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Abstract

This paper investigates whether the diffusion of tangible IT and CT capital and intangible capital asset types has an impact on labour demand growth and the share of labour income in total income at the industry and country level. The econometric analysis is derived from a Cobb-Douglas production function taking empirical stylized facts into account. The effects of technical progress embodied in the various forms of capital impact along inter-industry and intercountry production linkages, which are considered by using global value chain indicators. The analysis is broken down to examine the influence on different types of labour, including the dimensions of gender, age, and educational attainment. Accumulation of ICT assets have generally insignificant and in some cases small positive effects on labour demand and income shares, though patterns differ across types of labour. Intangible assets show a positive relation with respect to labour demand growth.

Keywords: capital accumulation, ICT capital, intangibles, labour demand, income distribution

JEL classification: J23, J31, O33, O52

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THE IMPACT OF ICT AND INTANGIBLE CAPITAL ACCUMULATION ON LABOUR DEMAND GROWTH AND FUNCTIONAL INCOME SHARES

1 Introduction

The current debate reflects widespread fear that new technologies may be disruptive and destroy many jobs and/or lead to significant shifts in income. In economic history, such debates have a long tradition, starting with David Ricardo's famous Chapter 31, 'On Machinery', in the third edition of his Principles (Ricardo, 1821) and followed by discussions on 'technological unemployment' by John Maynard Keynes (Keynes, 1930), Sir John Hicks, Wassily Leontief and many others. More recently, theorists such as Rifkin (1995) have claimed the "end of work". Today, a similar debate exists with a focus on digitalisation and disruptive technologies related to important new trends, such as the Internet of Things (IoT), big data, virtual and augmented reality, 3D printing, blockchain technologies, artificial intelligence (AI), robotics, nanotechnology, and biotechnology.[1] Recent literature discussing such concerns in a broad perspective include Brynjolfsson and McAfee (2011); Servoz (2019); OECD (2019a). However, despite these concerns, employment levels have generally increased over time, measured either by the number of persons employed or by employment and activity rates.[2] Compatible with these overall employment trends are other views, like this statement by Nobel laureate Bob Solow: 'You can see the computer age everywhere but in productivity statistics'. It is widely acknowledged that, despite the rise of information and communications technologies (ICTs), labour productivity growth has been at a historically low level in recent decades. The reasons for this productivity paradox are widely debated.

Thus, this debate seems largely unresolved (or the insights have been changing over time), with a number of studies raising both fears and expectations of the employment effects, which are selectively outlined in Section 2. The impacts of various channels have been argued from a purely theoretical perspective, resulting in arguments for both labour-saving and employment-creating effects (e.g. the labour-saving character of technical change also implies a higher real income, which leads to positive employment effects). Consequently, it remains mostly an empirical exercise to study the impacts of technical change on employment.

This paper therefore focuses on the effects of ICT capital formation (including capital asset accumulation of information technologies, communications technologies and software and databases) and other intangible assets and studies the influence on labour demand growth and the labour income share in value added. Additionally, the employment and income impacts are broken down into various categories, such as age, educational attainment and sex. In this manner, the paper adds to the existing empirical

[1] See Tegmark (2017) for an overview. For the measurement issues of digital transformation, see OECD (2019b) and IMF (2018).

[2] Such labour market performance may also be driven by demographic trends and changes in participation rates; see Prettner and Bloom (2020); Leitner and Stehrer (2019a,b); Leitner et al. (2019).

work on the relationship between technological change (in most cases, measured by the use of robots), employment and industrial growth, similar to Graetz and Michaels (2018), Abeliansky and Prettner (2017) or Acemoglu and Restrepo (2018b)). However, it also extends these contributions by focusing on a broader set of capital assets. Specifically, we address the impact of the accumulation of capital by asset types in EU member states on employment growth and changes in labour share by considering total factor productivity growth using panel estimation. The specification is derived from a Cobb-Douglas production function, which takes some stylised facts concerning the developments of capital-output and capital-labour ratios into account. Following Autor and Salomons (2018), we also provide estimations on inter-industry spillover effects. In addition, we distinguish between domestic and foreign spillovers. Other recent studies investigate the impact of robots, whereas we focus on capital stock data and the available asset types taken from national accounts.

The remainder of this paper is structured as follows: Section 2 provides a brief overview of the related literature. Section 3 describes some stylised facts used in the theoretical discussion in Section 4. Section 5 explains the econometric results. Section 6 concludes.

2 Literature

The world is facing a wave of technological change brought about by disruptive technologies, such as AI, machine learning and robotics.[3] It is thought that this range of new technologies will initiate an industrial revolution by fusing the physical, digital and biological worlds and impacting all disciplines, economies and industries Schwab (2017), which is then expected to affect the factors of production and the generation and distribution of value added by sectors and countries. One can argue that technological change has historically created more jobs than it has destroyed over the longer term (thanks to the process of creative destruction according to Joseph A. Schumpeter and discussed in Aghion et al. (2021). However, future developments are difficult to extrapolate from past experiences. The vast amount of uncertainty about the future trajectory of technology and its economic consequences in periods of rupture pose a serious problem for policymakers and raise questions about the effects of technical change on employment. In particular, digitalisation and employment have been attracting much attention.

The key concern that remains heavily debated is the influence of such new technologies on the labour market. Job losses due to automatisation range from 47%, found by Frey and Osborne (2017), to less than 10% as reported by the OECD in Arntz et al. (2016). The latter study is less alarming, particularly because the time spans over which this might occur have not been specified. The difference to Frey and Osborne (2017) is that, rather than looking at whole employment sectors, they evaluated the

[3] Recent successes in the field of AI, such as DeepMind's AlphaZero defeat of the world's leading chess-playing computer program after having taught itself how to play in less than four hours, have intensified the debate about the challenges and opportunities of the robot age and whether mankind can win the race against the machines Brynjolfsson and McAfee, 2014.

potential automatability (defined as the risk of automation being above 70%) of tasks within an occupation. Nedelkoska and Quintini (2018) subsequently expanded the coverage of countries and occupational titles. Their results suggested that about 14% of jobs in OECD countries face the risk of being highly automatable.

A number of papers have focused on the introduction of robots. Sachs and Kotlikoff (2012), Benzell et al. (2015) and Sachs et al. (2015) have come to the conclusion that the introduction of robots would boost productivity in the short term but decrease wages and consumption in the long term.[4] A recent and comprehensive framework was developed in a study by Acemoglu and Restrepo (2017). In this framework, robots can substitute for specific labour tasks, which is likely to reduce employment and wages. Nonetheless, labour may perform new tasks in which it has a comparative advantage over robots. Focusing on US labour markets, Acemoglu and Restrepo (2018b), using data from EU KLEMS and studies on robot use over the period of 1970-2007, found that the adoption of robots has led to large and robust declines in employment and wages. By contrast, Graetz and Michaels (2018) tested the effects of robot use on labour productivity growth, TFP growth, output prices and employment and did not find a significant negative impact on employment. The reason for this is although robots increase labour productivity growth and TFP growth, these productivity gains also decrease output prices and have an offsetting effect. A recent report by the European Bank for Reconstruction and Development (EBRD, 2018) found similar results for emerging economies. Autor and Salomons (2018) estimated the effect of TFP growth on employment via different channels: own-industry effects, upstream-industry effects, downstream-industry effects and final-demand effects. They concluded that TFP has negative direct effects but positive indirect effects on employment; however, other channels are dominant, and the overall effect of technological progress on employment is thus slightly positive.[5]

Ghodsi et al. (2019) used this framework and quantified the impacts of robots on employment using a wider sample of countries and controlling for TFP growth. Their results indicated no significant impact on employment but suggested a positive and significant effect on real value added growth.[6] Section 4 will outline in detail how such an approach that relies on a labour demand function derived from a Cobb-Douglas production function has been heavily criticised in Felipe et al. (2020).[7] Some recent papers have confirmed only a very modest impact of robotisation on employment growth in Europe (see Antón et al., 2020; Jestl, 2022).[8]

In other literature, not only the impact on the levels of employment but also the structure of employment have been considered.[9] Prettner and Bloom (2020) (Chapter 3) summarised a number of papers.

[4] Further literature includes Zeira (1998).

[5] See also Autor and Salomons (2017) and Autor (2015) for an overview.

[6] In earlier papers, R&D spillovers have been modelled in a similar way (see Nishioka and Ripoll, 2012). Adarov and Stehrer (2019a) focused on the roles of the accumulation of capital by asset types and foreign direct investments.

[7] See also Felipe and McCombie (2019) for a general discussion.

[8] We do not cover firm-level studies like Koch et al. (2019).

[9] For an earlier important contribution, see Berman et al. (1998). Other literature have focused more directly on inequality (e.g. Krusell et al., 2000; Dao et al., 2017 or more general aspects (Spitz-Oener, 2006.

They broadly concluded that automation has a positive impact on labour productivity. However, there are negative employment and wage effects for low-skilled workers (mainly in manufacturing), whereas the effects for high-skilled workers are insignificant or even positive. Overall, this leads to a decline in the labour income share. However, this should be seen in the longer-term context. Since the 1980s, the composition of the labour force and the remuneration of skills in advanced economies have undergone structural changes and a decline in the demand for high school graduates (medium skilled) relative to college graduates (high skilled) in particular, as documented in Goos et al. (2019). It has also been documented that the demand for medium-skilled workers has even declined relative to low-skilled workers, which has led to a so-called polarisation of the labour market, mostly documented in the US and the UK but to a lesser extent in the rest of Europe (Goos and Manning, 2007; Goos et al., 2009; Acemoglu and Autor, 2011). Specifically, the diffusion of digital technologies since the 1980s has accelerated this process (Autor et al., 2003). However, not only technological change but also international trade and offshoring may have been the main driving forces behind this pattern, as emphasised in (Goos et al., 2014; Autor et al., 2015; Acemoglu et al., 2016).

With respect to the introduction of ICTs, it can be argued that in the 1980s and 1990s, it was mainly high-skilled workers who possessed computer skills, as education was slow to adapt to the take-up of new technology (Goldin and Katz, 2009). Thus, the demand for high-skilled workers increased in the early adoption phase of digital technologies and raised skill premiums (Krueger, 1993). After the initial stage of the diffusion of digital technologies, they were adopted across all sectors, and education systems began providing students with the demanded digital skills. As a consequence, the increase in wage premiums for high-skilled workers and cognitive skills has slowed down or even stalled since the 2000s, as documented by several studies, notably in the US (Valetta, 2018; Acemoglu and Autor, 2011).

Michaels et al. (2014) found that, for 11 OECD countries in 1980-2004, a rise in a sector's ICT intensity, proxied by ICT capital compensation, was associated with a rising wage share for high-skilled workers to the detriment of medium-skilled workers. However, there is also evidence that these patterns may have changed after the global financial crisis. Pichler and Stehrer (0201) corroborated the main findings of Michaels et al. (2014) for that period. Focusing on more recent years and based on the EU KLEMS data released in 2019, they found that a larger increase in ICT intensity was generally not associated with an increasing (decreasing) demand for high- (medium-) skilled workers during the period of 2011-2016. In addition, contrary to the findings for the period of 1980-2004 for Western European economies, they argued that a higher ICT intensity was associated with an increase (decrease) in medium- (high-) skilled workers for Eastern European economies in 2011-2016. The driving force behind this pattern appeared to be the service sector. This result should be interpreted carefully, however, owing to the sensitivity to sample selection. The empirical analysis by the MNvR built on the so-called routinisation hypothesis proposed by Autor et al. (2003). Their theory suggested that ICT capital can substitute for labour more easily in routine tasks that follow a repetitive pattern and can be carried out by an algorithm or a programmable machine. Capital, by contrast, can complement labour in non-routine cognitive tasks, i.e. tasks that cannot easily be expressed as a set of programmable rules. As routine tasks are mainly concentrated among occupations located in the middle of the wage distribution, while non-routine cognitive tasks are mainly carried out by high-skilled workers, the diffusion of ICT (due to the falling prices of ICT) leads to an increase in demand for workers in well-paid occupations but a lower demand for middle-income jobs, such as clerks and craft workers. While employment in medium-paid occupations has declined and employment in high-paid occupations has increased in almost all developed economies, low-income jobs have seen gains mostly in the US (Autor et al., 2003) and the UK (Goos and Manning, 2007) but to a lesser extent in the EU (Goos et al., 2019).

The described structural shifts in labour demand have primarily been measured as a change in hours worked in specific occupations. For example, Acemoglu and Autor (2011) and Oesch and Menés (2011) ranked occupations based on their income in a base year and measured the changes in employment within these occupations. Based on 1980 US data, Michaels et al. (2014) linked the occupations to the skill level of the workforce (proxied by education). The authors found that occupations that were characterised by non-routine cognitive tasks were mostly occupied by high-skilled workers. Medium-skilled workers were more likely to conduct routine manual and routine cognitive tasks. Finally, low-skilled workers were the largest group within the non-routine manual and routine cognitive occupations. The routinisation hypothesis therefore predicts that ICT increases demand for high-skilled workers but reduces demand for medium-skilled workers, and it gives no clear prediction for low-skilled workers. More recent studies have shown that the wage premium for college graduates has been growing at a slower rate or even stalled around the turn of the millennium in the US (Valetta, 2018; Acemoglu and Autor, 2011). Similarly, Castex and Dechter (2014) found that the return to non-cognitive skills has increased since the 1990s. Beaudry et al. (2016) called this trend the 'reversal in the demand for skill'. Edin et al. (2017) summarised several explanations put forward to explain this trend. Deming (2017) claimed that the demand for skill is shifting and highlighted that wage growth has been stronger in occupations that require social skills. Beaudry et al. (2016) argued that the early investment stage saw high and growing demand for cognitive tasks to facilitate the adoption of digital technologies. As digital skills and the use of ICT became ubiquitous, the technology reached maturity and eventually reduced the premium for digital skills. Hershbein and Kahn (2017) corroborated this argument and showed that occupations that were traditionally characterised by routine tasks experienced upskilling, particularly during the global financial crisis. This implies that workers with cognitive skills are increasingly drawn to less well-paid occupations. A complementary argument by Brynjolfsson and McAfee (2014) suggested that the progress in computing technology has allowed capital to compete more effectively with non-routine cognitive tasks, thereby lowering demand for high-skilled workers.

3 Data and selected stylised facts

3.1 Data sources

For the analysis, we used various data sets. Most importantly, we used an updated version of the EU KLEMS Release 2019 data (documented in Adarov and Stehrer, 2019b).[10] For this research, we updated these data by including some more recent years.[11] These data, available from Eurostat, were based on national accounts data and provided us with information on value added and employment growth from which labour productivity growth was derived. Furthermore, the shares of compensation or labour income (i.e. including the income of self-employed workers) were available from these data. Moreover, data on capital stocks and capital accumulation from which information on capital-output and capital-labour ratios were derived were also taken from Eurostat. Capital stock data were available for various asset types (listed in Table 3.1).

Table 3.1: Asset types in national accounts and beyond

Code	Description
Asset types in national accounts	
N11N	Total fixed assets (net)
...N11KN	Total construction (net)
... ...N111N	Dwellings (net)
... ...N112N	Other buildings and structures (net)
...N11MN	Machinery and equipment and weapons systems (net)
... ...N1131N	Transport equipment (net)
... ...N1132N	ICT equipment (net)
... ...N11321N	Computer hardware (net)
... ...N11322N	Telecommunications equipment (net)
... ...N11ON	Other machinery and equipment and weapons systems (net)
...N115N	Cultivated biological resources (net)
...N117N	Intellectual property products (net)
... ...N1171N	Research and development (net)
... ...N1173N	Computer software and databases (net)
... ...N117XN*	Other intellectual property products
Supplementary asset types	
AdvMRes	Advertising and market research
Design	Design
POCap	Purchased organisational capital

*Note: N117XN = N117N - N1171N - N1173N

The software and databases on the capital accumulation of information and communication technology were of particular interest, although these were not the most important ones for explaining the observable trends (to be presented in the econometric results). In addition, we used data for supplementary asset types that captured advertising and market research, design and purchased organisational capital (for details, see Stehrer et al., 2019).

Furthermore, for the breakdown of labour income into various categories, e.g. age, educational attainment and sex, we also used data from the EU KLEMS Release 2019, which provided the shares for these groups for hours worked and income. Specifically, we differentiated between three age groups (15-29,

[10] See also Adarov and Stehrer (2020) for a detailed analysis of these data with respect to productivity drivers.
[11] These are published at www.euklems.eu.

30-49 and 50-64), three educational attainment categories according to ISCED groups (low, medium and high) and sex (male and female).

Finally, we used the OECD TiVA data (Release 2021) to include inter-industry and intercountry linkages. They provided a time series of intercountry input-output tables from which backward and forward linkages were derived. In this research, we faced various data constraints. As detailed asset types were not available for many countries at the 2-digit NACE Revision 2 industry level, or these details varied across countries, we restricted the analysis to the 1-digit industry level (see Table 3.2). For data reasons, we further aggregated industries M, N and P and R-U, which resulted in 15 industries in the sample. The time period was constrained to 2008-2019 (in some cases, differing across countries) as the hours worked and labour income shares were available only for these years in the EU KLEMS data.

Table 3.2: NACE Revision 2 industry list (A*21)

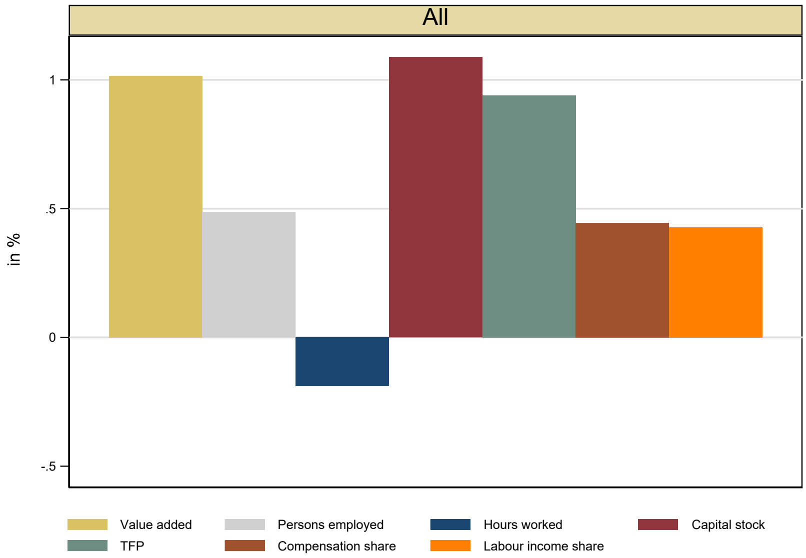
NrÂ	Code	Description	Divisions
1	A	Agriculture, forestry and fishing	01-03
2	B	Mining and quarrying	05-09
3	C	Manufacturing	10-33
4	D	Electricity, gas, steam and air conditioning supply	35
5	E	Water supply; sewerage, waste management and remediation activities	36-39
6	F	Construction	41-43
7	G	Wholesale and retail trade; repair of motor vehicles and motorcycles	45-47
8	H	Transportation and storage	49-53
9	I	Accommodation and food service activities	55-56
10	J	Information and communication	58-63
11	K	Financial and insurance activities	64-66
12	L	Real estate activities	68
13	M	Professional, scientific and technical activities	69-75
14	N	Administrative and support service activities	77-82
15	O	Public administration and defence; compulsory social security	84
16	P	Education	85
17	Q	Human health and social work activities	86-88
18	R	Arts, entertainment and recreation	90-93
19	S	Other service activities	94-96
20	T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	97-98
21	U	Activities of extraterritorial organisations and bodies	99

3.2 Stylised facts

Using these data, we will first present some selected stylised facts that motivated the theoretical approach outlined in Section 4 and also helped to explain the results reported in Section 5. Figure 3.1 shows the average annual growth rates over countries, industries and years for the sample.

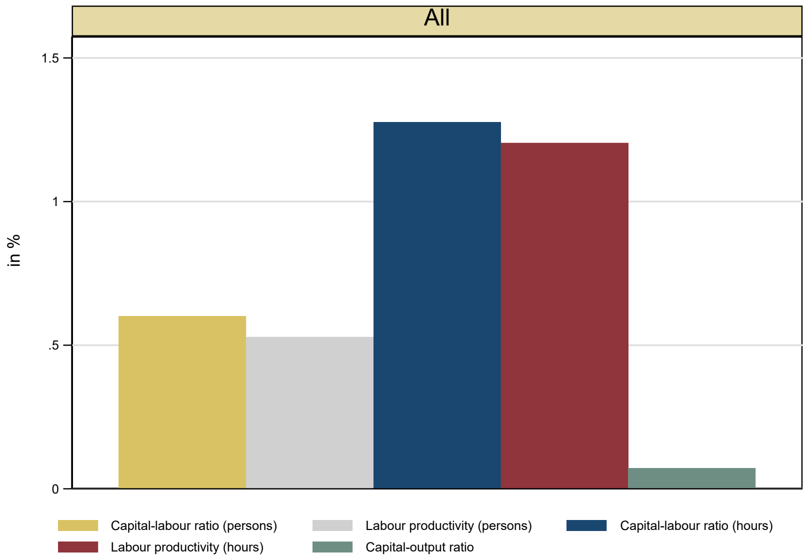
Value added increased on average by 1% per year, persons employed grew by 0.5% (in terms of persons employed), and hours worked declined on average by 0.2%. Total capital stock grew by slightly above 1% per year. Together, they implied a total factor productivity growth rate of slightly less than 1% per year. The compensation or labour income shares grew on average by about 0.4 percentage points per year. From these data and growth rates, various other indicators can be derived, which are presented in Figure 3.2. One can see an increase in the capital-labour ratio at about 0.5% growth rate per year, which

Figure 3.1: Stylised facts I



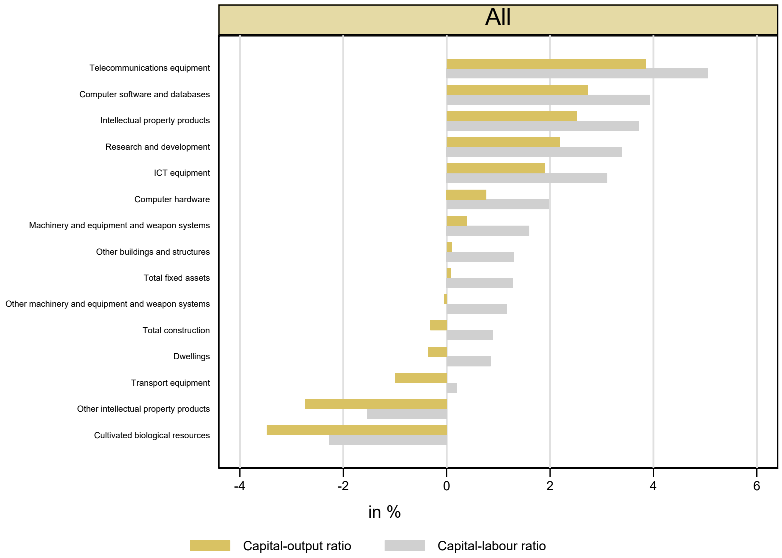
was similar to labour productivity growth when measured in persons employed. In hours worked, the respective growth rates were around 1%. Importantly, for the theoretical approach, the capital-output ratio only slightly increased with a growth rate of about 0.1% per year. Finally, Figure 3.3 presents

Figure 3.2: Stylised facts II



the average growth rates of the capital-output and capital-labour ratios (i.e. capital-deepening) by asset types. Two main insights can be gained from these: First, the capital-labour ratio in all cases increased faster (or decreased) slower than the capital-output ratio due to labour productivity growth. Second, the growth rates were larger for ICT capital asset types and intangible asset types.

Figure 3.3: Stylised facts III



4 Methodological approach

In this section, we introduce our framework to estimate labour demand equations and explain the role of capital accumulation in these and total factor productivity growth. The approach is inspired by the framework outlined in Autor and Salomons (2018) but takes the critique by Felipe et al. (2020) into account. This is achieved by arguing that there is an intimate relationship between the developments of the capital-output ratio as shown in the previous section. First, we discuss this approach for one asset type, then show the implications for labour demand for various asset types by taking asset-specific capital-output ratio dynamics into account.

4.1 One asset type

Our starting point is a Cobb-Douglas production function stated as

$$Y_{it}^c = A_0 \exp^{\lambda_i^c t} (K_{it}^c)^{1-\alpha} (L_{it}^c)^{\alpha}$$

where Y denotes value added, A_0 is the initial level of TFP, K is capital stock and L is labour input. λ denotes the growth rate of TFP, and $0 < \alpha < 1$ are the technological parameters (respective income shares or elasticities). Furthermore, i denotes the industry, c is the country and t is time. Taking the logs and differentiating them with respect to time shows this relation in growth rates:

$$y_{it}^c = \lambda_i^c + (1-\alpha) k_{it}^c + \alpha l_{it}^c$$

Reformulating it provides an expression for labour demand growth dependent on TFP growth, output growth and the growth rate of capital stock:

$$l_{it}^c = -\frac{1}{\alpha}\lambda_i^c + \frac{1}{\alpha} y_{it}^c - \frac{1-\alpha}{\alpha} k_{it}^c$$

As argued in Felipe et al. (2020) and Felipe and McCombie (2019), this is an identity, given that TFP is calculated as a residual term; therefore, estimating this equation poses a "catch-22 problem". To escape this problem, we use an assumption or restriction that $k_{it}^c = \xi y_{it}^c$ and $\frac{k_{it}^c}{y_{it}^c} = \xi$, i.e. capital and output growth, are tightly linked by parameter ξ. In fact, if $\xi = 1$, we can obtain Kaldor's stylised fact that the capital-output ratio is constant.[12] Imposing this assumption results in a labour demand equation stated as

$$l_{it}^c = -\frac{1}{\alpha}\lambda_i^c + \frac{1}{\alpha}\frac{1}{\xi} k_{it}^c - \frac{1-\alpha}{\alpha} k_{it}^c = -\frac{1}{\alpha}\lambda_i^c + \frac{1-\xi+\xi\alpha}{\xi\alpha} k_{it}^c$$

This shows that labour demand is negatively related to TFP growth and positively related to capital stock growth[13] if $1 - \xi + \xi\alpha > 0$ or $\xi < \frac{1}{1-\alpha}$.[14] The equation is rearranged to show that, under the assumption above, the capital-labour ratio (capital deepening) increases with TFP growth, whereas the impact of the growth rate of capital stock depends on parameter ξ. In fact, if $\xi = 1$, then capital deepening would

[12] In essence, this implies that when considering a version of an AL-model as (under the assumption $\xi = 1$), one obtains
$Y_{it}^c = A_0 \exp^{\lambda_i^c t} (Y_{it}^c)^{1-\alpha} (L_{it}^c)^{\alpha} = A_0 \exp^{\lambda_i^c t} (Y_{it}^c)^{1-\alpha} (L_{it}^c)^{\alpha} = A_0 \exp^{\lambda_i^c t} (Y_{it}^c)^{-\alpha} (L_{it}^c)^{\alpha}$
$(Y_{it}^c)^{\alpha} = A_0 \exp^{\lambda_i^c t} (L_{it}^c)^{\alpha} \Rightarrow Y_{it}^c = (A_0)^{\frac{1}{\alpha}} \exp^{\frac{1}{\alpha}\lambda_i^c t} L_{it}^c$
However, the formulation above allows us to also consider cases with $\xi \neq 1$.

[13] Felipe et al. (2020) used this assumption but replaced capital stock growth with value added growth and discussed the implications for the estimation results.

[14] For a labour share of $\alpha = \frac{2}{3}$, this condition is $\xi < 3$. For $\xi = 1$, the relationship would be $l_{it}^c = -\frac{1}{\alpha}\lambda_i^c + k_{it}^c$, and labour and capital growth would be positively related. Thus, the restriction on the developments of the capital-output ratio also imposes a restriction on the capital-labour ratio.

be a function of TFP growth only. However, if $\xi > 1$, the capital-labour ratio would also increase with capital accumulation:

$$k_{it}^c - l_{it}^c = \frac{1}{\alpha}\lambda_i^c - \Big(\frac{1-\xi}{\xi\alpha}\Big)k_{it}^c$$

Finally, some further manipulations leads to an expression of labour productivity growth as

$$y_{it}^c - l_{it}^c = \frac{1}{\alpha}\lambda_i^c - \frac{(1-\alpha)(1-\xi)}{\xi\alpha}k_{it}^c$$

which is then positively related to TFP growth and positively related to capital accumulation if $\xi > 1$, i.e. if the capital-output ratio increased.

Furthermore, one can infer from these equations that, under the assumption of similar growth rates of capital and TFP, the impact of TFP growth is stronger than that of capital accumulation for reasonable parameter constellations (e.g. a labour income share α of around two-thirds, and the parameter ξ above one but not unreasonably high). This can be seen using a numerical example that assumes $\alpha = \frac{2}{3}$ and $\xi = \frac{3}{2}$. Then, labour demand would grow with $l_{it}^c = -1.5 \cdot \lambda_i^c + 0.5 \cdot k_{it}^c$. The growth of the capital-labour ratio was formulated as $k_{it}^c - l_{it}^c = 1.5 \cdot \lambda_i^c + 0.5 \cdot k_{it}^c$, and labour productivity growth by $y_{it}^c - l_{it}^c = 1.5 \cdot \lambda_i^c + 0.167 \cdot k_{it}^c$. From this example, one can see that the (marginal) impact of TFP growth was larger than that of capital accumulation. Moreover, one can easily see that the larger the parameter ξ, the lower the impact of capital accumulation on labour demand and the larger the impact of capital accumulation on capital deepening and labour productivity growth. Of course, the relative impacts depended on the parameter constellations in the end.

From these results, one can also infer the developments of the wage share in value added. Assume that the (nominal) wage-rental ratio is constant (i.e. wages w and the rental rate to capital r are constant or growing at the same rates).[15] For $\xi > 1$, capital stock grows faster than labour, which implies that the level of returns to capital grows faster than wage income, i.e. $rk_{it}^c > wl_{i,t}^c$, and indicates a falling share of labour income. A similar result is derived from the labour productivity equation. Assume that the (nominal) price of output and the wage rate are constant (or growing at the same rate), one gets $py_{it}^c > wl_{it}^c$ (if labour productivity is growing), again implying a falling share of labour income.

As a special case, we rewrite these equations under the assumption that $\xi = 1$, i.e. the capital-output ratio is constant (one of Kaldor's stylised facts and also apparent in the descriptive statistics above). Therefore, labour demand growth decreases with TFP growth and increases with capital stock growth: $l_{it}^c = -\frac{1}{\alpha}\lambda_i^c + k_{it}^c$. The capital-labour ratio and labour productivity both increases with TFP growth: $k_{it}^c - l_{it}^c = y_{it}^c - l_{it}^c = \frac{1}{\alpha}\lambda_i^c$. Under the assumptions above, the labour income share falls with TFP growth.

[15] For example, this is the case in the standard trade model for a small open economy, such that relative factor prices are determined by relative goods prices (factor-price insensitivity theorem).

4.2 Various asset types

Next, assume that there is a second asset type. The Cobb-Douglas production function is written as

$$Y_{it}^c = A_0 \exp^{\lambda_i^c t} (K_{it}^c)^{\gamma(1-\alpha)} (P_{it}^c)^{(1-\gamma)(1-\alpha)} (L_{it}^c)^{\alpha}$$

where P denotes automation capital, and γ are the respective share parameters. In terms of growth rates, this becomes

$$y_{it}^c = \lambda_i^c + \gamma(1-\alpha)k_{it}^c + (1-\gamma)(1-\alpha)p_{it}^c + \alpha l_{it}^c$$

Then, labour demand growth is given by

$$l_{it}^c = -\frac{1}{\alpha}\lambda_i^c - \frac{\gamma(1-\alpha)}{\gamma}k_{it}^c - \frac{(1-\gamma)(1-\alpha)}{\alpha}p_{it}^c + \frac{1}{\alpha}y_{it}^c$$

Assuming that $k_{it}^c = \xi_k y_{it}^c$ and $p_{it}^c = \xi_p y_{it}^c$, this equation can be reformulated as

$$l_{it}^c = -\frac{1}{\alpha}\lambda_i^c + \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\alpha\xi_k}\Big]k_{it}^c + \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c$$

From this, one can expect that traditional capital $k_{i,t}^c$ has a larger impact on labour demand if γ is large and/or ξ_k is smaller than ξ_p. From the stylised facts in Section 3, it follows that $\xi_k < \xi_p$. Specifically, consider a special case with $\xi = 1$:

$$l_{it}^c = -\frac{1}{\alpha}\lambda_i^c + \gamma k_{it}^c + \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c$$

from which it is clear that traditional capital accumulation has a larger (marginal) effect compared with automation capital; that is, the larger the γ, the larger the ξ_p. The capital-labour ratios for each asset type can be derived analogously to the above as

$$\begin{aligned}
k_{it}^c - l_{it}^c &= \frac{1}{\alpha}\lambda_i^c - \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)-\alpha\xi_k}{\alpha\xi_k}\Big]k_{it}^c - \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c \\
p_{it}^c - l_{it}^c &= \frac{1}{\alpha}\lambda_i^c - \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\alpha\xi_k}\Big]k_{it}^c - \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)-\alpha\xi_p}{\alpha\xi_p}\Big]p_{it}^c
\end{aligned}$$

These equations show that capital-deepening dynamics mutually depends on the capital accumulation of the various asset types and the parameter constellations. Finally, labour productivity growth is derived as (see Appendix)

$$y_{it}^c - l_{it}^c = \frac{1}{\alpha}\lambda_i^c - \frac{\gamma}{\alpha\xi_k}\Big[1-\xi_k-\alpha+\alpha\xi_k\Big]k_{it}^c - \frac{(1-\gamma)}{\alpha\xi_p}\Big[1-\xi_p-\alpha+\alpha\xi_p\Big]p_{it}^c$$

Again, considering the special case with $\xi_k = 1$ and $\xi_p > 1$ gives

$$y_{it}^c - l_{it}^c \quad = \quad \frac{1}{\alpha}\lambda_i^c - \frac{(1-\gamma)}{\alpha\xi_p}\Big[1 - \xi_p - \alpha + \alpha\xi_p\Big]p_{it}^c$$

Thus, labour productivity grows only with TFP and automation capital if $\xi_p > 1$.[16] Furthermore, analogous to above, labour productivity would rise faster if ξ_p is larger, i.e. the capital-output ratio increases strongly.

5 Results

In this section, we present selected results that focus on the question of the effects of TFP growth and capital accumulation on labour demand and labour income. We first present the results using total fixed assets. In the following subsection, we use data on detailed asset types. In both subsections, we present the results for total employment, which are then broken down by the labour categories of age, education and sex.

5.1 One asset type

In this section, we report the results of estimating the equation

$$\gamma_{i,t}^c = \alpha_0 + \beta_1 k_{i,t}^c + \beta_2 \lambda_{i,t}^c + \mu_i^c + \varepsilon_{i,t}^c$$

where $\gamma_{i,t}^c$ denotes the growth rate or change of the respective variable, i.e. value added, persons employed and hours worked in (log) growth rates and the shares of compensation or labour income (compensation adjusted for self-employed) in percentage point changes. Furthermore, we present the results at the level of NACE Revision 2 1-digit industries. The reason for this is data on the detailed asset types used later are more widely available at this level than at the more detailed industry level.[17] The results are presented in Table 5.1.

The first column shows the impact of the growth of capital stock and TFP on value added, which in both cases are positive and significant. In line with the theoretical outline above, we also find a positive relation between the growth of capital stock and employment (measured in persons employed and hours worked) and a negative relation between TFP growth and employment growth (columns 2 and 3). Column 4 shows the relationship to labour productivity growth. TFP and capital stock growth are positively related, as predicted by the theoretical outline. In addition, the impact of TFP growth is much larger than that of capital accumulation. Columns 5 and 6 report the consequences of capital

[16] This follows from $1 - \xi_p - \alpha + \alpha\xi_p < 0 \Rightarrow \xi_p > 1$.

[17] The provision of data on detailed asset types at the industry level is not compulsory, according to the transmission programme.

Table 5.1: Capital accumulation and labour demand and income shares (total period)

VARIABLES	(1) Value added	(2) Persons	(3) Hours	(4) Labour productivity	(5) Compensation	(6) Labour income
Total fixed assets	0.450***	0.059***	0.052***	0.397***	-0.084***	-0.081***
	(0.007)	(0.012)	(0.012)	(0.008)	(0.009)	(0.009)
TFP	0.928***	-0.064***	-0.098***	1.025***	-0.287***	-0.280***
	(0.005)	(0.008)	(0.009)	(0.005)	(0.006)	(0.006)
Constant	0.003***	0.008***	0.006***	-0.003***	0.004***	0.004***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	7,152	7,152	7,152	7,152	7,152	7,152
R-squared	0.829	0.016	0.024	0.843	0.228	0.219
Number of i	335	335	335	335	335	335
F	16575	55.08	84.94	18290	1008	954.6

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

growth and TFP growth on the shares of compensation or labour income in value added. Both TFP growth and capital accumulation impact negatively on the labour and compensation shares, again in line with the reasoning outlined in the previous section. Moreover, the effect of TFP growth is larger. Table 5.2 provides the results from 2007 onwards, as this sample is compatible with the breakdown of labour studied next. It can easily be seen that these results are compatible with the results of the full sample reported in Table 5.1.

Table 5.2: Capital accumulation and labour demand and income shares (2007-2018)

VARIABLES	(1) Value added	(2) Persons	(3) Hours	(4) Labour productivity	(5) Compensation	(6) Labour income
Total fixed assets	0.509***	0.086***	0.101***	0.409***	-0.103***	-0.096***
	(0.014)	(0.022)	(0.025)	(0.015)	(0.020)	(0.019)
TFP	0.950***	-0.052***	-0.081***	1.031***	-0.336***	-0.317***
	(0.007)	(0.011)	(0.013)	(0.008)	(0.010)	(0.010)
Constant	-0.001	0.002**	-0.000	-0.001	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3,285	3,285	3,285	3,285	3,285	3,285
R-squared	0.849	0.016	0.023	0.858	0.266	0.269
Number of i	332	332	332	332	332	332
F	8289	23.92	34.27	8905	534.7	542.9

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In the next step, we break down hours worked and labour income into various categories. First, Table 5.3 shows the relationships between capital stock and TFP growth with hours worked and labour income by age categories. Capital accumulation is positively related to the hours worked by younger (aged 15 to 29) and older (aged 50 to 64) people. TFP growth is negatively related to hours worked for middle-aged (30-49) workers only. TFP growth is negatively related to the labour income shares of all age groups, and the relationship is strongest for middle-aged persons. Capital accumulation is negatively related to the income shares of the young and middle aged only.

With respect to educational attainment (see Table 5.4), capital accumulation and TFP affect only

Table 5.3: Impact of capital accumulation on labour demand and income shares by age

VARIABLES	(1) Hours worked	(2) 15 to 29	(3) 30 to 49	(4) 50 to 64	(5) Labour income	(6) 15 to 29	(7) 30 to 49	(8) 50 to 64
Total fixed assets	0.101***	0.257***	0.007	0.174***	-0.096***	-0.014**	-0.065***	-0.015
	(0.025)	(0.090)	(0.040)	(0.056)	(0.019)	(0.007)	(0.013)	(0.010)
TFP	-0.081***	-0.038	-0.111***	-0.042	-0.317***	-0.048***	-0.193***	-0.070***
	(0.013)	(0.047)	(0.021)	(0.029)	(0.010)	(0.004)	(0.007)	(0.005)
Constant	-0.000	-0.023***	-0.004**	0.020***	0.003***	-0.000	0.002***	0.002***
	(0.001)	(0.004)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	3,285	3,263	3,267	3,263	3,285	3,285	3,285	3,285
R-squared	0.023	0.004	0.010	0.005	0.269	0.059	0.210	0.064
Number of i	332	332	332	332	332	332	332	332
F	34.27	5.215	15.01	7.320	542.9	92.12	391.7	100.3

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

medium- and high-educated workers. TFP growth has a negative impact on the labour income of all groups (strongest for medium-educated workers), whereas capital accumulation impacts negatively only on the income shares of medium- and high-educated workers.

Table 5.4: Impact of capital accumulation on labour demand and income shares by educational attainment

VARIABLES	(1) Hours worked	(2) Low	(3) Medium	(4) High	(5) Labour income	(6) Low	(7) Medium	(8) High
Total fixed assets	0.101***	0.170	0.099**	0.122*	-0.096***	-0.005	-0.044***	-0.045***
	(0.025)	(0.128)	(0.044)	(0.074)	(0.019)	(0.011)	(0.014)	(0.010)
TFP	-0.081***	-0.027	-0.066***	-0.194***	-0.317***	-0.038***	-0.177***	-0.096***
	(0.013)	(0.067)	(0.023)	(0.039)	(0.010)	(0.006)	(0.007)	(0.005)
Constant	-0.000	-0.037***	-0.009***	0.032***	0.003***	-0.002***	0.002***	0.004***
	(0.001)	(0.005)	(0.002)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	3,285	3,224	3,263	3,263	3,285	3,285	3,285	3,285
R-squared	0.023	0.001	0.006	0.011	0.269	0.016	0.177	0.110
Number of i	332	332	332	332	332	332	332	332
F	34.27	1.128	8.539	16.80	542.9	24.21	316.4	182.8

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Finally, with respect to sex (see Table 5.5), we find a positive relation of capital accumulation for both male and female, whereas TFP growth impacts only male workers negatively. Both variables have a negative effect on the labour income shares, but it is more severe for male workers.

5.2 Detailed assets

In this subsection, we consider the role of detailed asset types. The equation estimated is

$$\gamma_{i,t}^{c} = \alpha_0 + \sum_{j} \beta_{1,j} k_{ij,t}^{c} + \beta_2 \lambda_{i,t}^{c} + \mu_i^{c} + \varepsilon_{i,t}^{c}$$

Table 5.5: Impact of capital accumulation on labour demand and income shares by sex

VARIABLES	(1) Hours worked	(2) Male	(3) Female	(4) Labour income	(5) Male	(6) Female
Total fixed assets	0.101***	0.088***	0.099**	-0.096***	-0.070***	-0.040***
	(0.025)	(0.034)	(0.045)	(0.019)	(0.020)	(0.011)
TFP	-0.081***	-0.068***	-0.004	-0.317***	-0.236***	-0.097***
	(0.013)	(0.017)	(0.023)	(0.010)	(0.010)	(0.005)
Constant	-0.000	0.000	-0.003	0.003***	0.002***	0.001***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.000)
Observations	3,285	2,965	2,965	3,285	2,972	2,972
R-squared	0.023	0.011	0.002	0.269	0.179	0.109
Number of i	332	332	332	332	332	332
F	34.27	14.58	2.563	542.9	288.0	161.9

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

where j denotes the specific asset types. From the asset types available (from national accounts and supplementary ones beyond the boundaries of national accounts), we include transport equipment (KN1131 - TraEq), information technology (KN11321 - IT), communication technology (KN11322 - CT), other machinery (KN11O), research and development (N1171 - R&D) and software and databases (KN1173 - SoftDB).[18] As mentioned, we include asset types beyond the boundaries of national accounts, such as advertising and market research (AdvMRes), design (Design) and purchased organisational capital (POCap).[19]

The results are reported in 5.6. With the exception of purchased organisational capital, all of them are positively related to value added growth. Many of these asset types are significantly positively related to labour growth, except for IT and CT in the case of persons employed and hours worked only, respectively. There are no significant relationships for software and databases, design and purchased organisational capital. Other machinery impacts negatively on the labour income or compensation shares, whereas software and databases capital accumulation has positive impacts. The results for R&D are significant and negative for labour income but not for compensation shares. As before, TFP growth is negatively related to output growth and labour income shares.

These results are also found by splitting labour demand and labour income into the categories of age (Table 5.7), education (Table 5.8) and sex (Table 5.9). With respect to age, we find that younger workers (aged 15 to 29) are the least affected by the variables considered, and the intangible asset, advertising and market research, impacted significantly on the demand for the other two age groups. Similarly, other machinery has a negative impact on the labour income shares of age groups 30-49 and 50-64, and SoftDB positively impact only the middle-aged group.

However, the drivers are much more diverse when the labour demand by educational categories is considered. The accumulation of various asset types is positively related to labour demand for medium-

[18] We do not include construction asset types (KN111 and KN112) and cultivated biological assets (KN115).

[19] These are taken from the EU KLEMS Release 2019 database (www.euklems.eu). For a detailed outline of how these are constructed, see Adarov and Stehrer (2019b).

Table 5.6: Asset-specific capital accumulation on labour demand and income shares

VARIABLES	(1) Value added	(2) Persons	(3) Hours	(4) Labour productivity	(5) Compensation	(6) Labour income
TraEq	0.065***	0.049***	0.057***	0.008	0.005	0.006
	(0.008)	(0.011)	(0.013)	(0.008)	(0.007)	(0.009)
IT	0.014***	0.009*	0.003	0.011***	0.003	0.004
	(0.004)	(0.005)	(0.007)	(0.004)	(0.004)	(0.004)
CT	0.015***	0.006	0.018***	-0.003	0.003	0.003
	(0.004)	(0.005)	(0.007)	(0.004)	(0.004)	(0.004)
OMach	0.114***	0.037**	0.046**	0.068***	-0.041***	-0.051***
	(0.011)	(0.015)	(0.018)	(0.010)	(0.010)	(0.012)
R&D	0.012***	0.008*	0.012**	-0.000	-0.004	-0.007**
	(0.003)	(0.005)	(0.006)	(0.003)	(0.003)	(0.004)
SoftDB	0.017***	0.002	0.002	0.015***	0.014***	0.015***
	(0.005)	(0.007)	(0.008)	(0.005)	(0.005)	(0.006)
AdvMRes	0.024***	0.044***	0.048***	-0.024***	-0.001	0.002
	(0.005)	(0.006)	(0.007)	(0.004)	(0.004)	(0.005)
Design	0.015*	0.014	0.004	0.010	0.003	-0.001
	(0.009)	(0.011)	(0.014)	(0.008)	(0.008)	(0.009)
POCap	0.012	-0.005	0.015	-0.003	-0.002	0.003
	(0.010)	(0.013)	(0.015)	(0.009)	(0.009)	(0.010)
TFP	0.943***	-0.007	-0.036**	0.979***	-0.278***	-0.321***
	(0.011)	(0.015)	(0.018)	(0.010)	(0.010)	(0.012)
Constant	0.001	0.000	-0.003**	0.004***	0.002***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,013	2,013	2,013	2,013	2,013	2,013
R-squared	0.804	0.066	0.068	0.838	0.316	0.297
Number of i	204	204	204	204	204	204
F	738.2	12.63	13.13	932.2	83.03	76.09

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.7: Impact of asset-specific capital accumulation on labour demand and income shares by age

VARIABLES	(1) Hours worked	(2) 15 to 29	(3) 30 to 49	(4) 50 to 64	(5) Labour income	(6) 15 to 29	(7) 30 to 49	(8) 50 to 64
TraEq	0.057***	0.086*	0.023	0.080**	0.006	0.006*	0.002	-0.001
	(0.013)	(0.052)	(0.022)	(0.031)	(0.009)	(0.003)	(0.006)	(0.004)
IT	0.003	-0.016	-0.009	0.034**	0.004	0.002	0.000	0.002
	(0.007)	(0.026)	(0.011)	(0.016)	(0.004)	(0.002)	(0.003)	(0.002)
CT	0.018***	0.042	0.008	0.007	0.003	0.002	0.001	0.000
	(0.007)	(0.026)	(0.011)	(0.016)	(0.004)	(0.002)	(0.003)	(0.002)
OMach	0.046**	0.115	0.030	0.077*	-0.051***	-0.008*	-0.027***	-0.016***
	(0.018)	(0.072)	(0.031)	(0.043)	(0.012)	(0.005)	(0.008)	(0.006)
R&D	0.012**	-0.002	0.016*	0.011	-0.007**	-0.002	-0.005*	-0.001
	(0.006)	(0.022)	(0.009)	(0.013)	(0.004)	(0.001)	(0.002)	(0.002)
SoftDB	0.002	-0.009	0.010	0.006	0.015***	0.001	0.010***	0.004
	(0.008)	(0.033)	(0.014)	(0.020)	(0.006)	(0.002)	(0.004)	(0.003)
AdvMRes	0.048***	-0.003	0.060***	0.057***	0.002	0.001	-0.002	0.002
	(0.007)	(0.029)	(0.013)	(0.018)	(0.005)	(0.002)	(0.003)	(0.002)
Design	0.004	0.007	0.018	-0.031	-0.001	-0.001	0.005	-0.004
	(0.014)	(0.054)	(0.023)	(0.033)	(0.009)	(0.004)	(0.006)	(0.004)
POCap	0.015	0.160***	0.003	-0.053	0.003	0.004	-0.000	-0.001
	(0.015)	(0.061)	(0.026)	(0.037)	(0.010)	(0.004)	(0.007)	(0.005)
TFP	-0.036**	0.145**	-0.128***	0.033	-0.321***	-0.050***	-0.197***	-0.074***
	(0.018)	(0.070)	(0.030)	(0.042)	(0.012)	(0.005)	(0.008)	(0.006)
Constant	-0.003**	-0.025***	-0.008***	0.019***	0.002**	-0.001*	0.001	0.002***
	(0.001)	(0.005)	(0.002)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	2,013	2,013	2,013	2,013	2,013	2,013	2,013	2,013
R-squared	0.068	0.013	0.034	0.018	0.297	0.065	0.264	0.086
Number of i	204	204	204	204	204	204	204	204
F	13.13	2.457	6.301	3.349	76.09	12.46	64.59	16.94

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

educated workers except for the intangible asset, design. With the exception of design, hardly any of the asset types impacts on labour demand for the low- and high-educated groups. However, for the low-educated group, a strong positive association was seen for transport equipment. With respect to labour income share, we find a negative impact of the accumulation of other machinery on medium- and high-educated workers, and a positive one for the accumulation of software and databases on medium-educated workers. With respect to sex, the labour demand for males relates to the accumulation of

Table 5.8: Impact of asset-specific capital accumulation on labour demand and income shares by educational attainment

VARIABLES	(1) Hours worked	(2) Low	(3) Medium	(4) High	(5) Labour income	(6) Low	(7) Medium	(8) High
TraEq	0.057***	0.219***	0.046*	-0.047	0.006	0.007**	0.000	-0.002
	(0.013)	(0.080)	(0.024)	(0.040)	(0.009)	(0.003)	(0.006)	(0.006)
IT	0.003	0.058	-0.009	0.018	0.004	0.000	0.005	-0.001
	(0.007)	(0.039)	(0.012)	(0.020)	(0.004)	(0.002)	(0.003)	(0.003)
CT	0.018***	-0.074*	0.036***	-0.025	0.003	-0.001	0.003	0.002
	(0.007)	(0.040)	(0.012)	(0.020)	(0.004)	(0.002)	(0.003)	(0.003)
OMach	0.046**	0.099	0.031	0.028	-0.051***	-0.003	-0.023***	-0.025***
	(0.018)	(0.111)	(0.034)	(0.055)	(0.012)	(0.004)	(0.009)	(0.008)
R&D	0.012**	0.030	0.020*	0.010	-0.007**	-0.003**	-0.003	-0.002
	(0.006)	(0.036)	(0.010)	(0.017)	(0.004)	(0.001)	(0.003)	(0.002)
SoftDB	0.002	-0.008	0.027*	0.009	0.015***	-0.003	0.012***	0.006
	(0.008)	(0.051)	(0.016)	(0.026)	(0.006)	(0.002)	(0.004)	(0.004)
AdvMRes	0.048***	-0.027	0.063***	0.014	0.002	0.001	0.003	-0.002
	(0.007)	(0.045)	(0.014)	(0.023)	(0.005)	(0.002)	(0.004)	(0.003)
Design	0.004	0.231***	-0.058**	0.107**	-0.001	0.001	-0.006	0.005
	(0.014)	(0.083)	(0.025)	(0.042)	(0.009)	(0.003)	(0.007)	(0.006)
POCap	0.015	0.239**	0.005	0.024	0.003	0.006	-0.000	-0.002
	(0.015)	(0.094)	(0.029)	(0.047)	(0.010)	(0.004)	(0.008)	(0.007)
TFP	-0.036**	0.084	-0.019	-0.116**	-0.321***	-0.046***	-0.169***	-0.105***
	(0.018)	(0.108)	(0.033)	(0.054)	(0.012)	(0.004)	(0.009)	(0.008)
Constant	-0.003**	-0.050***	-0.013***	0.031***	0.002**	-0.002***	0.001	0.003***
	(0.001)	(0.008)	(0.002)	(0.004)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	2,013	1,977	2,013	2,013	2,013	2,013	2,013	2,013
R-squared	0.068	0.024	0.029	0.010	0.297	0.071	0.183	0.099
Number of i	204	204	204	204	204	204	204	204
F	13.13	4.260	5.444	1.870	76.09	13.68	40.39	19.77

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

various asset types (transport equipment, communication technology, R&D and advertising and market research), whereas the demand for female workers is significantly related only to transport equipment and advertising and market research. Other machinery impacts negatively on the labour income shares for both males and females. In addition, the accumulation of IT and software and databases is positively related to the changes in the labour income share of males. The female income share is negatively related to the accumulation of R&D stocks.

5.3 Value chain linkages

Finally, we test whether value chain linkages are drivers of demand and income shares. We construct backward linkage variables by calculating the Leontief inverse of a multi-country input-output table[20]

[20]We used the OECD TiVA data (Release 2021), which are aggregated accordingly.

Table 5.9: Impact of asset-specific capital accumulation on labour demand and income shares by sex

VARIABLES	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female
TraEq	0.057***	0.042**	0.059**	0.006	0.005	0.004
	(0.013)	(0.018)	(0.025)	(0.009)	(0.007)	(0.005)
IT	0.003	0.011	-0.002	0.004	0.007**	-0.002
	(0.007)	(0.009)	(0.013)	(0.004)	(0.004)	(0.002)
CT	0.018***	0.021**	-0.005	0.003	0.002	0.002
	(0.007)	(0.009)	(0.013)	(0.004)	(0.004)	(0.002)
OMach	0.046**	0.044*	-0.007	-0.051***	-0.035***	-0.016**
	(0.018)	(0.025)	(0.036)	(0.012)	(0.010)	(0.007)
RD	0.012**	0.023***	0.013	-0.007**	-0.002	-0.005**
	(0.006)	(0.008)	(0.011)	(0.004)	(0.003)	(0.002)
SoftDB	0.002	0.002	0.008	0.015***	0.011**	0.002
	(0.008)	(0.012)	(0.017)	(0.006)	(0.005)	(0.003)
AdvMRes	0.048***	0.046***	0.035**	0.002	0.003	-0.001
	(0.007)	(0.010)	(0.014)	(0.005)	(0.004)	(0.003)
Design	0.004	0.031*	-0.026	-0.001	0.004	-0.007
	(0.014)	(0.018)	(0.026)	(0.009)	(0.007)	(0.005)
POCap	0.015	-0.001	0.027	0.003	-0.004	0.009
	(0.015)	(0.021)	(0.029)	(0.010)	(0.008)	(0.006)
TFP	-0.036**	-0.007	0.023	-0.321***	-0.242***	-0.088***
	(0.018)	(0.025)	(0.035)	(0.012)	(0.010)	(0.007)
Constant	-0.003**	-0.003*	-0.004	0.002**	0.001	0.001*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
Observations	2,013	1,831	1,831	2,013	1,831	1,831
R-squared	0.068	0.040	0.012	0.297	0.276	0.097
Number of i	204	204	204	204	204	204
F	13.13	6.784	2.035	76.09	61.69	17.34

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

and premultiplying it with the growth rates of capital stocks. For the forward linkages, we calculated the Ghosh inverse and postmultiplied it with the growth rates of capital stocks. Using these, we estimated the following equation (similar to the one above):

$$\gamma^c_{i,t} = \alpha_0 + \sum_j \beta_{1,j} k^c_{ij,t} + \beta_3 BL^c_{i,t} + \beta_4 FL^c_{i,t} + \beta_5 \lambda^c_{i,t} + \mu^c_i + \varepsilon^c_{i,t}$$

. The result are reported in Table 5.10 using only those asset types that were significant in most cases in the previous results. The results for these asset types remained qualitatively the same as above. With respect to the linkages, we find positive labour demand effects of capital accumulation in backward-linked industries, and negative labour demand effects of capital accumulation in forward-linked industries. However, there are no relationships of these linkages with respect to labour income shares.[21]

6 Conclusions

We studied the impact of the accumulation of capital (differentiated by various asset types) and TFP growth on labour demand growth and the labour income (or compensation) shares in value added. Furthermore, labour demand growth and the changes in compensation shares were segregated by age,

[21] The results by labour groups are reported in the Appendix and are similar to those found so far.

Table 5.10: Linkage effects of capital accumulation on labour demand and income shares

VARIABLES	(1) Value added	(2) Persons	(3) Hours	(4) Labour productivity	(5) Compensation	(6) Labour income
TraEq	0.026***	0.028***	0.029***	-0.003	0.006	0.007
	(0.006)	(0.009)	(0.011)	(0.006)	(0.006)	(0.008)
OMach	0.063***	0.035**	0.037**	0.026***	-0.022**	-0.030**
	(0.011)	(0.015)	(0.018)	(0.010)	(0.011)	(0.013)
R&D	0.010***	0.009*	0.012**	-0.003	-0.003	-0.007*
	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.004)
SoftDB	0.010**	0.006	0.008	0.002	0.016***	0.018***
	(0.004)	(0.006)	(0.007)	(0.004)	(0.004)	(0.005)
AdvMRes	0.026***	0.044***	0.052***	-0.027***	0.001	0.004
	(0.004)	(0.005)	(0.006)	(0.003)	(0.004)	(0.005)
BL x K	0.793***	0.458***	0.705***	0.088	-0.045	-0.058
	(0.075)	(0.105)	(0.124)	(0.068)	(0.074)	(0.090)
FL x K	-0.034	-0.315***	-0.430***	0.395***	-0.093*	-0.099
	(0.056)	(0.078)	(0.093)	(0.051)	(0.055)	(0.067)
TFP	0.962***	-0.015	-0.033**	0.995***	-0.271***	-0.314***
	(0.010)	(0.014)	(0.016)	(0.009)	(0.010)	(0.012)
Constant	-0.001	0.000	-0.003**	0.002***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,269	2,269	2,269	2,269	2,269	2,269
R-squared	0.832	0.062	0.073	0.863	0.285	0.264
Number of i	232	232	232	232	232	232
F	1253	16.82	19.86	1591	100.9	90.85

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

educational attainment and sex. The econometric specifications were derived from a simple Cobb-Douglas production function that took stylised empirical trends of asset-specific capital-output ratios into account. Specifically, we allowed for a close relationship between capital and output growth, which was in line with the stylised facts in the equations for labour demand growth and changes in labour income or compensation shares (under the assumption of the wage-rental ratios being determined externally, as suggested by the factor-price insensitivity theorem, for small open economies). Using a panel of 15 industries for the 27 EU member states (depending on data availability) within the period of 2007-2018 indicated that the econometric results were generally in line with these derivations.

Overall, the results point towards a positive relation between labour demand growth and capital accumulation and a negative one with respect to total factor productivity growth; the marginal impact of the latter is larger in absolute terms in most cases, which is in line with the theoretical derivations. Concerning the compensation shares, both variables impact negatively. These general results also hold true for the various types of labour (determined by age, educational attainment and sex), although there is some heterogeneity across the groups.

Taking into account asset-specific capital accumulation reveals only a limited impact of ICT or software and database capital growth on labour demand growth, but the relation is positive or insignificant in those cases. Software and databases impacts positively on the labour income or compensation share. Stronger effects are found for more traditional asset types, like transport equipment and other machinery, and the supplementary intangible asset, advertising and market research. These results are consistent with the findings in Stehrer (2022) at the total economy level using a long-run specification.

Finally, we include the impact of backward and forward linkages into the framework (similar to Autor and Salomons, 2018). Here, we find significant positive relations between labour demand growth and capital accumulation in backward-linked country-industries but negative ones in forward-linked country-industries. These virtually have no impact on the labour income or compensation share.

Overall, these results reveal an insignificant or even small positive effect of the accumulation of automation capital (i.e. ICT and software and databases) on labour demand growth in conformity with some recent literature (e.g. Antón et al., 2020; Ghodsi et al., 2019; Jestl, 2022) which focused on the impact of robots). Moreover, the results demonstrate insignificant effects on labour income shares, with software and databases even having a small but significant positive impact in general. This is supported by the recent findings of Pichler and Stehrer (0201), who found a much lower impact of ICT capital accumulation on wage shares after the global financial crisis.

Thus, there is no evidence of a strong negative impact of ICT capital accumulation on employment growth, as some of the literature (discussed in Section 2) has suggested. However, there may be significant differences in the impacts on different types of labour; therefore, a more detailed analysis beyond what has been presented in this paper is required.[22] Indeed, there may be other important aspects with respect to the impacts of digital technologies, such as our personal and social life or changes in work relations and organisations, work relationships and working standards, security issues and personal rights and other related societal challenges. The policy debate should therefore focus more on issues like developing new skills and the upcoming challenges for the education system (from the requirements of primary schooling to life-long learning and adult training). These issues will certainly pose challenges to policymakers and civil society in the coming years (Servoz, 2019). Finally, the potential of new technologies to address other important challenges, such as population ageing (Acemoglu and Restrepo, 2018a; Stehrer and Tverdostup, 2022) and climate change, also needs to be considered in the debates.

[22] See Kaltenberg and Foster-McGregor, 2022; Bachmann et al., 2022; Doorley et al., 2022.

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A Additional results

A.1 Full sample with detailed manufacturing industries

Table A.1: Baseline results: Total fixed assets (full sample)

VARIABLES	(1) Value added	(2) Persons	(3) Hours	(4) Labour productivity	(5) Compensation	(6) Labour income
Total fixed assets	0.498***	0.104***	0.109***	0.390***	-0.085***	-0.070***
	(0.007)	(0.011)	(0.011)	(0.006)	(0.009)	(0.008)
TFP	0.989***	-0.003	-0.008	0.997***	-0.320***	-0.286***
	(0.003)	(0.005)	(0.006)	(0.003)	(0.004)	(0.004)
Constant	-0.001*	0.002***	-0.000	-0.001*	0.005***	0.004***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Observations	10,031	10,031	10,031	10,031	10,031	10,031
R-squared	0.898	0.010	0.011	0.916	0.357	0.320
Number of i	458	458	458	458	458	458
F	42237	50.33	51.81	51852	2656	2255

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A.2 Results with National Accounts asset types only

Table A.2: Baseline results for NA asset types

VARIABLES	(1) Value added	(2) Persons	(3) Hours	(4) Labour productivity	(5) Compensation	(6) Labour income
TraEq	0.069***	0.054***	0.063***	0.006	0.006	0.007
	(0.008)	(0.011)	(0.013)	(0.008)	(0.007)	(0.009)
IT	0.014***	0.010*	0.004	0.010***	0.003	0.004
	(0.004)	(0.005)	(0.007)	(0.004)	(0.004)	(0.004)
CT	0.015***	0.005	0.018***	-0.002	0.003	0.003
	(0.004)	(0.005)	(0.007)	(0.004)	(0.004)	(0.004)
OMach	0.117***	0.041***	0.051***	0.066***	-0.041***	-0.050***
	(0.011)	(0.015)	(0.018)	(0.010)	(0.010)	(0.012)
R&D	0.012***	0.008*	0.013**	-0.000	-0.004	-0.007*
	(0.004)	(0.005)	(0.006)	(0.003)	(0.003)	(0.004)
SoftDB	0.018***	0.004	0.004	0.014***	0.013***	0.014**
	(0.005)	(0.007)	(0.009)	(0.005)	(0.005)	(0.006)
TFP	0.946***	-0.004	-0.032*	0.978***	-0.278***	-0.320***
	(0.011)	(0.015)	(0.018)	(0.010)	(0.010)	(0.012)
Constant	0.002**	0.001	-0.002	0.004***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,023	2,023	2,023	2,023	2,023	2,023
R-squared	0.799	0.031	0.036	0.835	0.314	0.295
Number of i	205	205	205	205	205	205
F	1028	8.275	9.532	1311	118.4	108.1

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.3: Baseline results by age for NA asset types

VARIABLES	(1) Hours worked	(2) 15 to 29	(3) 30 to 49	(4) 50 to 64	(5) Labour income	(6) 15 to 29	(7) 30 to 49	(8) 50 to 64
TraEq	0.063***	0.103**	0.030	0.078**	0.007	0.007**	0.002	-0.002
	(0.013)	(0.052)	(0.022)	(0.031)	(0.009)	(0.003)	(0.006)	(0.004)
IT	0.004	-0.012	-0.008	0.034**	0.004	0.002	0.000	0.002
	(0.007)	(0.026)	(0.011)	(0.016)	(0.004)	(0.002)	(0.003)	(0.002)
CT	0.018***	0.043*	0.007	0.005	0.003	0.002	0.002	0.000
	(0.007)	(0.026)	(0.011)	(0.016)	(0.004)	(0.002)	(0.003)	(0.002)
OMach	0.051***	0.130*	0.036	0.074*	-0.050***	-0.007	-0.027***	-0.016***
	(0.018)	(0.071)	(0.031)	(0.043)	(0.012)	(0.005)	(0.008)	(0.006)
R&D	0.013**	-0.001	0.017*	0.010	-0.007*	-0.002	-0.005*	-0.001
	(0.006)	(0.022)	(0.009)	(0.013)	(0.004)	(0.001)	(0.002)	(0.002)
SoftDB	0.004	-0.009	0.013	0.008	0.014**	0.000	0.010***	0.004
	(0.009)	(0.033)	(0.014)	(0.020)	(0.006)	(0.002)	(0.004)	(0.003)
TFP	-0.032*	0.156**	-0.123***	0.031	-0.320***	-0.049***	-0.197***	-0.074***
	(0.018)	(0.070)	(0.030)	(0.042)	(0.012)	(0.005)	(0.008)	(0.006)
Constant	-0.002	-0.021***	-0.007***	0.017***	0.002***	-0.000	0.001	0.002***
	(0.001)	(0.005)	(0.002)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	2,023	2,023	2,023	2,023	2,023	2,023	2,023	2,023
R-squared	0.036	0.009	0.016	0.012	0.295	0.062	0.262	0.086
Number of i	205	205	205	205	205	205	205	205
F	9.532	2.236	4.290	3.246	108.1	16.97	91.86	24.31

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.4: Baseline results by educational attainment for NA asset types

VARIABLES	(1) Hours worked	(2) Low	(3) Medium	(4) High	(5) Labour income	(6) Low	(7) Medium	(8) High
TraEq	0.063***	0.249***	0.051**	-0.040	0.007	0.008***	0.001	-0.002
	(0.013)	(0.080)	(0.024)	(0.040)	(0.009)	(0.003)	(0.006)	(0.006)
IT	0.004	0.059	-0.007	0.018	0.004	0.000	0.005	-0.001
	(0.007)	(0.039)	(0.012)	(0.020)	(0.004)	(0.002)	(0.003)	(0.003)
CT	0.018***	-0.071*	0.035***	-0.025	0.003	-0.001	0.003	0.002
	(0.007)	(0.040)	(0.012)	(0.020)	(0.004)	(0.002)	(0.003)	(0.003)
OMach	0.051***	0.136	0.033	0.036	-0.050***	-0.002	-0.023**	-0.025***
	(0.018)	(0.111)	(0.034)	(0.055)	(0.012)	(0.004)	(0.009)	(0.008)
R&D	0.013**	0.034	0.020*	0.011	-0.007*	-0.003**	-0.003	-0.002
	(0.006)	(0.036)	(0.010)	(0.017)	(0.004)	(0.001)	(0.003)	(0.002)
SoftDB	0.004	-0.007	0.029*	0.012	0.014**	-0.003	0.012***	0.006
	(0.009)	(0.051)	(0.016)	(0.026)	(0.006)	(0.002)	(0.004)	(0.004)
TFP	-0.032*	0.102	-0.016	-0.111**	-0.320***	-0.046***	-0.169***	-0.106***
	(0.018)	(0.107)	(0.033)	(0.054)	(0.012)	(0.004)	(0.009)	(0.008)
Constant	-0.002	-0.038***	-0.014***	0.034***	0.002***	-0.002***	0.001	0.003***
	(0.001)	(0.007)	(0.002)	(0.004)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	2,023	1,987	2,023	2,023	2,023	2,023	2,023	2,023
R-squared	0.036	0.012	0.015	0.005	0.295	0.068	0.181	0.099
Number of i	205	205	205	205	205	205	205	205
F	9.532	3.050	3.838	1.196	108.1	18.99	56.99	28.42

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.5: Baseline results by sex for NA asset types

VARIABLES	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female
TraEq	0.063***	0.046***	0.064**	0.007	0.006	0.005
	(0.013)	(0.018)	(0.025)	(0.009)	(0.007)	(0.005)
IT	0.004	0.011	-0.000	0.004	0.007**	-0.001
	(0.007)	(0.009)	(0.013)	(0.004)	(0.004)	(0.002)
CT	0.018***	0.019**	-0.006	0.003	0.002	0.002
	(0.007)	(0.009)	(0.013)	(0.004)	(0.004)	(0.002)
OMach	0.051***	0.047*	-0.004	-0.050***	-0.035***	-0.016**
	(0.018)	(0.026)	(0.036)	(0.012)	(0.010)	(0.007)
RD	0.013**	0.023***	0.013	-0.007*	-0.002	-0.005**
	(0.006)	(0.008)	(0.011)	(0.004)	(0.003)	(0.002)
SoftDB	0.004	0.006	0.010	0.014**	0.011**	0.002
	(0.009)	(0.012)	(0.016)	(0.006)	(0.005)	(0.003)
TFP	-0.032*	-0.002	0.029	-0.320***	-0.242***	-0.087***
	(0.018)	(0.025)	(0.035)	(0.012)	(0.010)	(0.007)
Constant	-0.002	-0.002	-0.004	0.002***	0.001	0.001*
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
Observations	2,023	1,840	1,840	2,023	1,840	1,840
R-squared	0.036	0.019	0.006	0.295	0.275	0.094
Number of i	205	205	205	205	205	205
F	9.532	4.606	1.339	108.1	88.20	24.05

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

A.3 Results of linkages effects by labour groups

Table A.6: Results by age

VARIABLES	(1) Hours worked	(2) 15 to 29	(3) 30 to 49	(4) 50 to 64	(5) Labour income	(6) 15 to 29	(7) 30 to 49	(8) 50 to 64
TraEq	0.029***	0.090**	-0.005	0.048*	0.007	0.006**	0.002	-0.001
	(0.011)	(0.042)	(0.018)	(0.026)	(0.008)	(0.003)	(0.005)	(0.004)
OMach	0.037**	0.083	0.018	0.078*	-0.030**	-0.001	-0.016*	-0.013**
	(0.018)	(0.072)	(0.031)	(0.044)	(0.013)	(0.005)	(0.009)	(0.006)
R&D	0.012**	-0.002	0.017*	0.011	-0.007*	-0.001	-0.005*	-0.001
	(0.005)	(0.021)	(0.009)	(0.013)	(0.004)	(0.001)	(0.003)	(0.002)
SoftDB	0.008	-0.004	0.011	0.008	0.018***	0.002	0.010***	0.006**
	(0.007)	(0.029)	(0.012)	(0.018)	(0.005)	(0.002)	(0.003)	(0.003)
AdvMRes	0.052***	0.033	0.065***	0.041***	0.004	0.003*	-0.001	0.002
	(0.006)	(0.025)	(0.011)	(0.015)	(0.005)	(0.002)	(0.003)	(0.002)
BL x K	0.705***	1.852***	0.558***	0.650**	-0.058	-0.023	-0.032	-0.003
	(0.124)	(0.492)	(0.214)	(0.303)	(0.090)	(0.033)	(0.058)	(0.043)
FL x K	-0.430***	-1.214***	-0.345**	-0.450**	-0.099	-0.023	-0.048	-0.028
	(0.093)	(0.368)	(0.159)	(0.227)	(0.067)	(0.024)	(0.043)	(0.032)
TFP	-0.033**	0.141**	-0.109***	0.013	-0.314***	-0.048***	-0.189***	-0.077***
	(0.016)	(0.064)	(0.028)	(0.040)	(0.012)	(0.004)	(0.008)	(0.006)
Constant	-0.003**	-0.022***	-0.009***	0.018***	0.003***	-0.000	0.001	0.002***
	(0.001)	(0.004)	(0.002)	(0.003)	(0.001)	(0.000)	(0.001)	(0.000)
Observations	2,269	2,269	2,269	2,269	2,269	2,269	2,269	2,269
R-squared	0.073	0.015	0.033	0.013	0.264	0.063	0.236	0.086
Number of i	232	232	232	232	232	232	232	232
F	19.86	3.980	8.730	3.233	90.85	17.04	78.35	23.81

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.7: Results by educational attainment

VARIABLES	(1) Hours worked	(2) Low	(3) Medium	(4) High	(5) Labour income	(6) Low	(7) Medium	(8) High
TraEq	0.029***	0.318***	0.001	-0.089***	0.007	0.007***	0.002	-0.002
	(0.011)	(0.065)	(0.020)	(0.034)	(0.008)	(0.003)	(0.006)	(0.005)
OMach	0.037**	0.067	0.009	0.025	-0.030**	0.003	-0.008	-0.024***
	(0.018)	(0.113)	(0.034)	(0.058)	(0.013)	(0.004)	(0.010)	(0.008)
R&D	0.012**	0.033	0.020**	0.011	-0.007*	-0.002*	-0.002	-0.002
	(0.005)	(0.035)	(0.010)	(0.017)	(0.004)	(0.001)	(0.003)	(0.002)
SoftDB	0.008	-0.063	0.027**	0.050**	0.018***	-0.001	0.014***	0.005
	(0.007)	(0.044)	(0.014)	(0.023)	(0.005)	(0.002)	(0.004)	(0.003)
AdvMRes	0.052***	0.057	0.059***	0.026	0.004	0.002	0.003	-0.002
	(0.006)	(0.039)	(0.012)	(0.020)	(0.005)	(0.001)	(0.003)	(0.003)
BL x K	0.705***	0.718	0.903***	0.388	-0.058	-0.046	-0.022	0.010
	(0.124)	(0.756)	(0.235)	(0.393)	(0.090)	(0.029)	(0.065)	(0.055)
FL x K	-0.430***	-0.024	-0.495***	-0.244	-0.099	-0.005	-0.079	-0.015
	(0.093)	(0.565)	(0.175)	(0.294)	(0.067)	(0.022)	(0.049)	(0.041)
TFP	-0.033**	0.147	-0.022	-0.111**	-0.314***	-0.044***	-0.168***	-0.102***
	(0.016)	(0.099)	(0.031)	(0.051)	(0.012)	(0.004)	(0.008)	(0.007)
Constant	-0.003**	-0.040***	-0.014***	0.030***	0.003***	-0.002***	0.001**	0.003***
	(0.001)	(0.007)	(0.002)	(0.004)	(0.001)	(0.000)	(0.001)	(0.001)
Observations	2,269	2,233	2,269	2,269	2,269	2,269	2,269	2,269
R-squared	0.073	0.020	0.028	0.010	0.264	0.069	0.165	0.093
Number of i	232	232	232	232	232	232	232	232
F	19.86	5.056	7.412	2.502	90.85	18.83	50.26	25.88

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A.8: Results by sex

VARIABLES	(1) Total	(2) Male	(3) Female	(4) Total	(5) Male	(6) Female
TraEq	0.029***	0.014	0.058***	0.007	0.005	0.003
	(0.011)	(0.014)	(0.020)	(0.008)	(0.006)	(0.004)
OMach	0.037**	0.043*	-0.022	-0.030**	-0.019*	-0.011
	(0.018)	(0.025)	(0.036)	(0.013)	(0.011)	(0.007)
RD	0.012**	0.022***	0.014	-0.007*	-0.002	-0.004**
	(0.005)	(0.007)	(0.010)	(0.004)	(0.003)	(0.002)
SoftDB	0.008	0.014	0.018	0.018***	0.011**	0.002
	(0.007)	(0.010)	(0.014)	(0.005)	(0.004)	(0.003)
AdvMRes	0.052***	0.049***	0.044***	0.004	0.003	0.001
	(0.006)	(0.008)	(0.012)	(0.005)	(0.004)	(0.002)
BL x K	0.705***	0.474**	1.751***	-0.058	-0.122	0.023
	(0.124)	(0.217)	(0.302)	(0.090)	(0.093)	(0.060)
FL x K	-0.430***	-0.226	-1.395***	-0.099	-0.022	-0.089*
	(0.093)	(0.163)	(0.227)	(0.067)	(0.070)	(0.045)
TFP	-0.033**	-0.008	0.015	-0.314***	-0.239***	-0.086***
	(0.016)	(0.023)	(0.032)	(0.012)	(0.010)	(0.006)
Constant	-0.003**	-0.003*	-0.005**	0.003***	0.002**	0.001**
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
Observations	2,269	2,064	2,064	2,269	2,064	2,064
R-squared	0.073	0.035	0.036	0.264	0.249	0.095
Number of i	232	232	232	232	232	232
F	19.86	8.272	8.396	90.85	75.77	24.01

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

B Technical details

B.1 Labour productivity with one asset type

For the derivation of labour productivity growth equation we first subtract output growth and rearrange:

$$\begin{aligned}
l_{it}^c - y_{it}^c &= -\frac{1}{\alpha}\lambda_i^c + \frac{1-\xi+\xi\alpha}{\xi\alpha}k_{it}^c - y_{it}^c \\
&= -\frac{1}{\alpha}\lambda_i^c + \frac{1-\xi+\xi\alpha}{\xi\alpha}k_{it}^c - \left[\lambda_i^c + (1-\alpha)k_{it}^c + \alpha l_{it}^c\right] \\
&= -\frac{1}{\alpha}\lambda_i^c + \frac{1-\xi+\xi\alpha}{\xi\alpha}k_{it}^c - \lambda_i^c - (1-\alpha)k_{it}^c - \alpha\Big(-\frac{1}{\alpha}\lambda_i^c + \frac{1-\xi+\xi\alpha}{\xi\alpha}k_{it}^c\Big) \\
&= -\frac{1}{\alpha}\lambda_i^c + \frac{1-\xi+\xi\alpha}{\xi\alpha}k_{it}^c - \lambda_i^c - (1-\alpha)k_{it}^c + \lambda_i^c - \frac{1-\xi+\xi\alpha}{\xi}k_{it}^c \\
&= -\frac{1}{\alpha}\lambda_i^c + \frac{1-\xi+\xi\alpha}{\xi\alpha}k_{it}^c - \frac{\xi\alpha(1-\alpha)}{\xi\alpha}k_{it}^c - \frac{\alpha(1-\xi+\xi\alpha)}{\xi\alpha}k_{it}^c \\
&= -\frac{1}{\alpha}\lambda_i^c + \frac{1-\xi+\xi\alpha-\xi\alpha+\xi\alpha^2-\alpha+\xi\alpha-\xi\alpha^2}{\xi\alpha}k_{it}^c \\
&= -\frac{1}{\alpha}\lambda_i^c + \frac{1-\xi-\alpha+\xi\alpha}{\xi\alpha}k_{it}^c
\end{aligned}$$

This results in the expression for labour productivity growth:

$$y_{it}^c - l_{it}^c = \frac{1}{\alpha}\lambda_i^c - \frac{1-\xi-\alpha+\xi\alpha}{\xi\alpha}k_{it}^c = \frac{1}{\alpha}\lambda_i^c - \frac{(1-\alpha)(1-\xi)}{\xi\alpha}k_{it}^c$$

For the special case $\xi = 1$ this results in labour productivity is just growing at the rate of TFP growth, i.e. $y_{it}^c - l_{it}^c = \frac{1}{\alpha}\lambda_i^c$. In the general case, capital accumulation impacts positively on labour productivity growth if $\xi > 1$.

B.2 Labour productivity with two asset types

$$l_{it}^c - y_{it}^c = -\frac{1}{\alpha}\lambda_i^c + \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\alpha\xi_k}\Big]k_{it}^c + \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c - y_{it}^c$$

$$l_{it}^c - y_{it}^c = -\frac{1}{\alpha}\lambda_i^c + \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\alpha\xi_k}\Big]k_{it}^c + \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c - \Big(\lambda_i^c + \gamma(1-\alpha)k_{it}^c + (1-\gamma)(1-\alpha)p_{it}^c + \alpha l_{it}^c\Big)$$

$$\begin{aligned}
l_{it}^c - y_{it}^c = {} & -\frac{1}{\alpha}\lambda_i^c + \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\alpha\xi_k}\Big]k_{it}^c + \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c \\
& -\lambda_i^c - \gamma(1-\alpha)k_{it}^c - (1-\gamma)(1-\alpha)p_{it}^c \\
& -\alpha\Big(-\frac{1}{\alpha}\lambda_i^c + \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\alpha\xi_k}\Big]k_{it}^c + \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c\Big)
\end{aligned}$$

$$\begin{aligned}
l_{it}^c - y_{it}^c = {} & -\frac{1}{\alpha}\lambda_i^c + \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\alpha\xi_k}\Big]k_{it}^c + \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c \\
& -\lambda_i^c - \gamma(1-\alpha)k_{it}^c - (1-\gamma)(1-\alpha)p_{it}^c \\
& +\lambda_i^c - \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\xi_k}\Big]k_{it}^c - \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\xi_p}\Big]p_{it}^c
\end{aligned}$$

$$
\begin{aligned}
l_{it}^c - y_{it}^c \quad = \quad & -\frac{1}{\alpha}\lambda_i^c \\
& + \Big[\frac{\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\alpha\xi_k}\Big]k_{it}^c - \frac{\alpha\xi_k\gamma(1-\alpha)}{\alpha\xi_k}k_{it}^c - \Big[\frac{\alpha\gamma\big(1-\xi_k+\alpha\xi_k\big)}{\alpha\xi_k}\Big]k_{it}^c \\
& + \Big[\frac{(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c - \frac{\alpha\xi_p(1-\gamma)(1-\alpha)}{\alpha\xi_p}p_{it}^c - \Big[\frac{\alpha(1-\gamma)\big(1-\xi_p+\alpha\xi_p\big)}{\alpha\xi_p}\Big]p_{it}^c
\end{aligned}
$$

$$
\begin{aligned}
l_{it}^c - y_{it}^c \quad = \quad & -\frac{1}{\alpha}\lambda_i^c \\
& + \frac{\gamma}{\alpha\xi_k}\Big[\big(1-\xi_k+\alpha\xi_k\big) - \alpha\xi_k(1-\alpha) - \alpha\big(1-\xi_k+\alpha\xi_k\big)\Big]k_{it}^c \\
& + \frac{(1-\gamma)}{\alpha\xi_p}\Big[\big(1-\xi_p+\alpha\xi_p\big) - \alpha\xi_p(1-\alpha) - \alpha\big(1-\xi_p+\alpha\xi_p\big)\Big]p_{it}^c
\end{aligned}
$$

$$
\begin{aligned}
l_{it}^c - y_{it}^c \quad = \quad & -\frac{1}{\alpha}\lambda_i^c \\
& + \frac{\gamma}{\alpha\xi_k}\Big[1-\xi_k+\alpha\xi_k-\alpha\xi_k+\alpha^2\xi_k-\alpha+\alpha\xi_k-\alpha^2\xi_k\Big]k_{it}^c \\
& + \frac{(1-\gamma)}{\alpha\xi_p}\Big[1-\xi_p+\alpha\xi_p-\alpha\xi_p+\alpha^2\xi_p-\alpha+\alpha\xi_p-\alpha^2\xi_p\Big]p_{it}^c
\end{aligned}
$$

$$
l_{it}^c - y_{it}^c \quad = \quad -\frac{1}{\alpha}\lambda_i^c + \frac{\gamma}{\alpha\xi_k}\Big[1-\xi_k-\alpha+\alpha\xi_k\Big]k_{it}^c + \frac{(1-\gamma)}{\alpha\xi_p}\Big[1-\xi_p-\alpha+\alpha\xi_p\Big]p_{it}^c
$$

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