those firms that *only* automated did realize productivity gains. The estimates of Δ_{11} suggest that firms that automated *and* introduced new or improved management practices realized the highest gains.

These ATEs, however, are in logarithmic scale; at the mean, these differences in linear scale imply that in the manufacturing sector, on average, firms that *only* automated are 22% more productive than firms than firms that *neither* automated *nor* introduced new or improved management practices, and firms that automated *and* introduced new or improved management practices are 37.6% more productive than firms that *do neither*. The corresponding percentages for firms in the service sector are 38% and 50% respectively, while the corresponding percentages for firms in the sector comprising of mining, utilities, and construction, are 34% and 73% respectively.

We, therefore, find that for firms in all the sectors, $\Delta_{11} > \Delta_{10} > 0$. In other words, as hypothesised in Section 5, we find that there exist complementarities between automation and the introduction of new or improved management practices. Complementarities between the two arise when the returns to automation, which substitutes for workers performing routine tasks, are highest when the firm also makes organizational changes so that (a) automation could complement workers in executing non-routine tasks, and (b) humans and machines by combining their complementary strengths, mutually learn to discover additional complementarities.

In Table 10, we also find that the ATE of automation on TFP for multinational firms, as hypothesized in Hypothesis 5, is larger than the same for the domestically owned firms. This suggests that FDI is accompanied by transfers of productivity enhancing knowledge and spillover effects.

The TFP impact of these transfers and spillovers accompanying automation increase, as we have seen in the reduced form regressions, Table 1, labour share of value-added among the automation adopting firms. In the Estonian economy, the employment weighted aggregate share of multinational automation adopters in Manufacturing, Services, and the sector comprising Mining, Construction and Utilities during the period, 2003 to 2018, are 35%, 10% and 7% respectively. These relatively large shares imply that the aggregate consequences of the spillover effects are likely to be substantial.

7 Concluding Remarks

While there is a growing body of theoretical and empirical work on the aggregate effects of automation on employment, labour share, and productivity, there is little micro-evidence on the implications of automation for labour related outcomes and productivity. The few that we are aware of study automation in developed economies. First, this paper provides estimates of aggregate implications of automation for Estonia, a catching-up economy, where automation is primarily imports-led and foreign direct investment (FDI) facilitated. Second, it provides microeconometric evidence of the impact of automation for the factor task content of production and productivity.

For the empirical study we use the universe of Estonian firms. For each firm, we have almost all information on automation activities from 1995 onward. Therefore, using firm-level data we are able to construct aggregate outcomes for automation adopters and non-adopters. A large body of research endeavours to understand the sources of firm-level growth and their aggregate consequences. Our results contribute to these studies by pointing to the role of automation in an open, catching-up economy.

At the aggregate level, we focus on labour share of value-added (labour share for brevity) and the productivity implications of automation as labour shares in Estonia and other catching-up Central and Eastern European countries are lower than that for the US and older EU member states. However, in contrast to evidence from developed economies, in Estonia, labour share for automation adopting firms is found to be higher than the same for non-adopters. Decomposing the changes in the aggregate labour share and aggregate total factor productivity (TFP), both of which increased during the last decade, showed that reallocation from non-adopters towards adopting firms resulted in an increase in the aggregate TFP as well as, remarkably, the aggregate labour share. This is in contrast to the findings for developed economies, where such a reallocation resulted in a decrease in labour share. However, the reallocation of resources among the adopting firms, which increased aggregate TFP, reduced labour share among the adopters. These results suggest that (a) it is primarily the "superstar" effect rather than automation that exerts a downward pressure on labour share for the adopting firms, and (b) the various channels of productivity growth – including that due to cost saving from automation and technology spillovers and transfers in imports-led and FDI-facilitated automation – more than offset the negative effects of the decline in labour task content of production due to automation.

Motivated by the finding that the productivity impact of automation contributed to the increase in aggregate labour share, we undertake a firm-level level analysis of its impact for factor shares of tasks and productivity. We find that there is heterogeneity in the adoption of automation and its impact on the share of tasks performed by labour (or labour task content of production) and TFP are heterogeneous. We find that the share of tasks performed declines with the frequency with which firms invest in automation, and that among the automation adopters, the same has declined over the years.

As far as the productivity impact of automation is concerned, we find that its impact is heterogeneous. First, firms that automate frequently, for various reasons, are among the most productive adopters. Second, multinational adopters are found to be more productive than their domestic counterparts, which suggests that FDI in automation is accompanied by knowledge transfer and spillover effects. Third, firms that realize complementarities between automation and innovative management practices are more productive than those that only automate; this establishes that the innovative management practices instituted by the automation adopters are those that help discover and facilitate synergies between automation and human labour.

There are certain limitations to our paper. While we have alluded to the various sources of productivity growth, which in turn affect the evolution of labour share, we do not delineate the contributions of the various sources for productivity growth and labour share. It would be worthwhile to explore methods for estimating the contributions of the respective sources and of automation for changes in the various outcomes of interest. Second, we assumed that elasticity of substitution between tasks is one for estimating the labour task content of production for firms with varying frequency/extent of automation. It would be a valuable contribution to the literature on microeconometrics of automation if this assumption is relaxed while estimating the same.

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A.1 Derivation of the Production Function as a Function of the Share of Automated Tasks

As stated earlier, the output market is monopolistically competitive, where each firm faces its own demand curve, $P_{jt}(Y_{jt})$. Let $\varepsilon_{jt} = \dfrac{dY_{jt}/Y_{jt}}{dP_{jt}/P_{jt}}$ denote the price elasticity of demand for firm j's good in time period t. In lemma 1 we show that:

Lemma 1 *The demand for task i is given as:*

$$y_{jt}(i) = Y_{jt}\left(\frac{\mu_{jt}p_{jt}(i)}{P_{jt}}\right)^{-\sigma}, \tag{A.1.1}$$

where $p_{jt}(i)$ is the unit cost that firm j in period t incurs in producing task i, and $\mu_{jt} = \dfrac{\varepsilon_{jt}}{1+\varepsilon_{jt}}$ is the mark-up.

Proof of Lemma 1 *The proof follows from the solution to the monopolistic firm's optimization problem, where in each period it chooses an amount of task i, $y_{jt}(i)$, $i \in [0,1]$, to maximize its profit, $P_{jt}Y_{jt} - \int_0^1 y_{jt}(i)p_{jt}(i)di$, subject to the constraint that the output, Y_{jt}, is given by the production function, $Y_{jt} = \left(\int_0^1 y_{jt}(i)^{\frac{\sigma-1}{\sigma}}di\right)^{\frac{\sigma}{\sigma-1}}$.*

To ease notations, we drop the subscript, jt. Since in all automated tasks, which are indexed lower than Φ, capital is cheaper, given equations (3.4) and (A.1.1), equations (3.2) and (3.3) imply that the factor demands for each task i is given by:

$$k(i) = \begin{cases} \dfrac{Y}{A^K\eta(i)}\left(\dfrac{\mu R_t}{PA^K\eta(i)}\right)^{-\sigma} & \text{if } i \le \Phi \\ 0 & \text{if } i > \Phi\,, \end{cases} \tag{A.1.2}$$

$$l(i) = \begin{cases} 0 & \text{if } i \le \Phi \\ \dfrac{Y}{A^L\gamma(i)}\left(\dfrac{\mu W_t}{PA^L\gamma(i)}\right)^{-\sigma} & \text{if } i > \Phi\,. \end{cases} \tag{A.1.3}$$

From equations (A.1.2) and (A.1.3) it follows that the total demand for capital and labour respectively are:

$$K = Y\int_0^{\Phi} \frac{1}{A^K\eta(i)}\left(\frac{\mu R_t}{PA^K\eta(i)}\right)^{-\sigma} di \text{ and } L = Y\int_{\Phi}^{1} \frac{1}{A^L\gamma(i)}\left(\frac{\mu W_t}{PA^L\gamma(i)}\right)^{-\sigma} di. \tag{A.1.4}$$

The cost of producing the final good, Y, therefore is

$$R_tK + W_tL = Y\left(\frac{\mu}{P}\right)^{-\sigma}\left[\int_0^{\Phi}\left(\frac{R_t}{A^K\eta(i)}\right)^{1-\sigma} di + \int_{\Phi}^{1}\left(\frac{W_t}{A^L\gamma(i)}\right)^{1-\sigma} di\right].$$

Since in a monopolistic set-up, the price of Y is mark-up times the marginal cost of producing it, we have

$$\left(\frac{\mu}{P}\right)^{1-\sigma}\left[\int_0^{\Phi}\left(\frac{R_t}{A^K\eta(i)}\right)^{1-\sigma} di + \int_{\Phi}^{1}\left(\frac{W_t}{A^L\gamma(i)}\right)^{1-\sigma} di\right] = 1. \tag{A.1.5}$$

Using the factor demand equations in equation (A.1.4) to substitute for factor prices in equation (A.1.5), we get the following CES production function:

$$Y = \left(\left(\int_0^{\Phi}\eta(i)^{\sigma-1}di\right)^{\frac{1}{\sigma}}(A^KK)^{\frac{\sigma-1}{\sigma}} + \left(\int_{\Phi}^{1}\gamma(i)^{\sigma-1}di\right)^{\frac{1}{\sigma}}(A^LL)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}. \tag{A.1.6}$$

For $\sigma = 1$, we get the following Cobb-Douglas production function,

$$Y = A\left(\frac{A^KK}{\Phi}\right)^{\Phi}\left(\frac{A^LL}{1-\Phi}\right)^{1-\Phi} = \Omega f(\Phi)K^{\Phi}L^{1-\Phi}, \tag{A.1.7}$$

where $\Omega = A(A^K)^{\Phi}(A^L)^{1-\Phi}$ is the total factor productivity (TFP). The term $A = \exp\left[\int_0^{\Phi}\ln(\eta(i))di + \int_{\Phi}^{1}\ln(\gamma(i))di\right]$ and $f(\Phi) = \left[\frac{1-\Phi}{\Phi}\right]^{\Phi}\frac{1}{1-\Phi}$, which is bounded between 1 and 2.

B.2 Estimation of the Production Function and of Average Treatment Effects

B.2.1 Identification and Estimation of Structural Coefficients

In this appendix we show that the control function method by Ackerberg *et al*. (2015) (ACF), which accounts for the correlation between unobserved productivity, ω_{jt}, and the inputs can be used to estimate the coefficients of interest in equations (5.4) and (5.12) in the main text. We discuss the identification and estimation of parameters of equation (5.12); the same for equation (5.4) is analogous. For convenience, we write equation (5.12) as

$$y_{jt} = h(k_{jt}, l_{jt}, D^A_{jt}, x_{jt}; \Theta) + \omega_{jt} + \tilde{\varphi}_{jt} + \tilde{\alpha}_{jt}l_{jt} + \tilde{\beta}_{jt}k_{jt} + \epsilon_{jt}, \tag{B.2.1}$$

where Θ is the set of parameters of interest in equation (5.12) and x_{jt} is the set of additional state variables. With unobserved productivity, ω_{jt}, assumed to be scalar (see Assumption 3) and the non-dynamic material inputs, m_{jt}, assumed to be strictly monotonic in ω_{jt} (see Assumption 4), we can write ω_{jt} as $\omega_{jt} = f_t^{-1}(l_{jt}, k_{jt}, D^A_{jt}, x_{jt}, m_{jt})$ (see equation (5.6)). We can therefore write the above equation as

$$y_{jt} = \phi(l_{jt}, k_{jt}, D^A_{jt}, x_{jt}, m_{jt}) + \tilde{\varphi}_{jt} + \tilde{\alpha}_{jt} l_{jt} + \tilde{\beta}_{jt} k_{jt} + \epsilon_{jt}, \tag{B.2.2}$$

where $\phi(l_{jt}, k_{jt}, D^A_{jt}, x_{jt}, m_{jt}) = h(k_{jt}, l_{jt}, D^A_{jt}, x_{jt}; \Theta) + f_t^{-1}(l_{jt}, k_{jt}, D^A_{jt}, x_{jt}, m_{jt})$.

Since in equation (5.11) we have defined $\tilde{\varphi}_{jt}$, $\tilde{\alpha}_{jt}$, and $\tilde{\beta}_{jt}$ as $\tilde{\varphi}_{jt} = \varphi_{jt} - \mathrm{E}(\varphi_{jt}|D^A_{jt})$, $\tilde{\alpha}_{jt} = \alpha_{jt} - \mathrm{E}(\alpha_{jt}|D^A_{jt})$ $\tilde{\beta}_{jt} = \beta_{jt} - \mathrm{E}(\beta_{jt}|D^A_{jt})$ respectively, by Assumption $2'$, we have

$$\mathrm{E}(y_{jt}|l_{jt}, k_{jt}, D^A_{jt}, x_{jt}, m_{jt}) = \phi(l_{jt}, k_{jt}, D^A_{jt}, x_{jt}, m_{jt}).$$

Therefore, $\phi(.) \equiv \phi(l_{jt}, k_{jt}, D^A_{jt}, x_{jt}, m_{jt})$ is identified, and, as in the method by ACF, is estimated in the first stage of the two stage estimation procedure. For the estimation, we assume $\phi(.)$ to be a polynomial function of its arguments of order 3. To avoid multicollinearity, exogenous/control variables like industry and time dummies, when included, are not interacted with the other polynomial terms.

In the second stage, given estimates of $\phi(.)$, the structural parameters, Θ, are estimated. Now, according to Assumption 6, ω_{jt} depends on $\omega_{j,t-1}$, $\mathcal{N}^{\mathcal{A}}_{jt}$, and $\mathcal{M}^{\mathcal{I}}_{j,t-1}$ to evolve endogenously according to the controlled Markov process:

$$\omega_{jt} = \mathrm{E}(\omega_{jt}|\omega_{j,t-1}, \mathcal{N}^{\mathcal{A}}_{jt}, \mathcal{M}^{\mathcal{I}}_{j,t-1}) + \xi_{jt} = g(\omega_{j,t-1}, \mathcal{N}^{\mathcal{A}}_{jt}, \mathcal{M}^{\mathcal{I}}_{j,t-1}, \mathcal{O}^{\mathcal{F}}_{j,t-1}) + \xi_{jt}.$$

To estimate the function, $g(.)$, and the structural parameters, Θ, we follow the procedure in Olley and Pakes (1996), where the function, $g(.)$, is estimated non-parametrically by approximating it using a polynomial function:

$$g(\omega_{j,t-1}, \mathcal{N}^{\mathcal{A}}_{jt}, \mathcal{M}^{\mathcal{I}}_{j,t-1}, \mathcal{O}^{\mathcal{F}}_{j,t-1}) = \sum_{k=0}^{3}\sum_{l=0}^{2}\sum_{m=0}^{1}\sum_{n=0}^{1} C_{klmn}\omega^k_{j,t-1}(\mathcal{N}^{\mathcal{A}}_{jt})^l(\mathcal{M}^{\mathcal{I}}_{j,t-1})^m(\mathcal{O}^{\mathcal{F}}_{j,t-1})^n. \tag{B.2.3}$$

For the estimation, we assume that k in equation (B.2.3) runs from 0 to 3, l runs from 0 to 2, and m from 0 to 1.[33]

As discussed in Section 5, $\mathcal{N}^{\mathcal{A}}_{jt}$, is the number of times since 1995 until period, t, the firm imported equipment and machinery for automation. The specification in (B.2.3) assumes that,

[33]Note that because $\mathcal{M}^{\mathcal{I}}$ is a binary variable that takes the values 1 and 0, and almost all the values of $\mathcal{O}^{\mathcal{F}}$ are 0 and 1; therefore, higher order terms of $\mathcal{M}^{\mathcal{I}}_{j,t-1}$ and $\mathcal{O}^{\mathcal{F}}_{j,t-1}$ do not appear in the polynomial function.

given $\omega_{j,t-1}$ and $\mathcal{M}^{\mathcal{I}}_{j,t-1}$, increasing $\mathcal{N}^{\mathcal{A}}_{jt}$ from, let us say, 1 to 2 has the same effect on productivity as increasing $\mathcal{N}^{\mathcal{A}}_{jt}$ from, 20 to 21. Though this could be potentially restrictive, it greatly simplifies the estimation.[34]

Second Stage: Estimation of Θ and the coefficients, C_{klmn}'s, of the function $g(.)$.

Now, since $\phi(.)$ in equation (B.2.2) is identified and estimated in the first stage and since we know the functional form of $h(k_{jt}, l_{jt}, D^{A}_{jt}, x_{jt}; \Theta)$ in (B.2.1), for a given value of Θ, we can obtain

$$\omega_{jt}(\Theta) = \phi(.) - h(k_{jt}, l_{jt}, D^{A}_{jt}, x_{jt}; \Theta). \tag{B.2.4}$$

Step 1. For a good initial guess of Θ – usually, OLS estimates of Θ in equation (B.2.1) – obtain $\omega_{jt}(\Theta)$ using equation (B.2.4).

Step 2. Estimate C_{klmn}'s in (B.2.3) by regressing $\omega_{jt}(\Theta)$ on $\omega^{k}_{j,t-1}(\Theta)(\mathcal{N}^{\mathcal{A}}_{jt})^{l}(\mathcal{M}^{\mathcal{I}}_{j,t-1})^{m}(\mathcal{O}^{\mathcal{F}}_{j,t-1})^{n}$'s.

Step 3. Given the estimates of C_{klmn}'s – of the function $g(.)$ – obtain the residuals

$$\xi_{jt}(\Theta) = \omega_{jt}(\Theta) - \sum_{k=0}^{3}\sum_{l=0}^{2}\sum_{m=0}^{1}\sum_{n=0}^{1} C_{klmn}\omega^{k}_{j,t-1}(\Theta)(\mathcal{N}^{\mathcal{A}}_{jt})^{l}(\mathcal{M}^{\mathcal{I}}_{j,t-1})^{m}(\mathcal{O}^{\mathcal{F}}_{j,t-1})^{n}.$$

Step 4. Using the orthogonality condition,

$$\mathrm{E}[\xi_{jt}(\Theta)Z_{jt}] = 0,$$

where Z_{jt} is the set of instruments, estimate the optimal value of Θ. We employ k_{jt}, $l_{j,t-1}$, D^{A}_{jt}, x_{jt}, the interactions between $(k_{jt}, l_{j,t-1})$ and D^{A}_{jt}, $\mathcal{N}^{\mathcal{A}}_{jt}$, $\mathcal{M}_{j,t-1}$, $\mathcal{O}^{\mathcal{F}}_{j,t-1}$, the lagged values of non-dynamic material inputs, $m_{j,t-1}$, and other variables in structural equations that are not correlated with ξ_{jt} as instruments. The estimation of Θ entails iterations over the previous three steps – the previous three steps have to be performed each time the criterion function to be minimized is computed – until Θ converges to its optimal value. In the process, we also obtain consistent estimates of C_{klmn}'s; that is, of the function $g(.)$.

[34] While it is possible that the productivity impact of automation differs depending on the value of $\mathcal{N}^{\mathcal{A}}_{jt}$, we do not estimate separate impacts for different values of $\mathcal{N}^{\mathcal{A}}_{jt}$. This is because, first, as can be seen in Table 4, the majority of firms (about 70%) imported just once or twice since 1995, and therefore including dummies for different values of $\mathcal{N}^{\mathcal{A}}_{jt}$ resulted in the problem of multicollinearity. Second, if instead of $\mathcal{N}^{\mathcal{A}}_{jt}$ we include dummy variables, one each for the different values of $\mathcal{N}^{\mathcal{A}}_{jt}$, the number of terms in the polynomial expansion in equation (B.2.3) increases substantially.

B.2.2 Identification and Estimation of Average Treatment Effects

Now we come to the question of testing for complementarity between automation and organizational innovation. To establish complementarity between the two, as shown in subsection 5.2, we can compare the average treatment effect (ATE) of automating *and* implementing newly innovated management practices on productivity, Δ_{11}, to the ATE of *only* automating, Δ_{10}.

Now, suppressing the subscript, jt, in equation (B.2.3), Δ_{11} defined in equation (5.14) in the main text is given by

$$\begin{aligned}\Delta_{11} =&\mathrm{E}(g_{11}) - \mathrm{E}(g_{00}) \\ =&\mathrm{E}\big[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} > 0, \mathcal{M}^{\mathcal{I}} = 1\big] - \mathrm{E}\big[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} = 0, \mathcal{M}^{\mathcal{I}} = 0\big].\end{aligned} \tag{B.2.5}$$

where the expectations are taken over the distribution of $(\omega_{jt}, \mathcal{O}^{\mathcal{F}}_{jt})$.

The term, $\mathrm{E}(g_{11}) = \mathrm{E}\big[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} > 0, \mathcal{M}^{\mathcal{I}} = 1\big]$, in the above is given by

$$\mathrm{E}(g_{11}) = \sum_{i=1}^{24} \mathrm{E}\big[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} = i, \mathcal{M}^{\mathcal{I}} = 1\big]\mathrm{Pr}(\mathcal{N}^{\mathcal{A}} = i|\mathcal{M}^{\mathcal{I}} = 1). \tag{B.2.6}$$

The i^{th} summand in the above expression is the expected productivity of an average firm that has invested in automation i times between 1995 and 2018 *and* implemented new or newly innovated management practices weighted by the conditional probability that it invests i times since 1995 in automation, where the conditioning is on the event that it has implemented new or newly innovated management practices. The summation runs over $i \in \{1, \ldots, 24\}$ as $\mathcal{N}^{\mathcal{A}}$ takes all values from 0 to 24 even as the proportions of firms in each sector that invest with increasing regularity in automation during the period 1995 and 2018 declines.

Given the estimates, $\widehat{C}_{klmn}$'s, of the coefficients in equation (B.2.3), we know the functional form of $g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})$. Let its estimate be represented by $\widehat{g}(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})$. We can obtain an estimate of $\mathrm{E}(g_{11})$ in (B.2.6) as

$$\widehat{\mathrm{E}}(g_{11}) = \sum_{i=1}^{24} \Big(\frac{1}{\sum_{j=1}^{N} T_j} \sum_{j=1}^{N} \sum_{t=1}^{T_j} \widehat{g}(\hat{\omega}_{jt}, \mathcal{N}^{\mathcal{A}} = i, \mathcal{M}^{\mathcal{I}} = 1, \mathcal{O}^{\mathcal{F}}_{jt})\Big)\widehat{\mathrm{Pr}}(\mathcal{N}^{\mathcal{A}} = i|\mathcal{M}^{\mathcal{I}} = 1), \tag{B.2.7}$$

where $\hat{\omega}_{jt}$, the estimate of ω_{jt}, is obtained by evaluating equation (B.2.4) at $\hat{\Theta}$, the set of estimated structural coefficients and $\hat{\phi}_t(.)$, which is obtained in the first stage of the two stage estimation procedure. T_j is the number of observations for the j^{th} firm and N, the total number of firms. The estimate, $\widehat{\Pr}(\mathcal{N}^{\mathcal{A}} = i|\mathcal{M}^{\mathcal{I}} = 1)$, of conditional probability is obtained as the empirical probability of investing i times in automation for firms that have implemented new or newly innovated management practices.

Because $\mathrm{E}(g_{00}) = \mathrm{E}\big[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} = 0, \mathcal{M}^{\mathcal{I}} = 0\big]$, its estimate is given by:

$$\widehat{\mathrm{E}}(g_{00}) = \sum_{k=0}^{3}\sum_{n=0}^{1}\widehat{C}_{k00n}\Big(\frac{1}{\sum_{j=1}^{N}T_j}\sum_{j=1}^{N}\sum_{t=1}^{T_j}\hat{\omega}_{jt}^{k}(\mathcal{O}_{jt}^{\mathcal{F}})^{n}\Big). \tag{B.2.8}$$

Given the estimates, $\widehat{\mathrm{E}}(g_{11})$ and $\widehat{\mathrm{E}}(g_{00})$, in equations (B.2.7) and (B.2.8) respectively, the estimate of the average treatment effect of automation *and* organizational innovation, $\widehat{\Delta}_{11} = \widehat{\mathrm{E}}(g_{11}) - \widehat{\mathrm{E}}(g_{00})$, is obtained.

The average treatment effect of only automation, Δ_{10} is given by

$$\begin{aligned}\Delta_{10} =& \mathrm{E}(g_{10}) - \mathrm{E}(g_{00}) \qquad \text{(B.2.9)}\\ =& \mathrm{E}\big[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} > 0, \mathcal{M}^{\mathcal{I}} = 0\big] - \mathrm{E}\big[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} = 0, \mathcal{M}^{\mathcal{I}} = 0\big],\end{aligned}$$

where

$$\begin{aligned}\mathrm{E}(g_{10}) =& \mathrm{E}\big[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} > 0, \mathcal{M}^{\mathcal{I}} = 0\big]\\ =& \sum_{i=1}^{24}\mathrm{E}\big[g(\omega, \mathcal{N}^{\mathcal{A}}, \mathcal{M}^{\mathcal{I}}, \mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}} = i, \mathcal{M}^{\mathcal{I}} = 0\big]\Pr(\mathcal{N}^{\mathcal{A}} = i|\mathcal{M}^{\mathcal{I}} = 0). \qquad \text{(B.2.10)}\end{aligned}$$

With the estimates of empirical probabilities of investing i times in automation for firms that did not implemented new or newly innovated management practices, $\widehat{\Pr}(\mathcal{N}^{\mathcal{A}} = i|\mathcal{M}^{\mathcal{I}} = 0)$, in hand, we can compute $\widehat{\mathrm{E}}(g_{10})$ as

$$\widehat{\mathrm{E}}(g_{10}) = \sum_{i=1}^{24}\Bigg[\sum_{k=0}^{3}\sum_{l=0}^{2}\sum_{n=0}^{1}\widehat{C}_{kl0n}\Big(\frac{1}{\sum_{j=1}^{N}T_j}\sum_{j=1}^{N}\sum_{t=1}^{T_j}\hat{\omega}_{jt}^{k}\Big)(\mathcal{N}^{\mathcal{A}} = i)^{l}(\mathcal{O}_{jt}^{\mathcal{F}})^{n}\Bigg]\widehat{\Pr}(\mathcal{N}^{\mathcal{A}} = i|\mathcal{M}^{\mathcal{I}} = 0). \tag{B.2.11}$$

Thus, given the estimates, $\widehat{\mathrm{E}}(g_{00})$, in (B.2.8) we can obtain $\widehat{\Delta}_{10} = \widehat{\mathrm{E}}(g_{10}) - \widehat{\mathrm{E}}(g_{00})$.

Finally, to compute Δ_{01}, we first estimate

$$\widehat{\mathrm{E}}(g_{01}) = \sum_{k=0}^{3}\sum_{m=0}^{1}\sum_{n=0}^{1}\widehat{C}_{k0mn}\Big(\frac{1}{\sum_{j=1}^{N}T_j}\sum_{j=1}^{N}\sum_{t=1}^{T_j}\hat{\omega}_{jt}^{k}\Big)(\mathcal{M}^{\mathcal{I}} = 1)^{m}(\mathcal{O}_{jt}^{\mathcal{F}})^{n}. \tag{B.2.12}$$

Given $\widehat{\mathrm{E}}(g_{00})$ in equation (B.2.8), we obtain $\widehat{\Delta}_{01} = \widehat{\mathrm{E}}(g_{01}) - \widehat{\mathrm{E}}(g_{00})$.

The ATE of automation for domestic firms, $\Delta_{\mathcal{N}^{\mathcal{A}}>0,\mathcal{O}^{\mathcal{F}}=0}$, and ATE of automation for multinationals, $\Delta_{\mathcal{N}^{\mathcal{A}}>0,\mathcal{O}^{\mathcal{F}}=1}$, in Hypothesis 5 are

$$\begin{aligned}&\Delta_{\mathcal{N}^{\mathcal{A}}>0,\mathcal{O}^{\mathcal{F}}=0}\\ &= \mathrm{E}\big[g(\omega,\mathcal{N}^{\mathcal{A}},\mathcal{M}^{\mathcal{I}},\mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}}>0,\mathcal{O}^{\mathcal{F}}=0\big]-\mathrm{E}\big[g(\omega,\mathcal{N}^{\mathcal{A}},\mathcal{M}^{\mathcal{I}},\mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}}=0,\mathcal{O}^{\mathcal{F}}=0\big]\end{aligned} \tag{B.2.13}$$

and

$$\begin{aligned}&\Delta_{\mathcal{N}^{\mathcal{A}}>0,\mathcal{O}^{\mathcal{F}}=1}\\ &= \mathrm{E}\big[g(\omega,\mathcal{N}^{\mathcal{A}},\mathcal{M}^{\mathcal{I}},\mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}}>0,\mathcal{O}^{\mathcal{F}}=1\big]-\mathrm{E}\big[g(\omega,\mathcal{N}^{\mathcal{A}},\mathcal{M}^{\mathcal{I}},\mathcal{O}^{\mathcal{F}})|\mathcal{N}^{\mathcal{A}}=0,\mathcal{O}^{\mathcal{F}}=1\big],\end{aligned} \tag{B.2.14}$$

where the expectations are taken over the distribution of $(\omega_{jt},\mathcal{M}^{\mathcal{I}}_{jt})$. The empirical analogue of these expectation can be computed in the same manner as we have computed Δ_{11} and Δ_{01} above.

B.2.3 Inference

For inference, we employ the bootstrapping technique suggested in Levinsohn and Petrin (2003). The value of the statistics – the coefficients Θ in equation (B.2.1) and the average treatment effects, Δ_{11}, Δ_{10}, $\Delta_{\mathcal{N}^{\mathcal{A}}>0,\mathcal{O}^{\mathcal{F}}=0}$, and $\Delta_{\mathcal{N}^{\mathcal{A}}>0,\mathcal{O}^{\mathcal{F}}=1}$ – are computed for each of the bootstrapped samples, and the distribution of estimates so generated provides the bootstrap approximation to the true sampling distribution of the statistics. The resampling rule, as in Levinsohn and Petrin (2003), treats each set of firm-level observations together as an independent, identical draw from the overall population of firms. We sample with replacement and with equal probability from the sets of firm-level observations in the original sample.

C.3 Decomposing Changes in the Labour Share and Total Factor Productivity

This section provides the details for the decomposition of aggregate labour share and total factor productivity (TFP) used in Figure 4. Let the aggregate labour share (or TFP) in a broad sector be given as

$$Z=\sum_j Z_j s_j=\bar{Z}+\Big[\sum_j (Z_j-\bar{Z})(s_j-\bar{s})\Big],$$

where the weight, s_j, is firm j's share of revenue in the sector, $s_j = P_jY_j/\sum_j P_jY_j$, $\bar{Z}$ is the unweighted mean labour share (or TFP) of the firms in the sector, and $\bar{s}$ is the unweighted mean market share.

Following Acemoglu *et al*. (2020) and Autor *et al*. (2020), we decompose changes in the labour share (or TFP) between time period 0 and time period 1 as

$$\Delta Z = \Delta\bar{Z}_S + \Delta\left[\sum_{j\in S}(Z_j - \bar{Z}_S)(s_j - \bar{s}_S)\right] + s_{X,0}(\bar{Z}_{S,0} - \bar{Z}_{X,0}) + s_{E,1}(\bar{Z}_{E,1} - \bar{Z}_{S,1}), \tag{C.3.1}$$

where $\bar{Z}_S$ and $\bar{s}_S$, are the unweighted averages of Z_j and s_j respectively of the set of surviving firms, S. Here, subscript S denotes survivors, subscript X denotes exiters and subscript E denotes entrants. The terms, $s_{G,t} = \sum_{j\in G} s_j$ and $\bar{Z}_{G,t} = \sum_{j\in G}(s_j/s_{G,t})Z_j$, respectively, represent the aggregate market share and the aggregate labour share of firms in group G and time period t, where $G \in \{S, X, E\}$ and $t \in \{0, 1\}$.

The first term in the above decomposition is the within component. The second term is the "reallocation effect," which seeks to capture the contribution of market share changes *between* surviving firms. The third term is the change due to exiting firms and the fourth is the change due to entering firms.

Similar to the decomposition in Acemoglu *et al*. (2020), we study the contribution to changes in the aggregate labour share (or TFP) arising from automation as follows. Let S_0^A be the set of surviving firms that have automated in period 0, S_1^A the set of surviving firms that automated sometime between period 0 and period 1, let S^{WO} be the set of surviving firms that remain without automation. Also, denote the total number of firms in the sector by N. For the set of firms, Γ, where $\Gamma \in \{S_0^A, S_1^A, S^{WO}\}$, let

$$\bar{Z}_{\Gamma,t} = \frac{1}{|\Gamma|}\sum_{j\in\Gamma} Z_j \text{ and } \bar{s}_{\Gamma,t} = \frac{1}{|\Gamma|}\sum_{j\in\Gamma} s_j, t \in \{0,1\},$$

and where $|\Gamma|$ denotes the cardinality of the set, Γ.

We can decompose the within-firm change component in the equation (C.3.1) as:

$$\underbrace{\Delta\bar{Z}_S}_{\text{Within Effect (Total)}} = \underbrace{\frac{|S_0^A|}{N}\Delta\bar{Z}_{S_0^A} + \frac{|S_1^A|}{N}\Delta\bar{Z}_{S_1^A}}_{\text{Within Effect (Adopters)}} + \underbrace{\frac{|S^{WO}|}{N}\Delta\bar{Z}_{S^{WO}}}_{\text{Within Effect (Non-Adopters)}}. \tag{C.3.2}$$

The first term accounts for the within-firm change in the labour share (or TFP) among surviving firms that have automated in period 0. The second term accounts for the within-firm change in the labour share (or TFP) among surviving firms that have automated in period 1. Finally, the third term accounts for the within-firm change in the labour share (or TFP) among surviving firms that remain without automation.

The reallocation term in equation (C.3.1) can be further decomposed as

$$
\begin{aligned}
&\underbrace{\Delta\Big[\sum_{j\in S}(Z_j-\bar{Z}_S)(s_j-\bar{s}_S)\Big]}_{\text{Reallocation Effect (Total)}} = \\
&\underbrace{|S_0^A|\Delta\Big[(\bar{Z}_{S_0^A}-\bar{Z}_S)(\bar{s}_{S_0^A}-\bar{s}_S)\Big] + |S_1^A|\Delta\Big[(\bar{Z}_{S_1^A}-\bar{Z}_S)(\bar{s}_{S_1^A}-\bar{s}_S)\Big] + |S^{WO}|\Delta\Big[(\bar{Z}_{S^{WO}}-\bar{Z}_S)(\bar{s}_{S^{WO}}-\bar{s}_S)\Big] +}_{\text{Reallocation Effect (Automation)}} \\
&\underbrace{\Delta\Big[\sum_{j\in S_0^A}(Z_j-\bar{Z}_{S_0^A})(s_j-\bar{s}_{S_0^A})\Big] + \Delta\Big[\sum_{j\in S_1^A}(Z_j-\bar{Z}_{S_1^A})(s_j-\bar{s}_{S_1^A})\Big] + \Delta\Big[\sum_{j\in S^{WO}}(Z_j-\bar{Z}_{S^{WO}})(s_j-\bar{s}_{S^{WO}})\Big]}_{\text{Reallocation Effect (Residual)}}.
\end{aligned}
\tag{C.3.3}
$$

The first line on the RHS of equation (C.3.3), which we term as *reallocation effect due to automation*, captures the effect of reallocating economic activities towards firms that automate. This is because firms that automate – those that automated in period 0 as well as those that automate during the time lapse between period 0 and period 1 – have a higher market share and even increase it over time, and therefore, if the labour share (or TFP) of firms that dominate the market increases, then the *reallocation effect due to automation* is positive. If, on the other hand, the labour share (or TFP) of firms that dominate the market decreases, then the *reallocation effect due to automation* is negative. The second line on the RHS of equation (C.3.3) captures the *residual reallocation effect* that is not explained by automation. The residual reallocation effect captures separately the allocation of economic activity among firms that automated in period 0, firms that automate between period 0 and 1, and firms that do not automate. The residual terms are due to those economic activities that generate the reallocation effect but are uncorrelated with automation.

D.4 Tables and Figures

Table 2. Categories of Intermediate Capital Goods for Automation in Acemoglu and Restrepo (2021a).

Categories	HS Codes
Automatic Conveyors	842831-842839
Dedicated Machinery (including robots)	847989
Industrial Robots	847950
Automatic Machine Tools	845600-846699, 846820-846899, 851511-851519
Numerically Controlled Machines	84563011, 84563019, 84573010, 845811, 845891, 845921, 845931, 84594010, 845951, 845961, 846011, 846011, 846021, 846031, 84604010, 84613010, 84614011, 84614031, 84614071, 84621010, 846221,846231, 846241, 84629120, 84629920
Automatic Regulating Instruments	903200-903299
Weaving and Knitting machines	844600-844699 and 844770-844799
Other Textile Dedicated Machinery	844400-845399
Automatic Welding Machines	851521, 851531, 851580, 851590
3D Printers	84779000

Table 3. Import Distribution of Categories of Intermediate Goods for Automation

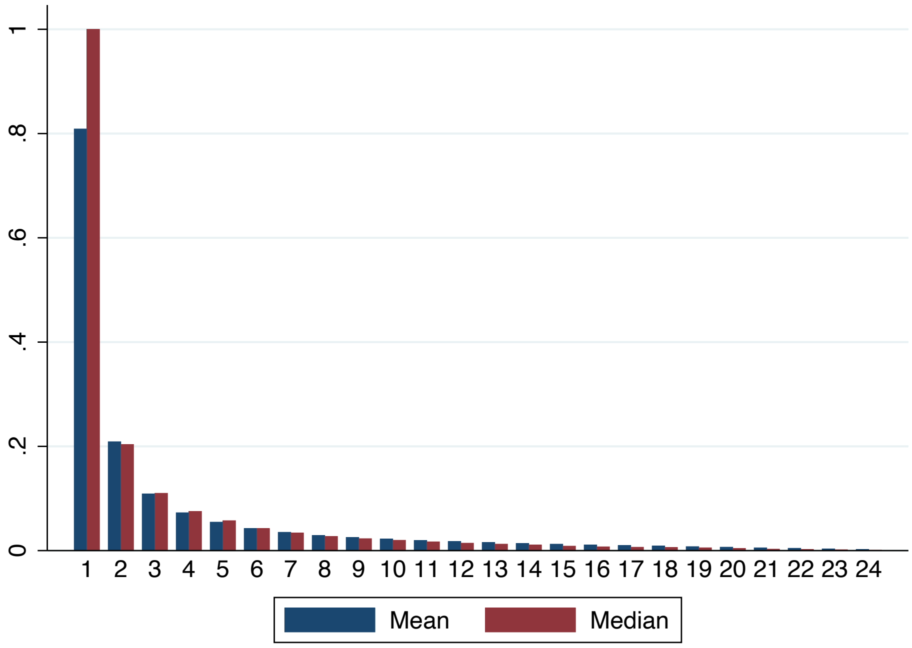
	Manufacturing	Services	Mining and Quarrying, Construction, Electricity and Gas
Industrial Robots	0.85	0.28	0.25
Dedicated Machinery (including Robots)	10.33	19.04	18.01
Numerically Controlled Machines	3.87	2.29	2.61
Automatic Machine Tools	43.26	28.36	31.08
Automatic Welding Machines	8.52	8.26	9.24
Weaving and Knitting Machines	1.57	0.91	0.12
Other Dedicated Machines	15.78	13.52	3.17
Automatic Conveyors	4.39	3.16	3.04
Automatic Regulating Instruments	11.43	24.16	32.49
3D Printers	0	0	0
Total	100	100	100

Table 4. Evidence of Lumpy Investment in Automation

	No. of Years Observed in the Data				Total
No. of Years in which Goods for Automation were Imported	1 to 6 Years	7 to 12 Years	13 to 18 Years	19 to 24 Years	
1	4696 (80.1)	1103 (50.6)	826 (42.8)	1319 (31.2)	7944 (55.95)
2	739 (12.6)	383 (17.57)	323 (16.74)	608 (14.4)	2053 (14.46)
3	235 (4.01)	205 (9.4)	173 (8.96)	372 (8.8)	985 (6.94)
4	121 (2.06)	137 (6.28)	108 (5.6)	231 (5.47)	597 (4.2)
5	49 (0.84)	103 (4.72)	80 (4.15)	195 (4.62)	427 (3.01)
6	23 (0.39)	76 (3.49)	71 (3.68)	143 (3.38)	313 (2.2)
7	0 (0)	77 (3.53)	66 (3.42)	145 (3.43)	288 (2.93)
8	0 (0)	40 (1.83)	58 (3.01)	135 (3.2)	233 (1.64)
9	0 (0)	36 (1.65)	43 (2.23)	109 (2.58)	188 (1.32)
10 or more Years	0 (0)	20 (0.92)	182 (9.43)	968 (22.91)	1170 (8.24)
	5863	2180	1930	4225	14198

Note: Column percentages in parenthesis.

Figure 12. Yearly Investment Shares by Rank as Evidence of Lumpy Investment in Automation.



Note: On the Y axis is the yearly investment shares. Rank 1 on the X axis is the highest yearly investment share in the firm's time-line.[a]

[a]Interpretation: On average, about 80% of all investments in automation are made in a single year; for a median firm, all investments are made in a single year.

Table 5. Descriptive Statistics of Variables by Sectors

	Automation: No New Organizational Practice: No	Automation: Yes New Organizational Practice: No	Automation: No New Organizational Practice: yes	Automation: Yes New Organizational Practice: Yes
		Manufacturing		
log(Value Added)	12.82	13.82	13.23	14.46
	(1.08)	(1.16)	(1.17)	(1.25)
log(Employees)	3.08	3.77	3.35	4.31
	(0.79)	(1.02)	(0.9)	(1.21)
log(Capital Stock)	11.60	13.14	12.02	13.77
	(1.93)	(1.79)	(2.06)	(1.75)
Age	11.45	15.55	9.88	13.63
	(6.05)	(5.55)	(5.68)	(5.63)
North Estonia	0.45	0.46	0.46	0.48
	(0.49)	(0.49)	(0.50)	(0.50)
		Services		
log(Value Added)	13.46	14.28	13.89	14.86
	(1.22)	(1.22)	(1.24)	(1.44)
log(Employees)	3.09	3.59	3.35	4.01
	(0.92)	(1.12)	(0.98)	(1.36)
log(Capital Stock)	11.82	13.26	11.71	13.73
	(2.15)	(2.14)	(2.09)	(2.28)
Age	13.41	17.21	11.64	15.77
	(6.15)	(5.75)	(5.83)	(6.18)
North Estonia	0.61	0.72	0.73	0.81
	(0.49)	(0.45)	(0.44)	(0.38)
		Mining, Utilities, and Construction		
log(Value Added)	13.35	14.45	14.27	15.95
	(1.32)	(1.42)	(1.64)	(1.70)
log(Employees)	3.04	3.68	3.52	4.96
	(0.87)	(1.37)	(1.30)	(1.68)
log(Capital Stock)	13.13	14.64	14.16	15.97
	(2.21)	(1.95)	(2.74)	(2.46)
Age	14.73	17.38	13.09	15.97
	(6.12)	(5.16)	(6.33)	(5.38)
North Estonia	0.29	0.38	0.49	0.54
	(0.46)	(0.48)	(0.50)	(0.50)

Note: Standard Error in Parenthesis

Table 6. Description of Automation and Management Activities of the Firms

		Has the firm Imported Capital Goods for Automation in the Current Period or in the Past?		
		No=0	Yes=1	Total
Manufacturing				
Did the firm introduce new Organizational Practices?	No= 0	2867 (36.3)	5031 (63.7)	7898 (100)
	Yes = 1	869 (28.04)	2230 (71.96)	3099 (100)
	Total	3736 (34)	7261 (66)	10997 (100)
Services				
Did the firm introduce new Organizational Practices?	No= 0	3595 (65.2)	1922 (34.4)	5517 (100)
	Yes = 1	1404 (60.4)	921 (39.6)	2325 (100)
	Total	4999 (63.7)	2843(36.3)	7842 (100)
Mining, Utilities, and Construction				
Did the firm introduce new Organizational Practices?	No= 0	673 (68.2)	314 (31.8)	987 (100)
	Yes =1	210 (62.6)	125 (37.4)	335 (100)
	Total	883 (66.8)	439 (33.2)	1322(100)

Note: (i) Since we do not have information on organizational activities for firms outside the CIS surveys, the above pertains to the firms from the CIS data, and the period covered is 2003-2018. (ii) Row percentages in parenthesis.

Table 7. Description of Imports Expenditure on Automation by Firms that Automate Occasionally and Firms that Automate Regularly

	Automating Occasionally				Automating Regularly			
	Expenditure		Expenditure / No. of Employees		Expenditure		Expenditure / No. of Employees	
Year	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1997	211.55	56.87	56.29	5.21	1888.59	111.75	391.41	9
1998	149.35	25.38	38.79	3.71	1651.09	107.95	359.46	10.05
1999	97.4	21.53	27.77	2.65	895.34	62.82	214.26	5.15
2000	209.2	34.53	29.61	2.99	1604.8	121.47	105.93	5.87
2001	1046.92	27.3	41.45	2.87	1857.65	116.56	105.43	6.45
2002	271.76	36.37	23.67	3.05	1498.61	133.38	96.75	6.84
2003	206.07	38.62	43.62	3.43	1700.66	124.46	231.64	5.89
2004	329.68	31.39	28.63	2.82	1760.32	159.14	79.97	5.24
2005	240.14	35.12	27.28	4.36	2220	198.74	129.33	7.55
2006	448.86	27.61	127.57	5.41	1965.28	228.9	165.39	7.67
2007	183.63	35.61	27.13	4.52	1956.68	187.44	227.3	7.92
2008	163.05	25.31	19.77	2.56	2149.73	147.94	211.77	5.28
2009	285.82	19.29	52.83	2.97	1197.01	94.43	83.63	5.11
2010	331.3	34.55	37.44	3.99	1324.77	117.66	116.32	4.79
2011	265.31	18.08	59.17	2.52	1783.68	124.32	179.71	7.27
2012	1039.3	23.8	134.04	3.57	2152.3	154.3	288.04	7.3
2013	121.23	12.22	30.31	2.84	1741.39	129	168.48	6.66
2014	189.77	17.71	35.85	2.6	1520.25	132.81	211.57	6.53
2015	495.56	19.59	143.14	3.72	1488.2	131.35	181.27	6.67
2016	238.79	12.92	65.71	2.34	1866.01	131.87	258.66	6.75
2017	353.86	20.15	100.43	2.57	1649.88	123.24	193.67	7.33
2018	230.96	21.85	20.62	2.63	2008.93	143.19	178.31	7.72

Note: The figures are in thousands of EUR at 2015 prices. To classify firms into those that automate *occasionally* and those that automate *regularly*, we begin by computing the cumulative frequency with which firms, starting from the first year they appear in the data until 2018, imported capital goods for automation. We then use the computed value for 2018 to classify firms (not firm-years) according to the criterion described in Section 5.1 as those that automate *occasionally* and those that automate *regularly*. However, because we have an unbalanced panel – mainly due to entry and exit and a few due to mergers, acquisitions, and spinoffs – not all firms are present in the year 2018. For such firms, we compute the cumulative frequency with which firms, starting from the first year they appeared in the data until 2017, imported machines for automation, and repeat the process of classification. We repeat this procedure for firms who are present till 2016, 2015, ... until we classify all firms in the data.

Table 8. Estimates of the Share of Tasks between Factors and Average Treatment Effects of Automation, and Descriptive Statistics for firms that Differ by Frequency of Automation

	Manufacturing			Services			Mining and Quarrying, Construction, Electricity and Gas		
	No Automation	Occasional Automation	Regular Automation	No Automation	Occasional Automation	Regular Automation	No Automation	Occasional Automation	Regular Automation
log(Employees)	0.983***	0.92***	0.51***	0.971***	0.88***	0.70***	1.042***	0.846***	0.416***
	(0.008)	(0.007)	(0.006)	(0.01)	(0.005)	(0.003)	(0.018)	(0.011)	(0.064)
log(Capital Stock)	0.23***	0.27***	0.38***	0.174***	0.214***	0.223***	0.196***	0.228***	0.41***
	(0.021)	(0.009)	(0.016)	(0.022)	(0.004)	(0.007)	(0.03)	(0.034)	(0.042)
North Estonia	0.392***	0.268***	0.265***	0.311***	0.336***	0.310***	0.217***	0.413***	0.525***
	(0.006)	(0.004)	(0.004)	(0.003)	(0.002)	(0.007)	(0.014)	(0.015)	(0.032)

Note: The dependent variable is logarithm of value-added. The control function method due to ACF was adapted for the estimation. All specifications include 2-digit NACE industry dummies and a year dummy. The regression results are based on 2017 and 2018 census data, while the descriptive statistics are based on 2018 data.

		Occasionally	Regularly		Occasionally	Regularly		Occasionally	Regularly
Average Treatment Effect (ATE) of Automating		0.251*** (0.044)	0.586*** (0.074)		-0.093* (0.056)	0.216*** (0.071)		0.278** (0.126)	0.967*** (0.192)
No. of Firms (Percentage in respective sector)	2,407 (73.7)	473 (14.7)	334 (10.4)	21,390 (90.3)	1,405 (5.9)	890 (3.76)	13,227 (97.3)	311 (2.3)	62 (0.5)
Market Share	23.4%	20.2%	56.4%	47.6%	16.9%	35.5%	58.6%	18.3%	23.1%
Size: No. of Employees	7.1	20.5	73.2	5.1	19.5	48.9	4.9	17.4	76.1
Age of the Firm	12.9	18.7	19.7	13.0	18.9	19.3	11.8	18.6	21.5
Labour Share (Mean)	51.1%	57.1%	55.0%	42.6%	45.2%	46.3%	46.8%	53.5%	49.7%
Labour Share (Median)	48.1%	55.2%	54.1%	39.0%	42.5%	44.6%	43.5%	50.6%	49.6%

Significance levels : $*$: 10% $**$: 5% $***$: 1%. Standard Error in Parenthesis

Table 9. Time-Dependent Average Fraction of Tasks Performed by Labour and Capital in Automating and Non-Automating Firms

	Variables	Manufacturing	Services	Other Sector
Automation Adopters	log(Employees)$\times D^A \times D_{T_1}$	0.701***	0.708***	0.459***
		(0.009)	(0.034)	(0.005)
	log(Employees)$\times D^A \times D_{T_2}$	0.612***	0.501***	0.445***
		(0.006)	(0.027)	(0.006)
	log(Employees)$\times D^A \times D_{T_3}$	0.456***	0.371***	0.417***
		(0.012)	(0.021)	(0.007)
	log(Capital)$\times D^A \times D_{T_1}$	0.275***	0.196***	0.401***
		(0.006)	(0.014)	(0.008)
	log(Capital)$\times D^A \times D_{T_2}$	0.285***	0.234***	0.416***
		(0.006)	(0.011)	(0.005)
	log(Capital)$\times D^A \times D_{T_3}$	0.357***	0.275***	0.435***
		(0.007)	(0.009)	(0.005)
Non-Adopters	log(Employees)$\times(1-D^A) \times D_{T_1}$	0.753***	0.732***	0.581***
		(0.005)	(0.026)	(0.005)
	log(Employees)$\times(1-D^A) \times D_{T_2}$	0.772***	0.742***	0.555***
		(0.006)	(0.025)	(0.007)
	log(Employees)$\times(1-D^A) \times D_{T_3}$	0.746***	0.624***	0.658***
		(0.006)	(0.020)	(0.005)
	log(Capital)$\times(1-D^A) \times D_{T_1}$	0.205***	0.176***	0.369***
		(0.005)	(0.011)	(0.006)
	log(Capital)$\times(1-D^A) \times D_{T_2}$	0.188***	0.155***	0.367***
		(0.003)	(0.010)	(0.005)
	log(Capital)$\times(1-D^A) \times D_{T_3}$	0.239***	0.196***	0.361***
		(0.007)	(0.008)	(0.009)
Common Coef.	North Estonia	0.276***	0.381***	0.283***
		(0.005)	(0.021)	(0.005)
	No. of Firms	6,492	40,906	8,640
	No. of Obs.	41,005	250,839	44,705

Note: The dependent variable is the logarithm of value-added. D_{T_1} is a dummy variable that takes the value 1 if the year from which the firm's data is lies between 2003 to 2007 and 0 otherwise. Similarly, D_{T_2} takes the value 1 if the data is from the years, 2008 to 2012, and D_{T_3} takes the value 1 if the data is from the years, 2013 to 2018. The control variables include industry and time dummies. The results are based on 2003-2018 census data. The 'Other Sector' comprises Mining, Construction and Utilities.

Significance levels : $*$: 10% $**$: 5% $***$: 1%. Standard Error in Parenthesis

Table 10. Estimated Average Treatment Effects (ATE)

	Manufacturing	Services	Other Sector
ATE of only Automation (Δ_{10})	0.198***	0.322***	0.289**
	(0.035)	(0.075)	(0.128)
ATE of Organizational Innovation and Automation (Δ_{11})	0.319***	0.407***	0.588***
	(0.068)	(0.086)	(0.196)
Average Market Share			
Neither Organizational Innovation *Nor* Automation	0.53	0.82	1.14
No Organizational Innovation *Only* Automation	1.92	1.01	3.37
Both Organizational Innovation *and* Automation	3.81	3.06	2.31
No. of Firms	2,070	2,106	287
No. of Obs.	10,997	7,841	1,322

Note: The results are based on 2003 to 2018 CIS data. Market share of a firm is calculated every year and is given by $\frac{\text{Firm Revenue} \times 100}{\text{Total Industry Revenue}}$, where industry is based on two digit NACE Rev. 2 codes.

	Manufacturing	Services	Other Sector
ATE of Automation for Domestic Owners	0.111***	0.085***	0.133***
	(0.023)	(0.005)	(0.028)
ATE of Automation for Multinationals	0.274***	0.267***	0.424***
	(0.021)	(0.026)	(0.074)
Unweighted Agg. Share of Multinationals Adopters	30.8%	23.4%	16.2%
	(43.3)	(39.9)	(34)
No. of Firms	6,492	40,906	8,640
No. of Obs.	41,005	250,839	44,705

Note: The results are based on 2003-2018 census data. The 'Other Sector' comprises Mining, Construction and Utilities.

Significance levels : $*$: 10% $**$: 5% $***$: 1%. Standard Error in Parenthesis

SISUKOKKUVÕTE

Automatiseerimine Avatud ja Järelejõudvas Majanduses: Agregeeritud ja Mikrotasandi Andmete Analüüs

Käesolev töö uurib Eesti ettevõtete üldkogumi põhjal, kuidas on seotud automatiseerimine ettevõtetes ning ettevõtete tootlikkus ja tööjõu osakaal loodavas lisandväärtuses. Esimese tulemusena leiab autor Eesti andmete põhjal, erinevalt varasematest muude arenenud riikide alastest uuringutest, et tööjõu osakaal loodavas lisandväärtuses on tootmise automatiseerimist juurutavates Eesti ettevõtetes võrreldes ülejäänutega kõrgem. Tööjõu osakaal loodavas lisandväärtuses agregeeritud tasandil on kasvanud ka tulenevalt ettevõtete turuosade ümberpaigutumisest automatiseerimisega tegelevate ettevõtete suunas. Teiseks, töö tulemused näitavad, et automatiseerimisega tegelevates Eesti ettevõtetes on kogutootlikkus kasvanud kiiremini kui ülejäänutes. Automatiseerimise mõjud tootlikkusele on samas väga varieeruvad sõltuvalt kontekstist. Automatiseerimise mõjud on tugevad, kui nende rakendamine ettevõttes on pikaajaline: ei piirdu vaid ühekordsete investeeringutega. Automatiseerimine ja organisatsiooniliste uuendused on Eesti ettevõtetes omavahel komplementaarses seoses. Ettevõtted, mis viivad koos automatiseerimisega sisse ka organisatsioonilisi uuendusi, on oluliselt tootlikumad võrreldes nendega, mis ainult automatiseerivad oma tegevusi. Ka on automatiseerimise mõjud tugevamad hargmaiste ettevõtete puhul.