From New Technology to Productivity
An Overview

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Abstract

This paper reviews briefly the scientific literature on new technologies and future trends and on how and why the technologies may affect production, labor relations, and living conditions. Recent evidence points towards a slowing of productivity growth and a growing sense of unease among households concerning the impact of future economic developments. The paper argues that new digital technologies not only have the potential to change economic interactions, but also change the framework needed by economists to analyze the supply side of the economy. With appropriate policies, the technological advances can continue apace and will translate into productivity growth, with households broadly contributing to and benefitting from the goods and services that the new production technology will produce.

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1. INTRODUCTION

Society appears to be at a crossroads, with new production technologies having the potential to disrupt the ways in which households contribute to and benefit from the circular flows of the economy. Political choices made today can have consequences for the direction taken and the economic and social outcomes far into the future. The production sector will condition its decisions concerning adoption of existing technologies and development of new technologies on its expectations for future outcomes, which partly depend on the policy environment. Similarly, households in their decisions concerning supply of productive resources, consumption of goods and services, and savings and investment respond not only to current production technology but also to their beliefs about future technology and policy environment. The policy stance of governments, even with unchanging social preferences, needs to adjust to the emerging changes in allocations brought about by new production technology.

A set of new products and services—among which universal robots, autonomous vehicles, and internet-connected devices—that have been under development for the past decade are coming to market more rapidly than expected. Much of the speedup in their development and blurring of lines between them, can be attributed to advances in machine learning algorithms. The new technologies have the potential to provide improvements in well-being because they allow the transformation of productive resources supplied by households into final goods and services consumed by these households at a better rate, in other words they increase the productivity of the economy. In their role as a driver for raising productivity, these technologies do not differ from earlier inventions, from the indoor plumbing and the internal combustion engine, to electrification and telecommunication, although Gordon (2016) argues that their quantitative impact may be lower. The new technologies do differ in their potential to change the organisation of production, improve the nature of work and broaden the experience of consumption, as argued by Brynjolfsson and McAfee (2011, 2014).

The effects of the new technologies likely already are occurring although it is difficult to draw firm conclusions from the seemingly conflicting macroeconomic trends until an encompassing theoretical framework and appropriate empirical measures have been developped. Aggregate productivity growth is low in all advanced economies, and median income remains stagnant despite falling unemployment rates. Investment as a share of GDP has not recovered to pre-crisis averages even as valuations of especially high-tech firms are increasing. At the same time, labor share of output is declining while profit rates and markups appear to be on the increase. The best firms acount for the bulk of aggregate profits and do seem to exhibit high rates of productivity growth. These firms that operate internationally are not constrained in their growth by domestic demand.

At the micro level, clearer signals of the impact of technologies are available. Market shares are shifting to more productive, technology intensive, firms and technology may be diffusing to the lagging firms. Both these processes can affect but also be affected by the new technologies. For workers, the technologies can be a substitute for their job, as self-driving taxis replace drivers, or for a portion of their work, as robots take over back-breaking or repetitive tasks. In the past, jobs at risk were mostly in the 'middle' of the skill distribution, but the pattern may well change with future technology, especially under influence of new algorithms applied to burgeoning datasets. For workers that become displaced by technology, some recent evidence points to a lifetime loss in income, through a combination of less future hours of work and lower pay. The technologies also may bring flexibility to the production processes so that labor supply can match with demand in different ways, for example as a sale of own-account hours rather than through wages from a labor contract. In the data, the emergence of alternative labor arrangements is observable, but the change may be attributable to factors other than technology. Finally, much change has taken place in the realm of consumption. First, many goods and services are provided at low or zero price, either because the ensuing increase of the customer base is seen as an investment or because revenue flows through the other side of a two-sided market, or because marginal costs are low and competition shifts benefits to consumer surplus. Next, the boundary between production and consumption may be shifting, with many tasks now being done by the household (e.g. travel arrangements) or by firms (e.g. goods delivery).

Despite the availability of new productivity boosting technology, discontent of households about income and agency and worries about financial well-being for their offspring are gaining ground in advanced economies. The uncertainty about future employment opportunities coupled with locally persistent effects of past job displacement and uneven distribution of past income gains makes the unease understandable. Further, the social distruptions of platform industries (e.g. rental housing, taxi transport, retail delivery), privacy concerns of networks, and winner-take-all dynamics of superstar firms also mask, if not over-take, the benefits of the technology. These issues are making their way to the top of policy makers agenda's, and many proposals such as increased minimum wages, basic income, more progressive income tax, higher corporate tax, taxes on robots, break-up of the largest tech firms, etc, have been launched recently. At the same time, there is worry about slow uptake of new technologies, inadequate supply of skilled workers, lack of flexibility for resource reallocation, and worry about policy that may slow the rate of innovation. The urgency with which the need for policy reforms has emerged has caught the economics profession off-guard, leaving debates on policy proposals without adequate guiding principles or facts, let alone a coherent framework for policy development, execution and evaluation.

This paper will review recent theoretical and empirical papers across a wide swath of subfields of economics that all are related to new technology, and in particular those associated with intangible assets, ICT, data, and articial intelligence (AI). Through this review, the paper will provide a new narrative on where we stand, where we could go, and what framework we can use to get there. The review makes clear that the new technology is replacing the workhorse 'production technology' used in economic analysis. Instead of using the standard constant returns to scale (CRTS) technology with which primary capital and labor inputs are transformed into final goods and services, the new framework considers production functions that give a prominent role to intangible, non-rival, assets. Other possibilities for production functions explicitly model the process of intermediation between household supply of primary resources and household consumption of final goods and services as an integral feature of production technology rather than as frictions or margins.

The paper will be organized as follows: In section 2, We will review the promise of new technology and provide some evidence on the development, implementation, adoption and diffusion of the new technology across firms and households. The next section 3 provides the recent evidence across advanced economies of productivity growth, at the aggregate, industry, and firm level, and discusses the findings from micro- and macro-level that have been so puzzling and worrisome to economists and policy makers. The analytical core of the paper is in section 4, where a prescription is given of the elements needed for an encompassing model and where some theoretical advances towards such a model are discussed. In this section we review how current analysis in labor economics, but also in macroeconomic measurment need to be revisited using a more encompassing framework. The implications of the new production framework for policy (labor, education, competition) aimed at enabling further technological innovation and boosting productivity are reviewed in section 5. The paper concludes in section 6 with some thoughts on future productivity growth and a roadmap for further research.

2. PROMISES

In the long span of human history, sporadic changes to production technology and concomittant social organization have radically changed the patterns of human life. With a broad sweeping view of such changes, the books of Jared Diamond (1997) and especially Yuval Harari (2014) are inspiring histories. For changes since the industrial revolution and particulary geared to the United States experience, Robert Gordon (2016) points out that genuinely major changes in technology are those that are accompanied by large changes in business practices, disruptions in the circumstances of labor, and changes in the way in which households live. Gordon vividly describes how in the US, at least outside the deep South, someone living at the end of the great depression would scarcely recognize the way people lived less than two generations earlier. By contrast, Gordon sees little change in business, labor, and living conditions coming from computers and internet. In particular, the always-on mobile communications and social networks that have arisen since the dot-com bubble bursting in 2000 and the wide diffusion of the smartphone since 2009, do not impress him. In clear contrast, Harari (2016) warns that these new technologies together with articial intelligence (AI) and recent developments in genetics, set the stage for a set of very disruptive potential paths for business, labor, and living conditions going forward.

Among economists there also is much work that challenges Gordon's view and instead posits that genuinely new technologies could have a profound impact in coming decades. At the depth of the financial crisis, Brynjolfsson and McAfee (2011) present the main arguments that portend a 'race against the machine.' The first argument comes from the exponential growth of computing power, through Moore's Law. After doubling nearly thirty times, each next doubling will add tremendous amounts of computing power. In the process, a significant part of investment in these technologies leads to intangible capital that is 'non-rival' in production and allows scaling at very low marginal costs. Finally, the increasing power of processing data and low marginal costs of production will substitute for many of the current production factors, pushing down their market value and, at least for human labor, setting up Tinbergen's race between technology and education (see e.g. Heckman, 2018).

2.1. TECHNOLOGIES

In this section, we provide an overview of new technologies that have the potential to be disruptive in the sense that they change business operations, labor market relations, and living conditions. McKinsey and Company (2013) published an influential monograph on twelve disruptive technologies with the potential to transform 'life, business, and the global economy' in the period to 2025. We track how these emerging technologies have developed at the halfway mark, as well as pointing out unexpected new developments.

The McKinsey (2013) technologies can be allocated to five groupings, related to energy, genomics, materials (processing), automation, and data (processing). While reductions in the price of exploration and recovery of traditional energy sources versus improvements in renewable energy and energy storage are important for assessing economic costs of climate change (see e.g. Heal, 2017), and thus may have immense consequences for future living conditions, we consider the issue to be outside the scope of this review article. Nonetheless, the improvements in the levelized cost of renewable energy, storage and delivery since 2013 have surpassed what was expected by McKinsey in 2013 (see e.g. Lai, 2017). Genomics likewise can have immense consequences for mortality and morbidity. The price declines in gene sequencing have been spectacular, even compared with Moore's Law for semiconductors, and the McKinsey prediction that it would cost \$100 by 2025 was quite pessimistic given that in 2019 the cost of sequencing already is about \$35. The potential for genomics to be disruptive has gone up especially since the development of the CRISPR-Cas9 gene editing technology (Doudna and Charpentier, 2014) that was not yet known to McKinsey (2013). Unfortunately, combining the narrative of one of the potential futures of Harari (2017) with the knowledge of a totally synthetic life form that was cut-and-paste in the lab (see Fredens et al., 2019) also will be outside of the scope of this review.

In the area of advanced materials and 3D printing likewise developments have outpaced the expectations of McKinsey. The direct effects of these technologies on productivity likely will remain small. First, the aggregate gains from improvements in direct use of new materials and processes in manufacturing runs up against a manufacturing-to-GDP ratio that is declining towards 10% in advanced economies. While there has been some advance in cost and speed, 3D printing does not provide advantages in mass production relative to traditional (reductive or extrusive) manufacturing equipment. Instead, the application of 3D technology allows 'mass customization' (for example, for person-specific consumer goods) and local production (for example for spare parts), in a way that improvements will be taking place along the value chain and in benefits to the end-user. To analyse these economic impacts, one needs to move beyond using the macro-economic CRTS production function with capital and labor to measure firm-level productivity gains, as will be explained in section 4.

The advances in robotics seem on track since the prognosis of McKinsey. As with many of the other disruptive technologies, acceleration since 2013 can be ascribed mostly to advances in AI. Recent robots have some features similar to the machine tools or numerically controlled machine tools used in manufacturing in previous decades. The robots substitute directly for human workers, or they take on tasks that go beyond their physical capabilities. Further, the robots work at the same time and location as labor, material, and other capital goods, in order to produce output. So far the similarities. The different vintages of machine tools and robots do differ in the skill requirements for their operators or workers that set them up. Some robots require programmers or engineers to install and set up, while others can mimic operations of skilled craftsman. Different from the earlier machine tools, the robots generally are more flexible in operations and can be used in generating different varieties of output, so-called mass customization.

More recently, there have been advances in universal programmable robots or so-called co-bots. These machines can work alongside humans without being surrounded by a protective cage. The rental rate for such robots can be as low as five to ten euros per hour.[1] These robots, which can be used in small businesses, have become better at sensitive tasks such as picking or slicing tomatoes owing to AI learning. While these robots could also be useful in the home, hourly rental would likely be prohibitive because of low utilization rates. However, coupled with complementary digital technologies, see below, one could imagine viability of local facilities with such co-bots for laundry, food preparation, or door-to-door delivery of co-bots for home cleaning services.

Self-driving cars have been capturing the imagination since the first DARPA grand challenge of 2004, where none of the entrants to the autonomous vehicle competition reached the finish line. In 2013, Google was testing autonomous vehicles on the road in the US state of Nevada that had changed laws to allow driverless cars. Since then, many competitors have joined (and left) the field, bringing forward the year that McKinsey expected level 4 autonomous vehicles to be availble for purchase from 2030 to 2020.

Besides transporting people, autonomous vehicles are particularly compelling for moving physical objects along production chains. In 2013, one of the fastest growing job titles in the US was an ’order picker’, or someone who goes through shelves in warehouses to pick items to be bundled for shipment. Now, autonomous robots scour the floors and are replacing many workers to move product at the growing number of fulfillment centers that are servicing e-commerce. In the US, nearly 3 million workers presently have as occupation to ’manually move freight, stock, or other materials.’ In conjunction with connected sensors and AI, there is a rapid rise in the locations and circumstances where autonomous vehicles can replace humans in such tasks.

Besides the hardware technologies of robots and self-driving cars, there has been continued progress in software and data communication and storage. Strictly speaking, it is likely that Moore’s law, the doubling of device density every two years, no longer can continue owing to quantum effects. Nonetheless, the economic gains of quality adjusted price declines seem to continue with technical tricks such as 3D chip stacking, or through the increased utilization of computing power that comes with cloud-based computing service. Also, as new releases of general-purpose CPUs occur less frequently more effort can be put into optimizing software. Similarly, special purpose chips, for example GPUs used for AI applications, can increase the computing power for specific uses more than can be achieved using generic chips.

[1] Assuming 8 percent interest, 10 percent depreciation rate, purchase price including installation of 50–100 thousand euro and utilization of 2000 hours per year.

The move to cloud computing and specialized chips thus is being accompanied by progress in software. Cloud-based apps allow businesses to scale up production without fixed investments in hardware by paying only marginal costs of more intense app usage instead. If the market for cloud services and for such apps is competitive, then the marginal payments will reflect resource costs. Given the concentration in the cloud service market and the potential to create customer lock-in, the assumption of perfect competition may not be warranted. However, open source software is generating tools that allow users to move their whole virtual computing and data environment between cloud vendors, and open application program interfaces (APIs) are generating the ability to substitute one app with another in more seemless ways.

In McKinsey (2013) it was acknowledged that AI would be complementary to many of the other disruptive technologies, speeding up their progress and increase the scale and scope of their impact. The breakthroughs in AI techniques since 2013 have sped up applications, especially in domains where large, annotated datasets are not available (e.g. Creswell at al., 2018). For all the earlier mentioned technologies, AI also could speed up their development and reduce their marginal costs (albeit likely at the expense of increased fixed costs). However, in conjunction with other technologies, some new features may become apparent. AI, especially in various applications of pattern analysis (see e.g. new advances in multimodel learning of Baltrusaitis et al., 2019), may be more complementary to knowledge workers than for example universal robots. Further, in combination with robots, 3D printing, mobile communications, autonomous vehicles and remote sensing, AI may allow production functions to 'produce and deliver' final goods and services in a manner that differs greatly from that described in traditional micro-economic CRTS production functions. To start, the flows of the various inputs and the flow of consumption do not need to occur at the same time and location, with AI and remote sensors aiding the coordination of the production process and output deliver. Further, AI and complementary technologies can jointly make inroads into 'home production' and thus shift the GDP boundary. Finally, AI can potentially speed up the process of innovation, as argued by Cockburn et al. (2018).

Agrawal et al. (2019a) edit a collection of papers entitled 'The Economics of Artificial Intelligence: An Agenda". One relevant aspect of AI for changing the structure of economic production is its strength in prediction and the automation of decisions conditional on the prediction (see Agrawal, 2019b). Economic processes can be set up to change dynamically on the basis of information being generated and algorithms deciding how to set which parts of the chain into action. For example, as discussed by Milgrom and Tadelis (2018), better prediction can be used to seemlessy bring together supply and demand, thereby reducing frictions that occur when activity changes. Athey (2019) discusses the role that AI can play in developing metrics that can be used to facilitate incremental innovation and experimentation.

3. TRENDS

In section 2 we discussed the trends in various technologies collected under the term digitalization, and use anecdotes and extrapolations to argue whether they would be disruptive to the economy and living conditions. When we juxtapose the above narrative with recent trends in advanced economies in output per capita, labor productivity and multifactor productivity we are left with a paradox, akin to the old Solow Paradow (Solow, 1987): "You can see the [digital] age everywhere but in the productivity statistics." Luckily, always-on connections and massive searchable cloud storage makes it easy to dig up and read the original Solow quote, rather than re-quoting the previous quoter. In a book review, Solow faults the authors of the volume on "The myth of the post-industrial society", Cohen and Zysman (1988), of not showing how and where the new programmable automation technologies create a break with past productivity growth patterns. The authors lament that "...[That] would depend not just on the possibilities the technologies represent, but rather on how effectively they are used." Solow retorts that "...they, like everyone else, are somewhat embarrassed by the fact that what everyone feels to have been a technological revolution, a drastic change in out productive lives, has been accompanied everywhere, including Japan, by a slowing-down of productivity growth, not by a step up."

Essentially, Robert Solow is asking for a detailed micro-to-macro analysis of the path from innovation to technology, to production, to delivery of goods and services, all the way to understanding how the boundary between the economy and the household changes, both for factor supply and consumption demand. The traditional CRTS Solow growth model with inputs capital and labor, only gives a reduced form answer to how an improvement in production technology affects income per capita. Even when augmented with an innovative sector that makes the production 'blueprints', as in Romer (1990), the model is not rich enough to have anything other than the supply of human capital or subsidy to innovative activity affect productivity (growth).

Jones and Romer (2010) give a brief overview of the traditional growth theory and how it can explain the so-called 'Kaldor facts', (Kaldor, 1961). The authors go through a new set of facts that have emerged from growth empirics in the past decade. In an attempt to match the new growth facts, they propose expanding the model to include: ideas, institutions, population and human capital as state variables, in addition to traditional capital. While formalizing the role of these new state variables would allow many of the aspects of digital technology to be analysed, expecially the aspect that it is a non-rival input, the aggregative nature of the model would still miss some important impacts of the new digital technologies.

Before turning to the features that a theoretical framework would need to have in order to analyse the possible paths through which the digital technologies could have an economic impact, we will review some of the recent macro evidence on the paradoxical productivity developments and on other indicators that seem to be at odds with the Kaldor Facts.

3.1. MACRO

Using a growth accounting framework, based on the traditional CRTS production function, labor productivity growth and multi-factor productivity growth (TFP, hereafter) is seen to be on a downward trend since the mid-1990s in most advanced economies.[2] In the US, the Bureau of Labor Statistics (BLS) compiles detailed aggregate and industry-level productivity series.[3] According to BLS, over the past generation (1987 through 2018), real output per hour in the non-farm private business sector has increased 2.1% per year on average, while TFP growth has been a shade above 0.8%. However, TFP growth decelerated strongly, from slightly above 1% on average between 1897 and 2004 to below 0.5% since then. Likewise, growth in real output per hour declined from about 2.5% to less than 1.5% per year.

The fact that TFP has been trending down in the past decade—or as Gorden (2016) says, since the 1970's outside of the blip upwards in the mid 1990s—does not necessarily provide information on what is to happen in the coming decade or generation. Crafts and Mills (2017) use a 20-year moving window of TFP growth to forecast TFP growth in the ensuing 5 years, and find no useful time-series information. In other words, the recent downward trend is more likely than not to provide no information for the coming years. By contrast, Bartelsman and Wolf (2014) find that augmenting the macro information used to forecast productivity with time-series moments from underlying within- and between-firm productivity growth improves such forecasts.

In subsequent sections we will provide a review of mechanisms that may be underlying the slowdown in productivity growth and discuss how policy may improve the path from innovative technolgies to increased well-being. For the remainder of this chapter we will show some evidence on other macro indicators that do not fit the Kaldor facts, as well as some novel findings that question the traditional model that links innovation to productivity and well-being.

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[2] For methodology see Jorgenson (1999) and for recent international evidence see OECD (2019) or Groningen Growth and Development Center EU-KLEMS data, O'Mahony et al. (2009).

[3] see www.bls.gov/mfp. Also note the new experimental Bureau of Labors Statistics and Bureau of Economic Analysis integrated industry-level production accounts, https://apps.bea.gov/scb/2018/07-july/0718-integrated-industry-account.htm

To start, there is by now clear evidence that labor and capital share of income are no longer constant, as they had been in industrial economies for nearly a century. In the past generation, the share of income going to labor has been declining, with half of the decline attributed by Karabarbounis and Neiman (2014) to a relative decline in prices of investment goods together with with an elasticity of substitution between capital and labor larger than one. In the Karabarbounis and Neiman (2014) paper, the capital-output ratio also increases in the case of non-unitary substitution between capital and labor and declining costs of investment goods. In US non-farm private business, the capital-output ratio declined 20 percent over the period, or .6% per year on average. Another pattern discussed as a possibility in Karabarbounis and Neiman (2014) and confirmed for the US and many other developed economies is the trend increase in mark-ups. De Loecker and van Eeckhout (2017) show substantial increases in mark-ups in the past 30 years. Other authors have replicated this work with other datasets, for example including all private firms, not just those listed or available in public access datasets. In general, while the magnitude of the increase in mark-ups is less severe, the pattern occurs in many countries and sectors.

The increase in mark-ups does not necessarily provide evidence of anti-competitive behavior. Nor does an increase in concentration, in industries, as documented by Autor et al. (2017). It is possible that the overall return to all investments in intangibles made by incumbents and (potential) entrants is not supra-normal, even while marginal revenue divided by marginal costs (the mark-up) is high for succesful firms. We will return to this below. To analyse this, the production function framework needs to include discrete entry decisions as well as factor input decisions. In more macro-oriented work, Eggertsson et al. (2019) also point towards rising mark-ups to explain the breakdown of the Kaldor facts and highlight the persistance of low equilibrium real interest rates. Again, in a different modelling framework it is possible that marginal returns to traditional (risk-free) capital are low in equilibrium, while returns to intangibles and human capital have higher mean and variance.

The macro developments of investment also are puzzling. Gutiérrez and Philippon (2016, 2017) tie the low rate of investment (given the level of Tobin's Q) to an increase in concentration. In their empirical work they state that the role of intangibles in keeping the investment rate low is quantitatively not important.

3.2. MICRO

Besides these macroeconomic trends that are at odds with the Kaldor facts, some evidence from worker- and firm-level data also seems to be discordant with the traditional production model. In section 4 we will discuss evidence on the diverging patterns of wages across workers with different skill levels. Much of this literature attempts to parse out whether the loss of wages in the middle of the skill distribution was attibutable to trade or to technology.

It is by now well known that there is much heterogeneity across firms, even in narrowly defined industries. The heterogeity occurs in firm size, age, product mix, labor characteristics, management quality, or any other feature that researchers have been able to measure. The facts about dispersion in productivity and how it is measured have been described in Bartelsman and Wolf (2018). A more recent finding is that the dispersion in productivity varies over time, and that the productivity growth patterns at different points in the productivity distribution may vary as well. Especially the work by Andrews et al. (2015) is of interest. They find that the productivity frontier, defined as top 5 percent most productive firms in an industry, has been growing at a rapid pace, while the rest of the firms have been fairly stagnant in the past 15 to 20 years. A plausible interpretation of the finding is that frontier firms are well able to make use of new technology, but that it does not diffuse to the rest of the firms. In this narrative, the rest of the firms are not adopting the technology, which could be because they lack the requisite complementary inputs, or it could be because their expected profit upon adoption is not high enough.

Another way of slicing the micro data is to look at aggregate productivity growth as a sum of the 'within-firm' component, namely the productivity growth of the average firm and the 'between-firm' component, namely the shifting of market share to more productive firms. A set of papers have been documenting dynamism in the business sector, or the process of entry, exit, and productivity enhancing reallocation. Recent trends show, for the US, a reduction in job and worker flows, a reduction in productivity dispersion, a reduction in business entry rates, and a declining share of output of young firms. (see Decker et al., 2014; 2018). This evidence does not bode well for future productivity growth because surviving entrants historically contribute much to aggregate productivity and employment growth. At present, the entrants do not seem to be growing as they had in the past, and anecdotal evidence suggests that they may exit or be acquired by other firms before they mature.

In the EU, the time period for which one can study firm dynamics is not long enough to see if firm dynamics trends have changed. In recent work by Bartelsman et al. (2018) it is shown that the pace of productivity reallocation was reduced at the time of the great recession, relative to typical cyclical episodes. However, in recent years the typical counter-cyclical patter of productivity enhancing reallocation has reappeard.

4. FRAMEWORK

The above trends make clear that the CRTS production function no longer provides a good framework for analysing at the macro level how inputs of productive resources, capital and labor, lead to output. The path from digital technologies to productivity is rather circumscribed in the traditional framework: innovative investment either directly accumulates into an intangible (knowledge) stock that enters the production function either in a Hicks-neutral or factor-biased manner or innovative investment indirectly boosts growth through increasing the marginal product of knowledge investments through knowledge spillovers from the intangible stock. Finally, digital technologies can be embodied in tangible capital and affect labor productivity akin to any other capital investment.

A framework that can properly account for the path from new, digital, technologies to aggregate productivity has a list of necessary ingredients. First, the framework needs to include intangible capital. Intangible capital is similar to traditional capital in that it builds through investment and declines through depreciation. Intangible capital is different from traditional capital in that it is non-rival in production: if I use a hammer to pound a nail, you cannot use it at the same time, while if I use an algorithm to nail a problem, you could use it as well at any time or location of choice at zero marginal cost.

Next, the framework needs to allow for a rich dynamic of heterogeneous producers. Firms make discrete decisions to enter or exit domestic or foreign markets and to invest in new intangibles. Firms continuously make decisions on labor and capital inputs, on scale of production, and on pricing in case they have some market power. Firms make all these decisions, taking into account their own circumstances, the market and policy environment, and their reflection on actions and reactions of other economic agents.

The framework also needs to account for the rich structure of production chains. While aggregate productivity is all about growth in well-being minus growth in primary inputs, at the micro level many firms deliver output to other firms. While under CRTS and perfect competition one can easily aggregate up from firm-level productivity to the aggregate, this is not the case under richer models with intangibles.

Finally, the framework needs to have a broader view of production and output than that implied by the traditional input-output framework. Economic production is not just the process of combining labor, capital, and intermediate inputs into output, but could also be the process of doing the combining or improving the doing of combining. In the input-output structure, these activities are entered as 'margins', such as wholesale and retail margins, or financial service margins, rather than as production of services that are used downstream. In search-theoretic models, matching a worker to a vacancy, or delivering a product to a customer is viewed as a cost rather than being seen as an economic good that has a price.

4.1. MODELS

The basic model of endogenous productivity growth with intangibles is Romer (1990). In order to have an equilibrium in a model with increasing returns to scale (arising from varieties of non-rival knowledge, or 'blueprints'), other deviations from the traditional framework are needed. In this case, the market for blueprints is subject to imperfect competition, while there is perfect competition in the market for output. Aggregate productivity is driven by the variety of blueprints, and growth in the variety of blueprints depends on innovative expenditures (and possible innovation spillovers from the stock of blueprints). Most subsequent models with intangibles either work with this variety-of-knowledge specification, or with a quality ladder specification where innovators have a chance of jumping to the frontier and becoming a monopoly supplier.

Hopenhayn (1992) provides one of the first dynamic models of heterogeneous firms. In this model, firms pay a fixed entry fee that can be thought of as an investment in intangible capital. Following this investment, firms receive a stochastic draw from a distribution that determines the quality of their intangible asset and conditional on the draw decide to continue with production or to exit the market. With slight diminishing returns to variable production factors, or with some imperfect substitutability between goods from different firms in the output market, the asset quality draw will determine the firm's productivity level and the optimal firm size.

The model has some interesting equilibrium features in the light of the macro and micro trends reported on in section 3. First, the size and productivity distribution of firms will be skewed. Also, the firms with the best intangible quality will have the highest profits, while those firms just above the exit threshold of quality will only break even in operating costs. That does mean that the marginal firms will not earn any return on their initial investment in intangibles, while the measured mark-up and total profits of the best firm will be high. Nonetheless, the economy does not exhibit any supra-normal profits in aggregate. In equilibrium, on average, the present value of the sum of operating profits will be just high enough to generate a normal market return on the aggregate initial investments, including those of failed innovators that never produce. Mrázová and Neary (2017; 2018) provide technical details about the range of demand specifications and production function specifications that will lead to equilibrium where the relationship between investment, asset quality, and profitability is monotonically positive.

Interestingly, in the Hopenhayn (1992) model setup, if the size of the initial investment increases along with a stochastically dominating shift of the asset quality distribution, then the income share going to traditional labor and capital will decrease. In other words, by itself the reduction in labor share of income could be signalling the increase in importance of intangible assets in production rather than shifts for example in bargaining power of labor.

The above does not imply that in this class of models, policy problems are ruled out. Akcigit and Ates (2019) provide a related model that can match the list of puzzling macro and micro trends, including mark-ups and labor share, but also declining entry rates, the gap between leaders and laggards, and changes in reallocation rates. In comparing possible explanations for these facts, they rule out the hypothesis that generating new ideas is becoming harder, and they rule out the role of low interest rates. They do point the finger at a reduction in knowledge diffusion as a potential driver of all the observed trends.

These models, while explicitly accounting for interactions between heterogenous firms, do not capture the richness of markets starting upstream with labor, continuing on to intermediates goods and service markets, to downstream final goods markets. Barqee and Farhi (2017a, 2019) provide a framework to assess how to traverse from micro to macro productivity and how to account for the macro effects of misallocation of resources and other market imperfections. Next, the Hopenhayn-style models do not account for economic activity aimed at making the chain of these markets more efficient, allowing missing markets to come into existence, or knocking out certain markets in the chain (see Oberfield, 2018, or Acemoglu and Azar, 2017). Aggregate productivity growth can be thought of as the reduction in the primary input weighted length of the chain of production. So, productivity can increase if each node in the chain does what it does more productively, but also if the connection between two nodes becomes shorter (in terms of primary input usage). Finally, the 'between-firm' component to aggregate productivity also can increase in these models if more resources are diverted from long chains and go through highly productive nodes instead. It is at least a defensible hypothesis that the impact of digital technologies can be found by measuring this later concept.

Assuming an encompassing model with the ingredients listed above, or using features from various special purpose models, we can look at examples of the impact of new digital technologies for various markets. We first look at the analysis in labor economics, and next turn to possible effects on macroeconomic measurement.

4.2. ANALYSIS

Much of the early work on the potentially disruptive effects of digital technologies on the economy was in the area of labor economics. Krueger (1993) was the first to document the differentials in earnings between workers who use computers and those who don't. While the causal effect was convincely refuted by DiNardo and Pischke (1997), the paper layed the groundwork for much of the work on skill-biased technical change and the substitution elasticities between various forms of technology and various types of workers (e.g. Acemoglu, 1998; Goldin and Katz, 1998; Bresnahan et al., 2002; Acemoglu and Autor, 2011).

Recent research on the effects of digital technology on workers attempts to answer the following questions: i) what are the effects of various technologies on the wages of different types of workers (continuing the earlier research). ii) what are the effects of new technologies on future wages and income trajectories of workers displaced by new technologies, iii) what are the general equilibrium effects of new technologies on employment and wages within a country.

Recent policy work on technologies, skills, jobs and wages (OECD Employment Outlook 2019) provides a good starting point to find analysis on the first two questions. The original work of Frey and Osborne (2017) that stated that half the jobs were at risk from being displaced by technology now appears overly pessimistic. Using a task-based approach to jobs, the OECD (2019) shows only 14% of jobs at risk, but augments this with the substitution of 30% of the tasks that are required for current jobs. Modelling and estimation of these quantities requires information on the demand for jobs and tasks, how these change with technology, and what the current distribution of skills are among workers that are required to execute these tasks. At present, the data hurdle remains high for further improvements in this type of analysis.

The last question is the most encompassing and relevant, at least for economic policymakers. Nonetheless, the last question also is the most difficult to answer. Bessen (2018) and Bessen et al. (2019) look not only at what happens to the wages and jobs of workers at firms that adopt digital technologies, but also at the future earnings of displaced workers. Also, they attempt to see what happens to employment at automating firms owing to increases to their demand that can arise if their prices drop relative to that of competitors. The difficulty is in disentangling the feedback from higher aggregate productivity to higher wages and thus higher demand, as well as the effect of higher aggregate productivity on demand for export products. Further, while it may be possible to define exogenous automation events at a particular firm, for a country as a whole, adoption of new technologies is tied both to supply of appropriately skilled workers and to policies relating to labor and product market competition.

Turning to macroeconomic measurement, there are worries that the new technologies have made this more difficult. Of course, macro measures are only interesting to the extent that they measure concepts that are analytically useful. We will start with a reduced form equation used by central banks for policy, namely the Taylor rule, to assess where and how digitization may affect the analysis.

$$i = r^* + \pi + \alpha_\pi(\pi - \pi^*) + \alpha_y(y - \overline{y})$$

where i is the nominal rate of interest, r^* is the equilibrium real rate, π the inflation rate, π^* the target rate, y is GDP, and $\overline{y}$ is potential GDP and their difference is the (negative) output gap. According to this rule of thumb, the nominal interest rate should be increased if inflation rises above the target and reduced if output falls below potential GDP. Starting with the last term, measures of potential GDP could be off. There are two ways in which practitioners operationalize measures of potential GDP. One is slightly circular, namely to use historical data to find the output gap at which no price pressure is evident. Alternatively, a growth accounting excercise is conducted to find the productive capacity at which the economy can operate without cost and prices pressures appearing. In this excercise, labor, labor quality, capital and capital quality, as well as some measure of TFP are combined. One problem is that current digital technologies are capital saving and thereby lower investment spending, thus also measured capital stocks, biasing down the estimate of potential. Further, it is unclear that the TFP extrapolation needed for such a measure would convey useful information, as argued above.

Instead, using the analytical framework described in section 4, the output gap could be measured using a combination of the two methods. However, the measurement would be done for marginal costs at the firms that are producing at the margin, ie those firms that are expanding when exogenous demand drivers go up, or that shrink when exogenous demand drivers go down. It is quite possible that one of the reasons price pressures are not occuring even though current estimates show that the output gap may be fully closed, is that intangible intensive firms are able to increase their production at low, and non-increasing, marginal costs. Further, using a micro-to-macro framework, it becomes clear that a given output gap has different meaning when high rents at productive (and growing) firms may decline as technology diffuses to competitors, or that slack can increase as resources reallocate to highly productive firms that are intensive in non-rival intangible assets.

For gap measures based on the labor market, labor-substituting digital technologies also may be changing the meaning of a given gap level in the Taylor rule. Again, if at the margin firms can hire robots for a given wage rate, it is unlikely that labor market tightness would put pressure on wages to rise to higher levels. Another measurement issue for labor market tightness is the extent to which platforms and apps have increased the granularity and lowered the adjustment costs for moving between labor market states, ie from out of the labor force to unemployed, to partly employed or to full employment. Also, the temporal and spatial disintermediation may mean that local measures of labor market tightness are less relevant to wages and output.

The equilibrium real rate of interest also may be affected by digitization (e.g. Eggertsson, 2019). For the demand side for loanable funds equilibrium, the possibility exists that business perceptions of marginal returns to (technology) investment may be improving, but indicators of tangible investment can remain weak. For this reason, lagging investment in an economy with low real interest rates may lead to misinterpretation that aggregate demand is low, rather than a sign that new profitable technology is a substitute for tangible capital. For the supply side of loanable, new digital technologies may provide new paths of intertemporal substitution for households (services vs durable goods; intangible asset investment) and thus change savings. Finally, there is the relationship between intangible investments, agency costs and risky returns. Also, the timing between intangible investment and return (as well as depreciation) may be more variable/less predictable. These likewise will change the supply of such funding.

Finally, the analytical framework may provide some thoughts on pricing behavior of firms. The effects of new technology on actual and measured inflation has not yet been studied extensively. Charbonneau at al. (2017) provide a nice starting point to explore the following four open questions: i) How do hedonic price declines from quality increases affect inflation expectations? ii) Has new technology reduced 'menu costs' and other pricing frictions enough to matter? iii) Is the real price decline in two-sided markets mostly on the 'eyeballs' side? iv) How will new technology change financial transactions and liquidity preference?

5. POLICY

Trajtenberg (2018) is eloquent about the urgency for developing policy to ameliorate potential negative effects of new digital technologies and to accentuate potential positive effects. With an eye in particular on job displacement coming from AI and on further demographic greying, he highlights the need for reforms in education, professionalisation of healthcare and social influence of the direction of future technological development. We expand this list to include policy targetted at income and social inclusion, but also look at competition policy and framework conditions that stimulate the transition to a digital future.

5.1. LABOR

Technological change is not a new phenomenon, and while it has disrupted job trajectories of individual workers in the past, it has not resulted in long-run changes in employment trends. In theory, the new digital technologies do not have an unambiguous effect on overall labor input. With perfect labor markets, the overall effect of productivity improvements on hours worked would depend on the slope of the labor supply curve which reflects the net effect of income and substitution as leisure becomes relatively more expensive. In this utopian scenario, any changes in the amount of labor supplied would not be cause for policy intervention.

In actuality, disruptive advances along the supply chain could cause closures of firms and dismals of workers whose tasks are displaced. The bargaining position of workers in locations where the incidence of such disruption is high will weaken greatly. Further, as seen above, new technologies could skew the income distribution among workers. Finally, the employment status of workers is becoming more diverse, partly brought on by technology changing the costs and benefits on both sides of the labor market between employment and self-employment. For this reason, policy should attempt to provide all workers with some form of protection and support, regardless of their employment status.

One such policy recently has received much public attention, namely basic income provision, ie an unconditional transfer payment to everyone. While the transition to such a policy from current conditional support schemes is not easy, the main benefit is that there is no need for means testing or other verification of conditions. On the other hand, the incentives for individuals to choose work over leisure could become unstable as tax wedges increase to pay for basic income for increasing numbers of non-workers. Using a welfarist approach, it can readily be shown that basic income generally is not an efficient means of redistribution (see e.g. Saez and Pikkety, 2013). But even if one assumes that hours worked do not respond to tax rates, thus leading to optimal taxation and redistribution of 100 procent of income, most people would consider it unfair not to let others retain some of the fruits of their labor.

The current protection policies, such as employment protection, income replacement, and other social insurance schemes mostly are conditional on (recent) employment status. The proper classification of workers is thus a necessary condition for such policies. Partly owing to new technologies that allow greater flexibility in forms of labor input and partly because incentives for the adoption of the new technologies may be improved with flexible labor markets, there likely will be a shift from standard employment to own-account work. While we would like the protection policies to be neutral with regard to choice of employment type, the shift will require increasing availability of insurance, if not protection for own-account workers. At the same time, this places increased requirements on proper classification and monitoring of opportunistic re-labelling by employers in order to avoid paying for the insurance.

One way out of the conundrum is to formulate policies that avoid conditioning on employment status, but use other characteristics instead. For example, regulations on working conditions could depend on location rather than on sector, firm, or employment contract type. Similarly, sick leave insurance or educational or training benefits could be formulated by occupation rather than by job, with solidarity enhanced and moral hazard reduced through the proper choice of peer group. No longer will worker training, a crucial ingredient in the 'race between technology and education', depend on the firm whose main objective is to optimize that timing with which it replaces these workers with technology.

A caveat on basing social insurance on location is that often technological disruptions hit hard in specific locations, resulting in mass layoffs. If the loss of income is a large share of aggregate local income, a negative spiral can set in generating long-lived depression and (population) decline, for example as seen in the US rust-belt. In these cases, cross-region transfer mechanisms could offer a solution.

5.2. EDUCATION

Turning to education, the main policy questions are who, what, and how? Traditionally, education has been predominately for the young, which makes sense given that the pay-back period for the investment in human capital declines with age. With technologies increasing depreciation for certain types of human capital, especially those that are relevant for tasks with high displacement risk, incentives for education and training are shifting towards older workers. With the institutional setting of higher education geared toward providing (subsidy) for the young, reforms should aim at opening up an educational market that also supplies older workers. Worker training further is predominately offered to employees at large firms, with relatively less spent at small and medium sized businesses and very little spending by own-account workers. Here, some shifting could take place from (tax) subsidies flowing through employers to direct (tax) benefits to the beneficiaries of the training. Worker training finally should be targetted at those whose occupations are subject to disruption and those whose initial training was less generic (and usually at a lower level).

Next is the issue of what types of training need to be offered. European policy makers have been crying for increases in science, technology, engineering and math (STEM) education, partly as a response to the fact that in recent years the advances in technology have been originating in the US and Asia, and partly owing to labor market tightness in these fields. In doing so, care should be taken not to fall behind the changes taking place in actual educational and training needs as technology progresses. Not only is the occupational structure of the economy being disrupted, but also the skill mix required in the occupations that remain is subject to change. When code-bots write code that programmers were writing just a few years earlier, training should be more about acquiring skills to acquire specific skills than it is about acquiring specific skills.

Finally, how will educational institutions need to change in order to provide the appropriate training to underserved groups? To start with funding, it is apparent that higher levels of expenditures overall will be needed to counter the higher depreciation of skills and the higher levels of job transitions. Partly, the returns to these investments will be private. In this case, policy that provides the financing will be enough to assure access. To the extent that education and training reduce social costs (e.g. in transitional income support) or reduce externalities (e.g. through preventing rises in income inequality), public funds can be used. Preferably, the funds could be spent on a mix of public-private endeavours that include vouchers and other forms of demand support, rather than the supply funding that is customary in higher education in the EU. Not only will this improve the efficiency of the service and the match between supply and demand, but it also frees up opportunities for entrepreneurial experimentation in a sector of the economy that likely will grow as robots take over the production of goods.

5.3. COMPETITION

The policies above were mostly geared at reducing the costs of job losses and transitions to new jobs. We now turn to policies that support further innovation and support the uptake of new technologies by the business sector. At the same time, policies in this area can be used to prevent outcomes of market power, higher mark-ups, more skewed profit distributions, lower market contestability and increased monopsony power of succesful firms. Also, a short discussion will be made concerning corporate taxation in a world with intangible-intensive production.

Based on the economic framework discussed earlier, investments in innovative activity and the uptake of new technologies by firms will depend on the availability of appropriately skilled workers, but also on other complementary inputs. Also, firms must have the expectation that succesful innovation and implementation of technology will result in increases in market share. The specific policies to achieve these conditions will differ by technology, but we will discuss a few.

For autonomous vehicles, a legal framework must be in place to reduce transactions costs of liability insurance. Further, complementary investments and coordination on standards could greatly reduce the investment needed to create a level 4 or even level 5 autonomous verhicle, as well as reduce the chance that the industry would turn into a monopoly. At present, much of the investment in autonomous vehicles in the US is taking place in technologies that are fully embedded in the vehicle. In this technological trajectory, the outside world must be fully characterized by the sensors and algorithms in the vehicle, even if external conditions are adverse and external actors are adversarial. Because knowledge of outlier conditions increases with collected data (or miles driven), the best technology to emerge eventually will be the one with a combination of the highest initial investments and the highest early uptake. The investments made in second best technologies will have much lower returns if the firm survives, or will have no return in case of exit. Essentially, monopoly will be the market outcome.

By contrast, an active role of government in complementary infrastructure, in coordination and standardisation of technology, and in secure sharing of collected data, could generate more rapid deployment of autonomous vehicles and ultimately a more competitive market structure. For example, the streets, sidewalks, signs, and signals could actively make their position known to autonomous vehicles. Further, coordination, standards, and regulations could allow or even mandate traffic participants (including other autonomous vehicles) to actively transmit their position and trajectory. For pedestrians, such technology could make use of the already near-ubiquitous mobile phones, but could also be based on information about their whereabouts transmitted by sensors in the sidewalks and streets. With standardisation of data transmittal, different vehicle technologies could compete for market share without leading to monopolistic market structures. At present, the European Strategy on cooperative intelligent transport system (C-ITS) is moving in this direction and could provide a boost to the chances that the EU will become a global leader in autonomous vehicles. Yet, standardisation of data transmission remains tricky, with a tradeoff between backward compatibility and technological neutrality.

Along with above policies to stimulate innovation and adoption of autonomous verhicles, some thought should be given to policies that adapt the physical environment to the new transportation systems. Especially urban planning and zoning should be cognizant of the changes coming, for example by reconsidering requirements for parking spaces for residential construction, or zoning for retail, wholesale and office spaces.

Another cluster of activities that has become available owing to new technologies has as common characteristic being a platform service connecting the supply and demand sides of a transaction, often location based. In this cluster, we find asset sharing (e.g. home rentals, car sharing), goods delivery (food delivery, online goods), and service trading (taxi service, hotel booking, labor markets). These platforms are the modern equivalent of Middle Eastern Bazars or Medieval European chartered markets. In the historical antecedants, economic activity and productivity picked up when the markets become well regulated. To start, timing and location of the market was coordinated amongst all participants on both sides of the market, and competition was proscribed, in order to ensure thickness and liquidity of the market. Next, certification of measures and coins, and enforcement of transactions were arranged by authorities to preclude opportunistic behavior of participants from unraveling the market. Finally, competition from geographically adjacent markets prevented the market owner (in medieval times, typically a local landlord) from collecting too much rent. In modern platform markets, externalities related to thickness and liquidity and to service quality based on proprietary collection of historical transaction data, lead to monopolies that are essentially unchecked. While similar platforms potentially could make the market contestable, network effects, but especially the ability to improve service based on historical transactions data result in increasing market power of the leader.

While the gains from better service through AI-driven data analytics at the expense of market power and industry concentration may seem a worthwhile tradeoff, dynamically such market concentration leads to problems. First, the platform can use their power to extend their reach to adjacent markets. Next, potential competitors may have as goal being purchased by the monopolist rather than replacing them. This thwarts true innovation and long-run drivers of growth. The large platform also may use their market power to hire scarce technical personnel to prevent competition. This is known in the literature as upstream market foreclosure.

The policy remedy should go to the source of the problem, namely ownership and control of historical transactions data. In principle, the EU GDPR gives transactions partners the right to receive back their own data in machine readible form. However, it is the total collection of such data across all transactions partners that has value. This leaves possibilities for two types of situations: First, local authorities with regulatory authority, for example in taxi service, could condition their licensing of the platform under the condition that all the data be shared (in a manner that protects privacy), by any competitor. Further, to combat user-side network externalities, the messaging protocol of the platform needs to be open so that any driver can meet up with any passenger, regarldess of which competing app is being used or which analytical and payments platform is processing and coordinating the rides. In this way, the taxi market becomes more like a medieval market, with non-discriminatory access to buyers and sellers. But now, there also is competition between platforms, with some being better than others at predicting and director drivers to proper locations, or some being better at designing user friendly apps and payment systems. The platforms will thus compete on quality and on margin (the wedge between buyer and seller price of service). While any particular location may find it difficult to set up such a system on their own when faced with huge international platforms and their lawyers, a consortium of cities would be able to take on the challenge.

Next, if the platform is one without a local regulatory authority, an EU-wide approach would be needed. Using GDPR as the basis for a new framework, steps must be taken to ensure that platforms must give non-discriminatory access to their historical data. Finding a legal path to mandating an open protocol for exchange of messages between buyer and seller on the platform may be more of a challenge, but is a necessary part of the policy remedy.

A more complicated platform to regulate operates in so-called two-sided markets. In these markets, buyers and sellers do not transact directly with each other, but both sides interact with the platform. In a common version, consumers sell their attention (eyeballs) to the platform in exchange for content, such as news, entertainment, or other information, while business place their advertisements in front of these eyeballs (they buy eyeballs) in exchange for money given to the platform. Such markets have existed for well over a century, in the form of newspapers, radio, and television. What is new, is that now, historical transactions data is collected by the platform from all sides of the market. The massive increase in the (share of) advertising revenue flowing to these platforms proves the efficiency with they conduct their business relative to the old media. But not only the typical content delivery platforms are getting in on the game, any other service that collects data potentially could sell eyeballs, for example internet-connected household devices or mobile-phone based payment processors.

In these markets, the issue of privacy and the issue of (ownership of) economic value of historical transactions data interact. GDPR mostly is concerned with privacy, and did not address directly the division of rents between the three parties involved that arise in the future from each datapoint. Solutions are not readily available, but some examples may point in the right direction. In the financial sector, the EU payment service directive (PSD2) allows bank customers to allow third parties access to historical payments information, thus breaking the monopoly that banks had on his information. A similar approach to other valuable stores of data could be envisioned. Another direction may be to allow 'micro-payments' contracts, so that when a consumer uses a service that collects data, they can put a (small) price on future use of this data. While payments flows for any individual may be small, rents collected by platforms with market power will be greatly reduced.

While not strictly an issue of competition policy, intangible-intensive firms are able to gain competitive advantage shopping for regulatory and tax jurisdiction. Because sales, labor, capital, and intangibles no longer need to take place at the same time in the same place, owners of the residual rights to rents on intangibles can shift the other resources to gain advantage, for example by placing labor in low wage areas, or financing capital in location with low taxes on financing operations. A way forward is to no longer base taxes on the location of production or by using exclusions, deductions and credits, but instead basing local taxes on the share of global sales in each location, with as argument that even accounts nail down the location of an intangible.

6. CONCLUSIONS

We would like to conclude this paper with the data-driven prediction that productivity growth will come in at 2.5 percent per year, on average, for the next 30 years, leading to a doubling of well-being in the next generation. But, we can not. Time-series extrapolations of the past 30 years of labor productivity growth data gives no reason for such optimism, although most of this forecast will be driven by the low growth in the latter half of the period and not the 2.5 percent growth of the first half. Nonetheless, there are some positive stories concerning time lags between the introduction of new technology and the productivity effects that would point towards a sharp uptick in productivity growth in the not too distant future. Balancing this, there are some negative observations of market imperfections, possibly brought on by the new technologies themselves, that do not portend well for future productivity.

Starting with the more positive note, Brynjolfsson et al. (2018) introduce the 'technology J-curve'. Essentially, the story is one of mismeasured investment coupled with a 'time-to-build' before assets start being productive. Firms are investing in intangible assets, but much of this investment is not being recorded as such in the national income accounts. Next, the assets being put in place do not start delivering measured output immediately. Because new digital technologies are quite disruptive to existing value chains, it takes time for the new business models, with their own complementary investment in capital and in forward and backward supply linkages, to reach a new, more productive equilibrium. So, the measured capital that is complementary to the unmeasured intangibles is not yet generating output and the intangible investment is misclassified as intermediate expenditure, thus reducing the numerator and increasing the denominator of measured productivity. Once the investments are complete and the production chain is up to speed and scaled up, productivity will more than rebound. Brynjolfsson et al. (2018) concede that the omission of the J-curve effect in historical data does not explain the slowdown of productivity from the period before 2004 to the period since. But, going forward, the large recent surge in AI spending may boost future growth as the economy transition from the bottom to the upward sloping part of the J-curve.

More worrisome is the evidence by Decker et al. (2018) about changing business dynamism and related work on early stage entrepreneurs. In this work, it is seen that, conditional on the magnitude of demand shocks hitting firms, the response in output to changes in firm productivity has been declining. This says that markets are less able to reallocate resources and market shares to those firms that are most efficient at production. Further evidence shows that the entry rates of firms is declining and that conditional on survival the growth rates of young firms is declining. Together, these trends do not bode well for incentives for firms to invest in productivity upgrades nor for direct boosts to aggregate productivity growth through the process of reallocation across firms. Although this evidence is from the US, the mechanisms with which large, dominant, firms can prevent efficient reallocation of resources and a market and policy environment which prevents young firms from starting and growing could easily be translated to the EU. Further research on these matters with EU firm-level data sets is urgently needed.

This paper has provided a policy discussion for a world with an increasing importance of new, digital, technologies. Partly these new technologies exhibit network externalities and partly, owing to quality improvements from analyzing historical data, the technologies favor leading firms. The policy points concerning competition address how to counter these problems. The other set of policy points look at education, needed for society to be ready for the new technologies, and at labor and income to mitigate potential losses from job disruptions and increases in income inequality associated with the new technologies. Whether one believes in a positive or a negative narrative concerning the impact of technology, there is an important role for government policy to enable, guide, and stimulate the path from new technology in order to increase productivity growth above what it would otherwise be.

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