Master Thesis

Will Machine Learning accelerate productivity growth in the United States?

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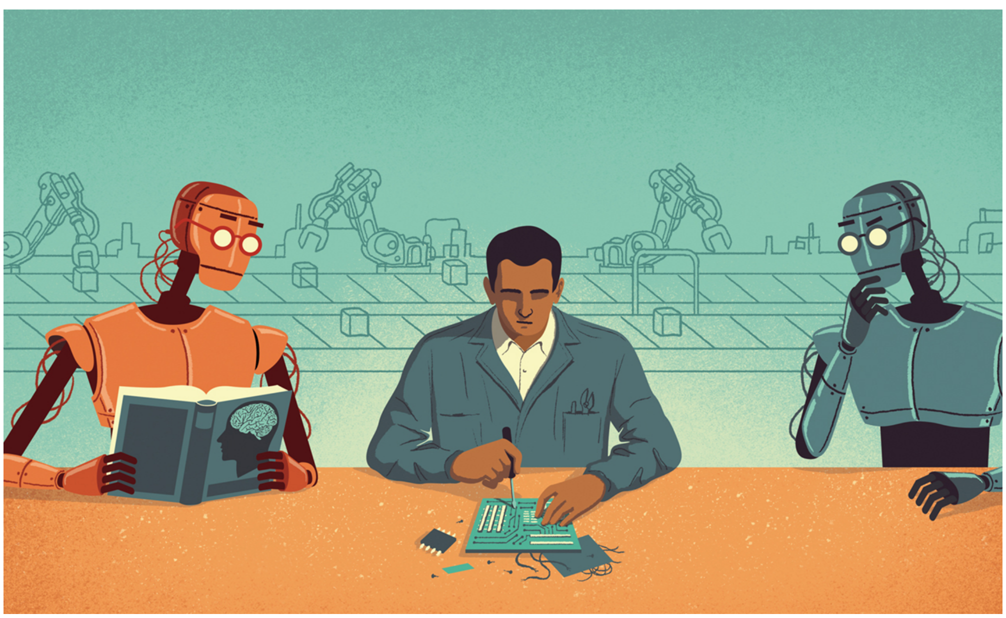

Will Machine Learning accelerate productivity growth in the United States?

by

Matthijs J.M. Poot

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TUDelft

No amount of (apparent) statistical evidence will make a statement invulnerable to common sense.

Robert Merton Solow

We are suffering just now from a bad attack of economic pessimism. It is common to hear people say that the epoch of enormous economic progress which characterised the *nineteenth century* is over; that the rapid improvement in the standard of life is now going to slow down; that a decline in prosperity is more likely than an improvement in the decade which lies ahead of us.

John Maynard Keynes

Acknowledgements

This thesis is the final graduation requirement for obtaining the Master's degree in Management of Technology at the TU Delft. The master went differently than expected when, after only a few months, the COVID pandemic forced the world to go into lockdown. The TU Delft managed to adapt to these circumstances quickly, and I had some of the most fun academically during this time. The Economics & Finance track introduced me to the productivity paradox, and I was triggered by this fascinating disparity between productivity growth and technological innovation.

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Matthijs Poot
30 November 2021, Rotterdam

Executive summary

Across the advanced western economies, productivity growth decelerated to near zero per cent despite marvellous technological advancements. Machine Learning (ML) based technology surpasses human-level performance in an increasing number of domains (Brynjolfsson and McAfee, 2014). The juxtaposition between incredible technologies and non-existent productivity acceleration is known in the literature as the *productivity paradox* (OECD, 2019). Resolving the productivity paradox is a primary concern of academics and politicians. Suppose growth were to return to long-run historic levels of 2% (Vollrath, 2020). In that case, many political issues such as rising health care costs and record levels of debt could be less politically divisive (Obama, 2016). Techno-optimists claim ML technology will create profound economical gains (Brynjolfsson et al., 2017). Therefore we ask the question:

Will Machine Learning accelerate productivity growth in the United States?

We considered four candidate explanations for the modern productivity paradox. We expect too much, we have to wait longer, we measure it incorrectly, and productivity growth happens only in a few industries. This last one is known in the literature as Baumol's *model of unbalanced growth* (Baumol, 1967). In this model, the industries can be divided into two groups: stagnant and progressive industries. The stagnant industries are industries that are inherently difficult to increase productivity growth due to the nature of the occupations in the industries. These are typically labour-intensive and provide the time and attention of workers as the product. These industries have constant productivity growth, or relatively low compared to the progressive industries. The progressive industries enjoy higher productivity growth because technology can automate occupations.

A consequence is that the increasing share of stagnant industries reduce the aggregate US productivity growth. In other words, the economy showed a structural shift towards low productivity growth industries and in turn reduced the aggregate productivity growth. Nordhaus (2008) identified that as the Growth Disease effect. Our first test analyses if this effect is still present. We rely on the methodology by Nordhaus (2008) and use the US KLEMS data provided by Eldridge et al. (2020). We compare the average annual labour productivity growth rate over four periods (1963-1973, 1973-1989, 1989-2001, 2001-2016) and the nominal output shares of 61 industries of five fixed years (1963, 1973, 1989, 2001, 2016). This period extends the Nordhaus (2008) analysis, who found the rising share of stagnant industries reduced the aggregate US productivity growth in the US over the period 1948-2001. Using the US KLEMS data set, we also find this for the period 1963-2016. However, this effect is zero over the period 2001-2016. We conclude that aggregate US productivity growth was unaffected by the continued structural shift towards service-providing industries. The labour productivity growth in service-providing sectors mitigates the declining shares of goods-producing industries between 2001 and 2016.

To test the assumption of technologically progressive industries, we investigate the expectation of IT potential. Our IT potential metric is based on the Routine Based Technological Change (RBTC) model of Autor et al. (2003). In this model, occupations are a combination of tasks. Tasks can be either improved by automation currently available or not available at all. RBTC follows the assumptions of the unbalanced growth of industries (Autor and Dorn, 2013). Therefore we expect industries that show high automation potential to exhibit higher productivity growth.

Therefore, as a second test, we assess if the expectation for IT holds any predictive power. More specifically, we investigate if the assessment of expectations of IT predicts labour productivity growth from 1989 through 2016 and its periods 1989-2001, 2002-2016. We rely on the occupational data of the 'Routine Task Intensity' (RTI) by Autor and Dorn (2013). The higher the RTI score, the more tasks are substituted by computers. RTI is based on the assumptions of the RBTC model and therefore Autor and Dorn (2013) claim that RTI is consistent with the unbalanced growth of industries. Therefore we test if industries with high RTI industry scores correspond to *progressive* industries, and low RTI to *stagnant* industries. We rely on the Occupational Employment Statistics (OES) data to aggregate the RTI occupation values and match it to the industries of the US KLEMS data. We perform a clustered ordinary least squares regression on the labour productivity growth, with IT investment and industry-level RTI as variables. We find no statistical significance for the aggregated assessment of the expectation of IT potential. We do find, in the period 1989-2001, that investment in IT and software did predict labour productivity growth. This is consistent with Jorgenson et al. (2006).

As the third test, we assess the expectation of ML. In the RBTC model, tasks are categorised as routine and non-routine. The expectation was that automation is possible in routine tasks. The possibilities of Machine Learning are such that some non-routine tasks can potentially be automated. If ML automation is concentrated in historically stagnant sectors, there is reason to believe it could resolve the productivity paradox.

For ML potential, we rely on the occupational data of 'Suitability to Machine Learning' (SML) provided by Brynjolfsson et al. (2018). We again use the OES data set to aggregate SML from occupational-level to industry-level. We find that the expectation of ML potential is concentrated in historically stagnant industries. Furthermore, we show a low correlation with the measure of IT potential. This implies the expectation is that ML will impact different industries than what was expected with IT automation. This is in line with the claims of techno-optimists.

Based on these results, we expect historically stagnant industries to show the highest ML potential.

These industries are 36% of the US economy's 2016 nominal output and would therefore significantly impact the aggregate US labour productivity growth. However, the future is uncertain, and we do not know when ML automation will significantly accelerate productivity growth.

Returning to the four explanations of the productivity paradox. It can take decades before sustained long-term growth is recorded. Furthermore, many of the promised ML technologies may never actually happen. Although SML is based on near-term ML applications, it is still uncertain if organisations use ML to its full benefit.

Despite this, we should recognise there is no economic law that guarantees perpetual productivity growth (Gordon, 2012). Productivity growth deceleration can be an inconvenient truth of maturing economies. Policymakers should be aware of this and the consequences. As long as essential service-providing industries remain stagnant, we can expect costs such as education and healthcare to increase above inflation and median household income (Baumol, 2012).

Contents

1 Introduction

1.1 General Introduction

Since the beginning of the third Industrial Revolution, academics and politics have been disappointed by the recorded productivity growth. Previous industrial revolutions significantly impacted economic welfare and dramatically improved the standard of living. In 2021, we are again on the verge of the next industrial revolution. The optimists claim the confluence of emerging technology breakthroughs technologies is so profound that the scale and breadth of the coming technological revolution are impossible to envision (Schwab, 2017). In the widely discussed book ”The Second Machine Age”, Brynjolfsson and McAfee (2014) claim the economy is on the cusp of the biggest transformation since the first Industrial Revolution.

However, these claims are eerily analogous to the expectations of the third Industrial Revolution. The technologies enabled by Information Technology (IT) would usher in ”the biggest technological revolution men have ever known” (Snow, 1966). Although it is indisputable that computers have changed our lives significantly, we fail to measure them in the productivity statistics. Nobel Laurette Robert Solow (1987) famously quipped, ”We can see the computer age everywhere but in the productivity statistics”, and it became known as the productivity paradox. Although productivity growth was high during the 1990s and mid-200s, a short decade of 2 % growth is lacklustre to the century-long productivity growth of the first and second Industrial Revolutions. Since 2004, the US economy has continued to decelerate.

Politicians and academics are greatly concerned with accelerated productivity growth. Today, United States leadership is faced with record level national debt, an expensive energy transition and rising health care costs. Obama (2016) argues the decades of declining productivity growth rates created rising inequality and slow income growth for low- and middle-income households. As he argues, if the economic pie does get bigger, we cannot solve the problems regardless of how we divide it.

However, Machine Learning (ML) technology is different from previous automation technologies. The potential of ML is that it can automate tasks that always require human input. For example, advancements in image recognition software currently surpass human capabilities, which could substitute tasks such as interpreting MRI scans Brynjolfsson and McAfee (2014). This thesis investigates, if ML technology can revive productivity growth and therefore solve the productivity paradox.

1.2 Research Gap

A powerful explanation for the productivity paradox is Baumol's model of unbalanced growth of industries (Baumol, 1967). The implication is that the aggregate US productivity growth is reduced by a growing share of low growth industries, known in the literature as the *Growth Disease*. Literature has not investigated the implications of Baumol's model for the US after 2001 (Nordhaus, 2008). The model divides the economy into two types of industries. Progressive industries and stagnant industries, that show high and low productivity growth, respectively. In the stagnant industries, Baumol assumes occupations are inherently less suitable for substitution by technology. For the first time in history, some of these occupations can now be automated through ML technology. If ML can enable high productivity growth in historically stagnant industries, the aggregate US productivity growth can accelerate.

However, previous literature is concerned with the impact of technological advancement on occupations primarily in the US (Autor and Dorn, 2013; Frey and Osborne, 2016; Brynjolfsson et al., 2018). Others have investigated it for other advanced economies (Arntz et al., 2016; Goos et al., 2014). All these disregard analysis on the industrial- or aggregate level and its correlation with productivity growth.

1.3 Research Questions

The main research question of the thesis is: **Does data support the expectation of acceleration of productivity growth through ML?**

To answer this question, we study the productivity growth of the US at the industry- and US aggregate-level. We use industry-level data to answer three questions that help to answer the main questions.

We ask **question 1: Is the Growth Disease effect still present in the US economy?** This question analyses if stagnant industries have rising shares of the total US output. This is one of the consequences of Baumol's model of unbalanced growth, as identified by Nordhaus (2008). The implication is that a growing share of stagnant industries reduces the aggregate US productivity growth. Unless technology is capable of transforming the stagnant sectors into progressive sectors, US productivity growth is reduced. Questions two and three to analyse Baumol's assumption that high productivity growth occurs only in technologically progressive industries.

We ask **question 2: Did the expectation of IT potential predict productivity growth in the US over the period 1989-2016?** Productivity growth has decelerated since the third

Industrial Revolution despite the diffusion of IT. Therefore we assess if industries that have high productivity growth correspond to industries high IT potential.

Finally, we ask **question 3: Is the expectation of automation of ML concentrated in historically stagnant industries?** The expectation is that ML automation can automate previously impossible tasks. This suggests Baumol's assumption of hard-to-automate stagnant industries can, through ML, show high productivity rates. We cannot predict the future, but we can analyse if ML is different from IT automation. Furthermore, we can test what types of industries are expected to show the highest potential for ML.

1.4 Outline

The outline of the thesis is as follows. In chapter 2 'Literature Review', take stock of the current productivity levels and productivity growth. We analyse four explanations for the productivity paradox and conclude to use Baumol's model of unbalanced growth of industries. In chapter 3, 'Data', we discuss the data we chose to answer the three questions. This includes data on the occupational- and industry-level. We explain how the occupational-level data, for IT and ML, is transformed to industry-level. In chapter 4, 'Methodology', we the econometric tests to answer the three questions. Chapter 5, 'Results', then discusses the results based on the data and tests of the previous chapters. Finally, in chapter 6, we present a research summary, recommendations, and future work.

2 Literature Review

This chapter presents the current state of the literature of the productivity paradox. We define the paradox and evaluate explanations. From there we analyse the framework that allows us to do econometric tests. Finally, we discuss the expectation techno-optimists have for ML technology.

2.1 The Productivity Paradox

Productivity measures the efficiency of the volume of inputs to create the volume of outputs (Schreyer, 2001). To increase productivity, the key drivers are physical capital, human labour and technology (Dieppe, 2020). Firstly, physical capital depends on the size of investments and the physical assets in the economy. Secondly, human labour depends on the number of workers, the hours they work, the level of skill and the experience. The higher the education and the better the health of workers, the higher the productivity. Thirdly, technology is determined by the rate of innovation and the diffusion of technology. To support the drivers, they require a supporting environment including institutions, infrastructure, policies, and social conditions (Dieppe, 2020). These four create an environment for the exchange of ideas, goods and services. A well-functioning economy then lubricates technological and economical progress (Pinker, 2018).

However, productivity growth has declined in the last several decades. Figure 1 shows the labour productivity growth rates over four intervals prepared by Gordon (2012). He selected these periods to reflect the contributions of the Industrial Revolutions. Such that period 1891-1972 coincides with IR2. The three periods after 1972 all cover the third Industrial Revolution. Where 1972-1996 and 2004-2012 reveal a deceleration of growth. Only in the period 1996-2004 did growth return to its historic average. In this thesis, we define productivity growth as slow if it is below 2%. This is consistent with the observations of Gordon (2012) and Vollrath (2020).

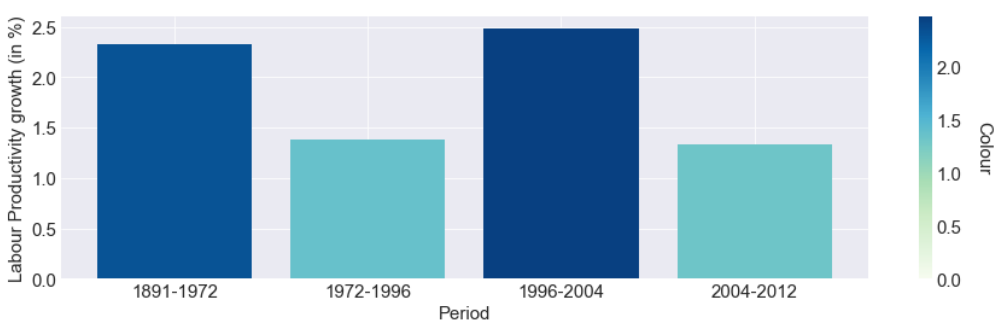


Figure 1: Average labour productivity growth rates over selected intervals over 1891-2012 prepared by Gordon (2012).

The deceleration of productivity growth is not unique to the US and is recorded across the advanced Western economies. Figure 2 shows the labour productivity growth for the Group of Seven (G7) since 1950. The countries include US, United Kingdom, France, Italy, Germany, Canada and Japan. For example, Japan showed growth rates above 7% in the 1960s, significantly higher than the below 1% growth rates after 2004. This pattern occurs across all countries in the G7, with decelerating recorded growth. Not one country had growth rates above 4% after the 2000s, while 4 out of 7 showed had growth above 4% before 1970.

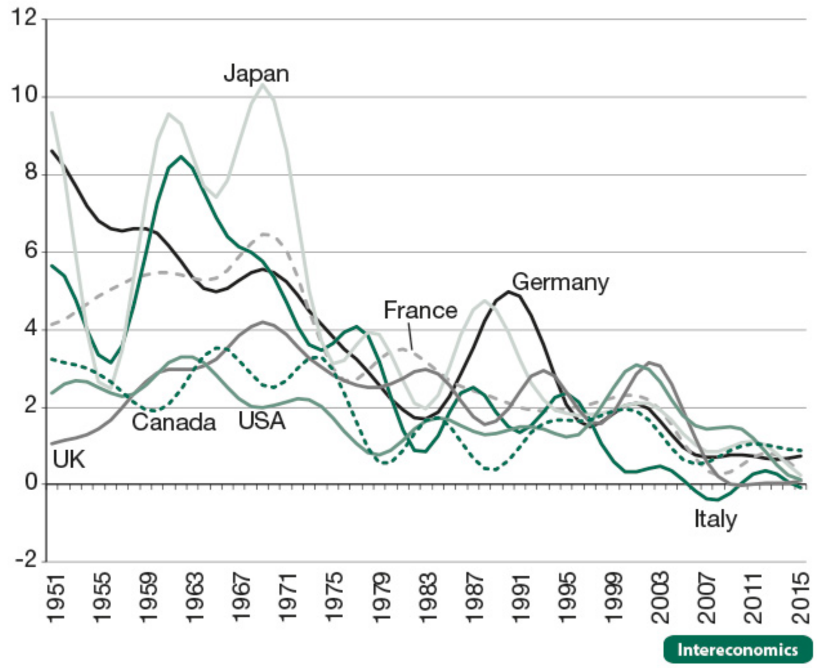


Figure 2: Erber et al. (2017) plot the labour productivity growth using data of the Conference Board Total Economy Database for the period 1950-2015 for G7 countries.

All G7 countries show a long-run decline in productivity growth to near 0 % despite different environments. It is much debated why productivity growth has continued to slow since the start of the third Industrial Revolution. Although the period 1996-2004 crossed the 2% threshold of productivity growth, it is disappointing compared to the century-long growth of the second Industrial Revolution. The deceleration of productivity growth at a time of significant technological change is known in the literature as the *productivity paradox* (OECD, 2019).

2.2 Why productivity growth matters

One of the objectives to measure productivity is assessing standards of living (Schreyer, 2001). Higher productivity growth can lead to higher income, more leisure time or a combination of both

(Sprague, 2017). Consider the US and Columbia, countries with vastly different standards of living. In 2019, the labour productivity was 78$\$/h$ and 15.2 $\$/h$ respectively (OECD, 2019). Productivity growth creates growth in labour income and profits such that the economy has more wealth to distribute.

Publications such as "The rise and fall of American Growth" by Robert Gordon (2016) imply the deceleration of productivity growth a sense of failure. However, the author of the book argues that productivity growth is assumed to be a continuous process without end, even though growth before 1750 was non-existent. Most of the population worked in agriculture. As economies develop, workers shift from agriculture to manufacturing to produce cheap and necessary goods. As the economy increases, basic needs are satisfied, and the fraction of money spent on services increases in proportion to goods. As people get wealthier, their spending shifts toward services (Vollrath, 2020).

However, the costs of essential services such as education and health are increasing dramatically. Between 1980 and 2008, the price of college tuition in the US increased by 440%, far more than the increase of inflation (110%) over the same period (Baumol, 2012). Over the same period, median family income rose 150 %, while medical care rose 250%. So, while the productivity still grows, it becomes harder for median households to afford college and medical care in the US. One of the biggest policy problems of the US is the student debt crisis, with total debt surpassing 1.6 trillion dollars in 2019 (Kantor, 2019). US graduates are burdened with over a hundred thousand dollars in debt at the start of their careers. The declining affordability of essential services makes them politically contentious, as shown by the universal health care coverage, known as Obamacare, since its introduction (Green, 2021).

While costs for essential services have increased dramatically, productivity growth has decelerated. The annualised Gross Domestic Product per Capita over the 20th century averaged 2.25% in the US, and between 2000 and 2016, the annualised GDP per Capita declined to 1 % (Vollrath, 2020). With the power of compounding, this makes a significant difference. Over a 20 year period this difference compounds to 41 % difference is productivity ($1.0225^{20} - 1.01^{20}$). Economic growth is in part driving by productivity growth. And economic growth is a determinant to solving problems such as rising healthcare costs or the student debt crisis in the US. Brynjolfsson and McAfee (2014) argue if the growth rates were 1% higher between 2013 and 2033, the US would be five trillion dollars richer. At current levels, the total student debt of 1.6 trillion dollars could easily be paid off. To quote Nobel Laurette Paul Krugman (1997): "Productivity is not everything, but in the long run, it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker".

2.3 Explanations for the Productivity Paradox

From the literature, we consider four candidate explanations for the disparity between technological optimism and the lower than expected productivity growth. We identified four explanations based on work of Brynjolfsson et al. (2017), Adler and Siegel (2019) , and OECD (2021). We summarise the explanations as follows:

1. We are too pessimistic, or the mismeasurement hypothesis.
2. We have to wait longer, or lagged learning.
3. We are too optimistic, or over-promised potential.
4. Innovation happens only in a few types of industries, or unbalanced growth of industries.

2.3.1 The Mismeasurement Hypothesis

The mismeasurement hypothesis implies the benefits of new technologies are enjoyed but escape measurement in growth accounting. For example, services such as Youtube and Facebook are free to consumers and provide many benefits. The services make money from selling advertisements, but these are excluded from the national output of the economy. Because the statistics ignore the direct benefits of innovation, we underestimate output growth (Feldstein, 2017).

Syverson (2017) argues that the productivity growth slowdown, analysed over 1994-2015, is not explained by the underestimated gains of new technologies. He recognises that fast diffusing technologies, such as smartphones and online social networks, consume large amounts of time of users but have insignificant impact on the aggregate output measures. He argues that the underestimation cannot explain the full extent of the productivity growth deceleration across advanced economies.

We agree there is a mismeasurement of productivity. The Internet allows for fast and costless expansion of services through marketplaces like the app store. When a software developer launches a calculator app for the iPhone, she will not incur extra costs for each download. Whereas in the traditional marketplace, one has to produce a calculator each time one is sold. Through the Internet, the developer has only development costs. However, better measuring of productivity will not solve the policy problems reviewed in the previous sections. Therefore we review other explanations to analyse the productivity paradox quantitatively.

However, from the Feldstein (2017) analysis, we want to discuss two arguments. Firstly, inflation is overcompensated. In economics, the output is measured in real and nominal value. Real refers to the total money spent, measured as nominal, stripped of inflation. These are the real quantities or stocks of goods and services in the economy each year. The prices are chained on a base year, for example, 2021, such that all observed values are for the 2021 dollar value. Feldstein argues that the methodology for compensation inflation introduces error. In growth accounting, inflation is the total spending change of a basket of goods and services such as commodities or housing. This implies that certain products are more heavily weighted than they are in actuality. As a consequence, we underestimate the benefits. Secondly, Feldstein (2017) reviews a recent set of studies that show output statistics, in especially the service industries as health care, are poorly measured. These are exactly the industries that show historically low productivity growth.

2.3.2 Lagged Learning

We distinguish two contrasting views of the role of technology in the productivity paradox. We have the techno-optimists who claim we still have to see the true potential of recent technological progress. In the other camp, we have the Luddites who claim new technological innovation can never be as important as those that came before. This section discusses the arguments made by the techno-optimists, the next section discusses the arguments of the Luddites.

The fundamental assumption of techno-optimists is that IT and ML are a General Purpose Technologies (GPT). Some technologies are so disruptive that they serve to create enormous welfare and productivity (Bresnahan and Trajtenberg, 1995). GPTs include steam power and electricity. These technologies significantly increase the production output of many sectors within the economy. They are a building block for new technologies on top of it. Brynjolfsson et al. (2017) argue it takes longer for society to reap the fruits it has sowed, longer at least than it appreciates. A new GPT must iterate and evolve before it has a measurable aggregate effect. Moreover, Ortt (2010) estimates that it takes 33 years on average for a disruptive technology for innovation to adapt to reach large-scale diffusion in the economy.

Syverson (2013) compared the labour productivity growth since the introduction of the GPTs electricity and IT, as shown in Figure 3. The initial diffusion of electricity was slow and analogous to IT. The period 1890-1915 resembles the period 1970-1995. This period was followed by a decade long acceleration before slowing down again. Only after 1932 did annual labour productivity growth average 2.7%. The point Syverson makes is that GPT arrives in multiple waves, and sluggish growth is to be expected of a GPT. In the case of electricity, it took decades before organisational change, management techniques, and complementary innovations created the productivity acceleration (Brynjolfsson and McAfee, 2014). Whether IT continues to follow the productivity growth pattern of electricity remains to be seen.

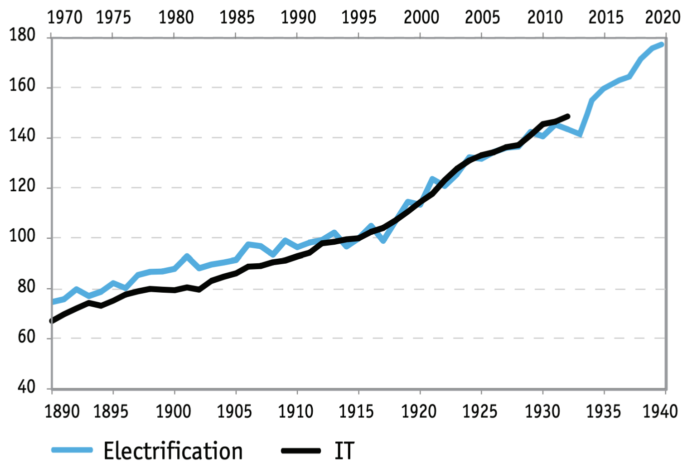


Figure 3: Labour Productivity Growth During the Electrification Era (1890-1940) and the IT Era (1970-2012) in the U.S. chained to 100 for in 1915 and 1995. Image by Syverson (2013).

2.3.3 Over-promised potential

Luddites claim high productivity growth is over for advanced economies as all-important innovations have occurred. New technologies can never be as important as those that came before. Gordon (2016) identifies 1870 – 1970 as the 'special century' when prosperity in the United States increased dramatically and completely transformed American life. People's standard of living improved in all major effects of their life, including improved homes with electricity, water and telephone, transportation with cars, health with better nutrition and increased life expectancy. The most recent innovations occurred in entertainment communication and information processing. These technologies are comparatively less important, Gordon claims, than what came before them. Gordon's (2016) view is that productivity growth will continue to decline because the innovations and facilitating drivers of the 'special century' are unique and cannot be repeated. Other academics such as Summers (2014) and Krugman (2014) agree that low economic growth is here to stay. We picked the "low-hanging fruit", and today's innovations such as IT and AI are pale in comparison.

We considered the claims made by the techno-optimists and the Luddites. The two arguments are based on anecdotes and comparisons. They lack any empirical validation because we cannot predict the future.

Furthermore, some promising technologies never actually deliver on their potential. Brynjolfsson et al. (2017) uses nuclear energy as an example. It never delivered people expectations of cheap energy and further advancements to nuclear fusion. Cognitive and emotional capabilities promised by ML might thus never materialise. Until today, the most profitable ML applications are consumer targeting & marketing by, for example, Facebook (Brynjolfsson et al., 2017). The applications have thus far had little impact on aggregate impact on productivity.

However, Mokyr (2014) states the 'human shortfall of imagination is largely responsible for much of today's pessimism. The current labour market, with video-game designers and cybersecurity experts, were unimaginable occupations in the early 1900s (Mokyr, 2014). Therefore it is impossible to determine if the techno-optimists or Luddites are correct because the future is uncertain.

2.3.4 Unbalanced Productivity Growth of Industries

Consider a two-sector economy that is evenly divided. For illustrative purposes, let industry 1 show 4% productivity growth per annum due to technological advancements. Industry 2, has no improvements and produces the same each year. The stable productivity growth (0%) of industry 2, thereby, lags the total productivity growth of the two-sector economy. The 50/50 shares split, ceteris paribus, creates 2% total productivity growth.

With this example, Baumol and Bowen (1965) introduced the model of unbalanced growth of industries. In the model, industry 2 is defined as a *stagnant* sector. The nature of the occupations that reside here are hard to automate, and therefore fail to show any productivity growth. For example, the performing arts industry consists of live entertainers such as violinists and "the output per hour playing a Schubert quartet in a standard concert hall is relatively fixed" (Baumol and Bowen, 1965). In subsequent papers, Baumol and others observed specifically that service-providing sectors were hard to automate due to the labour-intensive characteristics of occupations.

Returning to the example, if after 20 years, half of the employees shift from progressive industry 1 to stagnant industry 2 the average growth rate will decline. Such that average productivity growth decreases from 2% to 1%: $(0.5)4 + (0.5)0 = 2.0$ to $(0.25)4 + (0.75)0$ to 1.0, respectively. The decrease, compounded over time, has an enormous result on overall growth. For a 20 year period this a 1 % difference creates a productivity difference of 38.5 %: $1.04^{20} - 1.03^{20} = 1.385$. If US GDP in 2020 was 38.5% higher then it was (21 trillion dollars), and the total number of hours remained equal, an additional 8 trillion dollars of wealth would be available to US citizens. So the compounded effect of percentage differences cannot be understated.

Nordhaus (2008) investigated how the rise in the share of *stagant* sectors slowed the overall productivity growth in the US over the second half of the twentieth century and called this the *'Growth Disease'*. His methodology allows for empirical tests. Therefore we consider this a good model to test for the expectation of technological automation.

2.4 The Growth Disease

In the previous section, we shortly described the Growth Disease. This was identified by Nordhaus (2008) as one of six consequences of the *Cost Disease*. In 1965, Baumol and Bowen (1965) observed that the cost of stagnant industries outpaced the cost of progressive industries. Consider a consumer who attends a concert. A violinist must perform for there to be music and to create value. It is hard to reduce the amount of labour because it is part of the experience. A violinist can play an electric violin, but it will not change the price of the ticket. The violist is part of a stagnant industry with constant productivity growth. In contrast, progressive industries excel due to technological advancement. The strong productivity growth in progressive sectors means higher output with fewer inputs (such as workers' time). If it is assumed wages rise pari-passu across industries, then the productivity of stagnant industries is lower. In these industries, the input (labour) becomes more costly; therefore, productivity is lower ceteris-paribus. For example, when wages grow equally in the economy, then the salary of a violinist, in the stagnant sector, does so too. Despite no productivity gains, the violinist's wage increases. If the violinist's job succeeds at keeping income equal to progressive sectors, the performance cost continues to increase indefinitely over time. So, the price of services grows relative to the price of goods.

Furthermore, Baumol further simplified the model such that stagnant industries are identified as service-providing industries and progressive industries as goods-producing industries. He assumed demand for services is income elastic and demand for goods is income inelastic (Baumol et al., 1985). Income elasticity describes how money allocation changes as incomes grow. For example, if one has a weekly budget of 100 dollars, one would spend 50 on goods and 50 on services. However, as one's budget increases, their allocation does so too. The fraction of money spends on services increases in proportion to goods. The wealthier people get, the more their spending shifts toward services. The combination of higher spending and higher costs results in a bigger relative size of service industries. Consequently, the aggregate productivity growth declined as the share of stagnant industries increased, while progressive industries declined. Nordhaus (2008) defined this the Growth Disease.

2.4.1 Empirical Evidence

Nordhaus (2008) tested the Growth Disease hypothesis on the US. That is if stagnant sectors increase in relative share size to progressive sectors, it decelerates the aggregate US economy. His results show that the US was negatively affected by the Growth Disease over the period 1948-2001. The shares of progressive industries decreased over time, such that productivity growth was a 1.5 % lower between 1948 and 2001. The composition of the US economy shifted from manufacturing to stagnant sectors such as education and construction.

Hartwig (2011), did a replication study of Nordhaus (2008) on the European Union over 1971–2005. Despite many differences between the US and the EU, the union exhibits similar patterns. Hartwig notes that this is confusing considering the countries have different policies, institutions and economies. His suggestion is that the structural change in combination with Baumol's assumption of progressive and stagnant sectors is so strong that it overrides the differences between countries.

2.4.2 Not all services are stagnant

To illustrate the effects of Cost Disease, Baumol and Bowen (1965) oversimplified the economy. They argued that stagnant sectors show constant labour productivity growth because they are labour intensive and difficult to automate. However, not all stagnant industries slow aggregate productivity growth and not all service industries show constant productivity growth.

Oulton (2001) nuances Baumol's model and argues that stagnant industries can create higher aggregate productivity growth. To illustrate, consider again the example of section 2.3.4 about progressive industry 1 and stagnant industry 2. Let industry 1 be a car manufacturer and 2 be hairdressers. The car industry uses only two inputs: labour and intermediate services. We introduce a third sector that is a (low-growth) financial & business services industry. This industry's only input is labour and supplies intermediary inputs for the car manufacturing industry. Oulton found that, paradoxically, if labour shifts from the "progressive" industry 1 to the "stagnant" industry 3, aggregate productivity growth rises. Even though labour moves from a high growth industry to a low growth industry, the aggregate productivity of this 3 industry economy increases. Later research corroborates this observation and Baumol endorsed Oulton's argument Baumol (2012); Hartwig and Krämer (2019).

Moreover, Oulton (2001) showed that not all service industries that produce intermediary inputs show low productivity growth. Industries that are large producers of intermediary inputs are transport & communications, distributive trades, finance & business services, and miscellaneous personal services (Oulton, 2001). Table 1 on page 13 shows the annualised labour productivity growth rates over the period 1973-1996 for five countries. The four industries mentioned above exceed the technologically progressive industry manufacturing. Furthermore, note that the US annualised labour productivity growth over period 1972-1996 in the US, of Figure 1 on page 1, was only 1.4 %. This makes the industries growth rates of construction and transport & communications more impressive. Therefore not all labour-intensive industries are stagnant.

Table 1: Labour productivity growth rates for selected high growth industries over period 1973-1996.

Sector	UK	US	France	Germany	Japan
Agriculture, forestry, fishing	3.66	3.93	6.03	5.05	2.87
Manufacturing	4.96	1.39	4.22	2.95	2.93
Utilities	2.60	-0.77	2.37	1.04	1.07
Construction	3.14	2.21	3.65	2.93	4.47
Transport & communications	3.88	2.01	3.95	4.23	2.66
Financial & business services	2.07	-0.08	0.26	3.06	1.87
Miscellaneous personal services	1.57	0.46	0.65	3.00	1.60

Notes: The table is from Oulton (2001). The numbers are based is value-added labour productivity reported in per cent per year.

2.5 The potential of Artificial Intelligence

Autor (2014) defines ML as ”applying statistics and inductive reasoning to supply best guess answers in cases where formal procedural rules are unknown”. Brynjolffson, Mitchell and Rock (2018) write, ”ML automation is expected to be radically different from previous automation waves”. However, thus far, ML has lived short of the economic possibilities, only creating added value for advertising (Brynjolfsson et al., 2017).

In section 2.4, we discussed how stagnant industries slow economic growth. One promising technology that could revolutionise these sectors is ML. Figure 4 shows the predicted productivity growth of sectors by ML. The biggest increase is for the ’other public and personal services’ with 21%. This sector includes healthcare, education, public, and recreational services. ’Consumer goods, accommodations, and food services’ with 15% productivity growth by ML. This suggests that the largest productivity gains by ML are concentrated in stagnant industries. This prediction would mean the structural composition of the economy has no negative effect on the US aggregate productivity growth. Then assumptions of the Baumol’s model have run their course.

Artificial Intelligence (AI) is the next evolution of ML technology, and Accenture investigated the potential effect that AI can have on the US economy. Accenture (2017) claims AI is ’the future of growth’ and predicts the US economy to grow by 4.6% per year with AI. The consultancy office finds three key accelerators to support its claim for productivity growth.

Firstly, AI enables businesses to create a new virtual workforce. This ’intelligent automation’, can sense, comprehend, and act to drive down errors and cost. This type of automation removes

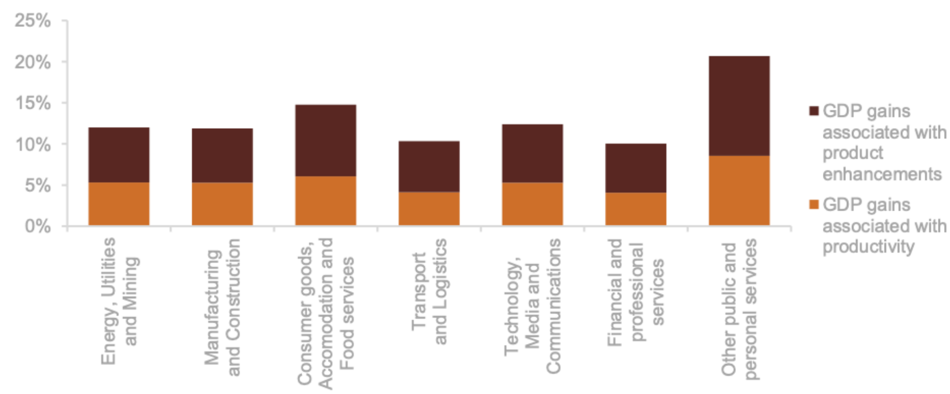


Figure 4: The Gross Domestic Product gains from only AI by 2030 (**?**)

labour input and leaves humans to focus on other tasks. This is a widely discussed topic within the literature because it is unclear if AI, and other types of computer automation, will destroy or complement occupations. The seminal paper by Frey and Osborne (2016) claims about 47 % of total US employment is at risk of automation by 2030. Theoretically, US productivity would be two times higher because nearly half of US occupations are displaced, ceteris paribus. Over 20 years that is an annualised productivity growth rate of over 3.5% (= $\sqrt[20]{2}$). This is significantly higher than the current productivity rate.

Secondly, Accenture claims AI allows for 'labour and capital augmentation'. Brynjolfsson et al. (2018) argue similar things. They claim that AI-related technologies will create a significant reorganisation of business processes and redesign of jobs. Accenture (2017) predicts economic growth will not come from cost-saving automation but enabling more effective labour and capital.

Thirdly, 'Innovation diffusion' allows researchers to use AI to create new ideas. A recent example is how biotechnological company Moderna developed COVID-19 vaccines using AI. Moderna disclosed AI is central to accelerating mRNA based vaccines (Damiani, 2017). The company claims critical insights without AI were otherwise inaccessible and unachievable. It goes so far as to claim AI is one of the core digital building blocks of research and development.

However, technological progress is not the only factor that determines productivity growth. Other factors such as demographics have a significant impact on the US productivity (Vollrath, 2020). However, Manyika (2018) argues that other factors than technological feasibility can stall the pace of innovation implementation. These include the cost of automation, regulatory barriers and social acceptance.

2.6 Conclusions

Since the 1970s, productivity growth has decelerated, and the reason for it is unknown. This is not unique to the US and is recorded for other advanced western economies. At the same time, we saw the diffusion of IT. In the literature, this is known as the *productivity paradox* or the disparity of impressive technology and disappointing productivity growth. We argued it is important for productivity growth to increase such that important political issues could be resolved. Essential services such as education and healthcare are increasing dramatically, with household income barely keeping up.

We considered four explanations for the productivity paradox and concluded Baumol's model of unbalanced growth. The consequence, known as the Growth Disease, allows for empirical testing. The model classifies industries as either technologically progressive or stagnant. Progressive industries benefit from cost-reducing automation, whereas stagnant industries do not. Due to the shifting consumption pattern of consumers towards services and the cost-reducing automation in progressive industries, the aggregate US productivity growth decelerated. This holds empirically for the US and European countries. However, techno-optimists expect ML technology to create cost-reducing benefits in historically stagnant industries.

3 Data

This chapter presents the data to analyse the impact of technology on productivity growth. As explained in the literature review, we use the assumption of the paper by Baumol and Bowen (1965) that the nature of some occupations is such that labour cannot be substituted by automation. The consequence is Baumol's (1967) model of unbalanced growth such that the aggregate productivity growth decelerates due to an increasing share of constant productivity growth industries.

In the thesis, we first test the Growth Disease using the methodology from Nordhaus (2008) and a newer dataset. Secondly, we investigate the assumption of stagnant and progressive industries using data sets that measures IT and ML's technological potential. Current research captures technological potential at the occupational-level; therefore, we propose a new method for analysing the potential at the industry-level. The following list is an overview of the data sets used to answer each research question:

- Q1: Is the Growth Disease effect still present in the US economy?- Industry-level macro variables.
- Q2: Did the expectation of IT potential predict productivity growth in the US over the period 1989-2016? - Industry-level macro variables and occupational-level technology potential on IT.
- Q3: Is the expectation of automation of ML concentrated in historically stagnant industries? - technological potential of IT and AI at the occupational-level.

To answer these questions, we rely on four data sets. In chapter 4 Methodology, we discuss how the data sets are used. This chapter focuses on the input variables for the analysis and the data cleaning to conduct the analysis. The data sets are:

- **Industry-level data**, known as **US KLEMS**. This data set contains macro-economic variables for 63 industries in the economy.
- **Occupation-level data**, known as **RTI** and **SML**. For the analysis, we use two data sets to analyse the expectations of the technological potential for (1) IT and (2) AI. The data set is given at the occupational-level. These technological potential metrics and rationale for them are discussed in sections 3.2 and 3.3
- **Industry - Occupational crosswalk data**, Occupational Employment Statistics or hereafter **OES Matrix**. This crosswalk file allows occupational-level data to be aggregated into industry-level data. So that the RTI and SML data can be compared to the US KLEMS data.

3.1 Industry data - US KLEMS

For industry-level data, we follow the technical paper by Eldridge et al. (2020). The paper is a collaboration between the Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS) to provide a consistent data set over the 1947 to 2016 period. The paper is inspired by the work of Jorgenson et al. (2006), who identified the need for an integration of national accounts. The data set (Eldridge et al., 2020) provides a "new architecture" of US industry data. Let this data set be called "US KLEMS". It contains estimates of the sources of economic growth, including capital (K), labour (L), and intermediary inputs such as energy (E), materials (M), and services (S). The benefit of this data set is that it is consistent for industries over time over two periods (1947-1962 and 1963-2016). Due to major changes in industry classification, other data set sources are incompatible for time-continuous analysis. When classifications change over time, there may be breaks in the historical data due to reclassification. This logic also applies to omitting 1947-1962 from the analysis; this earlier period includes only 44 industries. Some of these industries, such as 'Finance and Insurance' came to be more narrowly defined in the later period of the dataset, such that we have 4 separate industries. It is possible to mitigate this issue, but due to the thesis's time constraint of the thesis, it was not included in the analysis. A critique of the US KLEMS data is that this is not official data but rather provides a proof of concept. Eldridge et al. (2020) created a data set that is harmonised for a long time horizon, which is not readily available and would cost considerable time to match changing industry classification over time.

The US KLEMS data provides industry accounts over $t \in \{1963, ..., 2016\}$ for 63 industries. In the analysis, the last two sectors (62) 'Federal' and (63) 'State and local' are excluded from the analysis. These industries are governmental whose value-added are more difficult to measure accurately; for more information, see Harper et al. (2009). The remaining 61 industries included data on gross output, intermediary inputs, and capital in nominal value-added and quantity index. Capital includes 'Research & Development', 'IT capital' and 'Software'. For all industries, 'total hours worked' is included. These data allow for the construction of real-value added and productivity of industries. How this is done can be read in chapter 4 Methodology. For an overview of variable names and respective data names refer to Table 2 on page 18.

The 61 industries are classified by using the 2007 North American Industry Classification System (NAICS 2007). In Appendix C Table 14 is a list of the 61 industries with industry names and NAICS 2007 code. The US KLEMS file has different digit depths for each sector, and some include multiple digits. We have 61 industries with 88 respective NAICS 2007 codes. We make the strong assumption that the 61 industries with respective NAICS code represents the whole private US economy and are well-measured. As discussed in section 2.3.1, recording service sector productivity is very difficult and prone to underestimation.

Table 2: Macro variables of the US KLEMS data set.

Symbol	Description	US KLEMS notation
H	Hours worked	*hrs.*
X	Gross output quantity index	*goqi.*
B	Intermediate input quantity index	*iiqi.*
IT	IT capital quantity index	*qkit.*
S	Software capital quantity index	*qks.*
nX	Nominal gross output	*goqi.*
nB	Nominal intermediate inputs	*iiqi.*
nIT	Nominal IT capital	*vkit.*
nS	Nominal Software capital	*vksoft.*

Notes: All nominal variables are in current dollars.

3.2 Occupation data on IT Potential

Several measures of the impact of IT on occupations in the US exist in recent literature. This section evaluates the models and available data for measuring the potential of IT. We can test the assumption of technological progressive and stagnant industries of Baumol's model of unbalanced growth.

3.2.1 IT potential metric

In the literature, there exist two prominent theories which try to explain the relationship between technology and the labour market (Sebastian and Biagi, 2018). The fundamental assumption of both theories is that technological innovation affects labour demand. In that way, we can use these as a substitute to analyse the productivity growth. Technology might substitute workers, such that technological progress can have a strong impact on industries. The Skill-Biased Technical Change (SBTC) hypothesis states the technology improvements of IT create capital accumulation such that high skilled (computer) workers have increased wages, but low skilled workers are displaced by the automation (Acemoglu and Autor, 2011). In other words, high-skilled workers are better able to use new technology, such that low-skilled workers are at risk of substitution. However, SBTC is unable to capture the relationship of technological advancement and the labour market (Sebastian and Biagi, 2018).

This led Autor et al. (2003), ALM-03 hereafter, to put forth the Routine Biased Technical Change (RBTC) hypothesis. The RBTC hypothesis states the technology improvements of IT leads to a decline in jobs that heavily rely on either or both routine components (manual or cognitive) (Sebastian and Biagi, 2018). ALM-03, defined occupations as a bundle of tasks. This insight means we can categorise how likely tasks can be automated. The more routine a task, the more automatable it becomes. This implies the substitution of human labour activities. A task is defined as "routine" if a machine can follow an explicit set of programmable rules. ALM-03 define "non-routine" when a task has a rule that is not sufficiently understood to translate it to lines of code. This is built on the idea of "We can know more than we can tell" (Polanyi, 1966). In other words, a human understands intuitively what to do (tacit knowledge) but cannot verbalise it (explicit knowledge). In the RBTC model, it is assumed that occupations of the same title are equal. The underlying tasks in the occupation create the jobs in the O*NET database. O*NET is a database by the US department of labour to study the changing skills and tasks of occupations over time in the US.

ALM-03 developed a framework to look *back* at how automation by IT altered labour requirements. Routinised jobs are more likely to have computer invested capital to substitute labour. In contrast, non-routinised tasks saw increased demand and complemented computer capital. ALM-03 was later updated by Autor, Katz and Kearney (2006) (AKK-06) to reduce the task categories from five to three. ALM-03 included task categories routine manual, routine cognitive, non-routine analytic, non-routine interactive and non-routine manual. AKK-06 reduced the task categories to abstract, routine and manual, which are defined as:

- Routine – a task is based on a set of rules and procedures which can be automated with a computer.
- Manual – a task requires physical dexterity and interpersonal skills, thus hard to automate.
- Abstract – a task requires creative thinking, problem-solving and other tasks that can only be performed by highly skilled professionals.

Then Autor and Dorn (2013) (AD-13) formalised AKK-06 and created the Routine Task Intensity (RTI). AD-13 use RTI to study how technology displaces routine-based professions. This model implies that technological change creates decreased costs of computerising routine tasks. Therefore, the authors state that the model broadly implies Baumol's model of unbalanced growth of industries. The assumption is that well-defined and repetitive work can be 'computerised', such that it substitutes for workers.

The RTI measure is the logarithmic sum of measures for the three types of tasks and assigns a score for the degree to which occupation is affected by computerisation. Formula 1 shows RTI for each occupation k.

$$RTI_k = ln(T_k^R) - ln(T_k^M) - ln(T_k^A) \tag{1}$$

Where T_k^R,T_k^M and T_k^A are respectively routine, manual and abstract task inputs. The formula is logarithmic, so RTI becomes a summary measure of occupations. In other words, the log transformation allows the authors to analyse the skewness and kurtosis of all occupations in the model. Hence, a 1% in routine task translates to a 1% increase of RTI. Similarly, a 1% increase in either manual or abstract tasks results in a 1% decrease of RTI. Figure 5 is an illustration of how the RTI, and underlying variables, behave for major occupations groups.

	RTI index	Abstract tasks	Routine tasks	Manual tasks
Managers/prof/tech/finance/public safety	−	+	−	−
Production/craft	+	+	+	−
Transport/construct/mech/mining/farm	−	−	+	+
Machine operators/assemblers	+	−	+	+
Clerical/retail sales	+	−	+	−
Service occupations	−	−	−	+

Figure 5: Routine Task Intensity for Major Occupation Groups, Table 2 from Autor and Dorn (2013).

Notes: The table shows several major occupation groups, to illustrate how RTI works. Occupation with above average values show a (+) and below average (-). The shaded field indicates which type of task has the highest value within the major occupation group.

Occupations within service sectors show low RTI scores, as they consist of non-routine and highly manual tasks. Furthermore, the paper finds that service-providing sector employment grew significantly since the 1980s after remaining constant for more than two decades. These observations are consistent with the growing shares of stagnant industries of Nordhaus (2008).

Sebastian and Biagi (2018) critique the computerisation, by AD-13, because the approach relies on the 1977 O*NET Database. Although O*NET is updated every five years, the metric is not. Therefore RTI cannot be compared over time.

After AD-13, several papers were published that use using RTI (Goos et al., 2014; Squicciarini et al., 2016). Because the literature that followed was based on David Autor's model, and he created a model that implies Baumol's theory, we chose his RTI as a measure for the expectation of IT potential.

3.2.2 Routine Task Intensity

Table 3 on page 21 shows the summary statistics of the the RTI metric. Figure 6 shows a histogram of the frequency of RTI scores. It counts 330 occupations, based on 1977 task description, indexed to Census 2000. Census 2000 is the US official data of occupations released in 2000. This is not directly compatible with the US KLEMS data set nor the OES Matrix data set. Therefore we need to do a crosswalk to match the RTI score to the classification of OES Matrix. We discuss this in the next section. The aggregation of occupation scores to industry score, with OES Matrix, is discussed in section 3.4.

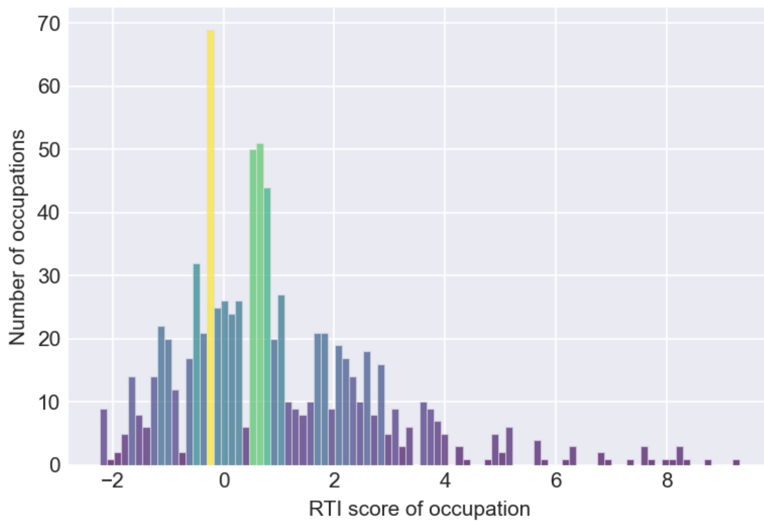


Figure 6: Histogram of frequency of occupation scores of RTI

Table 3: Description statistics of the RTI dataset used in the paper by Autor and Dorn (2013).

	Abstract Task	**Routine Task**	**Manual Task**	**RTI**
Count	330.0	330.0	330.0	330.0
Mean	2.886	4.627	1.309	1.469
Std. Dev	2.265	2.236	1.405	2.194
Minimum	0.042	1.186	0.001	-2.411
25th Percentile	1.119	2.461	0.189	-0.044
75th Percentile	4.057	6.776	2.143	2.492
Maximum	9.002	8.642	10.0	9.325

3.2.3 RTI crosswalk

In section 3.1, we discussed how the US KLEMS data is consistent over time for all industries. This is, however, not the case for the RTI occupational data. The data set contains RTI scores for

330 occupations indexed to Census 2000. This classification is not compatible with the crosswalk data of the OES matrix (formatted to 2010 Standard Occupational Classification or SOC 2010). The simple fact is that classification of Census and SOC is different. Furthermore, the occupations become more granular over time when newer versions of the classification system are introduced. In SOC 2010, we have 840 occupations, adding 510 occupations. To mitigate this problem, we have to make the strong assumption that tasks of granular occupations overlap. So we cannot correct for occupational changes, such as new tasks within jobs. What further complicates matters is that Census and SOC are regularly updated and require multiple extra crosswalks [1]. The crosswalk steps between datasets can be summarised as follows:

1. Match Census 2000 to Census 2002. From 330 to 510 occupations.
2. Match Census 2002 to SOC 2000. From 510 to 525 occupations.
3. Match SOC 2000 to SOC 2010. From 525 to 840 occupations. Here we assume that missing RTI score can be constructed using broader groups such that tasks are overlapping.

For the 310 occupations of Census 2000, we find a perfect match to 763 occupations of the SOC 2010 data. Again, we assumed more narrowly defined occupations, in later versions, have overlapping tasks and therefore equal RTI scores. Table 4 shows an example of how occupations codes are matched using Python. Occupation 'Computer scientists and system analysts' (or 100 in Census 2000) has four respective occupation codes after three crosswalks. A full version is shown in Appendix B, Table 13 on page 67 with titles for all occupation codes. The crosswalk from Census 2002 to SOC 2000 shows one occupation is more narrowly defined to correspond to three occupations. In the final step, the occupation 15-105, in SOC 2000, splits to 15-1121 and 15-1143.

Table 4: Crosswalk match for 'Computer scientists and system analysts' from Census 2000 to SOC 2010.

Census 2000	**Census 2002**	**SOC 2000**	**SOC 2010**	**SOC 2010 title**
100	1000	15-101	15-1111	Computer & Information Research Scientists
100	1000	15-105	15-1121	Computer Systems Analysts
100	1000	15-105	15-1143	Computer Network Architects
100	1000	15-109	15-1199	Computer Occupations, All Other

Notes: The table shows how one occupation for the Census 2000 data set is matched to four occupations of SOC 2010. The first crosswalk (of step 1) has an identical crosswalk of 100 to 1000. In the second crosswalk, 1000 is matched to three occupations 15-101, 15-105, and 109. In the third crosswalk occupation 15-105 has two matches for 15-1121 and 15-1143. The final dataset has four occupations with and RTI score that is equal for all four occupations.

[1] For more information, please refer to `https://www.bls.gov/soc/soc_2010_user_guide.pdf`

However, 77 occupations do not have an RTI score. To solve this, we assigned the mean RTI score of the larger group of occupations it belongs to. This works as follows: The SOC data is classified at four levels of aggregation: major group, minor group, broad occupation and detailed occupation. Figure 7 shows how the six digits classification works. The first two digits specify the major groups and end with 0000. The majors are then divided into more specific minor group or the third digit. The minor groups generally end with 000, but there are exceptions such as 15-1100 Computer Occupations and 51-5100 Printer Workers, which end with 00. The fourth and fifth digits represent the broad occupation and end with 0. The final digit corresponds to the detailed occupation.

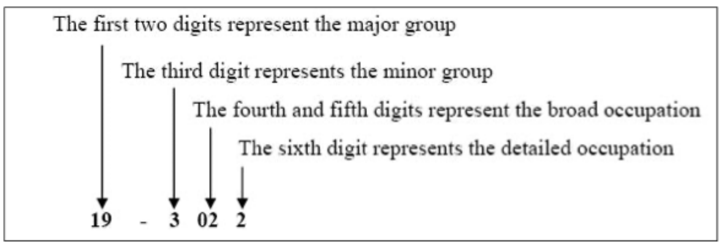


Figure 7: SOC classification.

Notes: SOC 2000 and SOC 2010 consist of six digits split. The two digits before the hyphen represent the major group of an occupation. Additional digit(s) further specify the occupation. This specific occupation is 'Survey Researchers' falling within 'Life, Physical, and Social Science Occupations' major group.

The BLS (2010) claims the SOC dataset encompasses all occupation in the United States economy. If a specific occupation is not listed, then it is part of the broad occupation. The 2010 version of the dataset consists of 23 major groups, 97 minor groups, 461 broad occupations and 840 detailed occupations. A small number of occupations are indexed to more than one SOC code. After adjusting for this, the total number of detailed occupations expands to 860.

Returning to the problem, consider the major group 'Education, Training and Library Occupations' (25-0000). It has five minor groups beneath it. These scores end with 1000, 2000, 3000, 4000, 9000. More recent data becomes more granular. For example, in SOC 2000 there is only one minor group for Postsecondary teachers (25-1000), but in SOC 2010 this is more granular and includes 38 detailed occupations such as 'Law Teachers, Postsecondary' (25-1112). Thus in a later version of the classification, occupations are assumed to be different. Here we assume the tasks are overlapping (although specialisation is different). Such that we match the RTI score with the larger unit groups, if occupations become more granular. Occupations that become more granular from minor groups are: Postsecondary Teachers (25-1000), Other Teachers and Instructors (25-3000), Other Healthcare Practitioner and Technical Occupations (29-9000), Funeral Service Workers (39-4000), Construction Trades Workers (47-2000), Plant and System Operators (51-8000), and Supervisors, Transportation and Material Moving Workers (53-1000).

Finally, the following minor groups do not a not have corresponding RTI values, as this type of occupation was not measured by the RTI score of Autor and Dorn (2013): Military Officer Special and Tactical Operations Leaders/Managers (55-1000), First-Line Enlisted Military Supervisors/Managers (55-2000), Military Enlisted Tactical Operations and Air/Weapons Specialists Crew Members (55-3000). These occupations are excluded from the analysis.

3.3 Occupation data on ML Potential

To asses, if the technological potential of AI can revive productivity growth acceleration, we require ML potential scores for industries as we did for IT. The potential of ML, is that it can do more than 'simple' computers. Section 3.2.1 described how computers can automate routine tasks. The promise of ML is that it can do "non-routine tasks"; therefore, we are interested if these type of potential autonomous "non-routine" tasks are highly concentrated in service sectors (Autor and Dorn, 2013). For example, in the health care sector, dermatologists primarily diagnose skin visually (Esteva et al., 2017). This task can be automated using image recognition software to diagnose skin cancer. The ML application allows one to take a picture of the skin and upload it to the machine. In a test environment, scientists showed ML matched dermatologist accuracy for diagnosing skin cancer. Here, ML could alter critical tasks within occupations, such as recognising cancer. If so, then the technological potential suggests service industries, which Baumol and Bowen (1965) argue are more likely to be stagnant, can become progressive. To analyse this we can consider three notable papers based on US occupation data by Frey and Osborne (2016), Brynjolfsson et al. (2018), and Felten et al. (2019).

Frey and Osborne (2016) tests the susceptibility to computerization. They define computerisation as "job automation by means of computer-controlled equipment". With this new measure, the authors hope to address the gap of technological automation beyond routine tasks. In other words, the measure addresses the emerging innovations capable of "non-routine" tasks through AI or robotics. The metric is a ratio scale measurement and modifies the theoretical model of Autor et al. (2003) by identifying three engineering bottlenecks that prevent the automation of jobs. These include (1) perception and manipulation tasks, (2) creative intelligence tasks, (3) social intelligence tasks. The sum of these labour inputs produces the most likely occupations to be *fully* automated.

Then Frey and Osborne (2016) surveyed experts from Oxford categorised occupations as *fully* automated or *partially* automated for 70 occupations. The papers label only 70 out of 702 occupations in the O*NET database. The authors only selected jobs that are assumed to be highly susceptible to 'computerisation' to reduce bias. In doing so, over 90 % of the jobs are excluded from the forecast. Therefore we do not consider using this data set because 90 % omission of occupations is too large to aggregate occupation-level score to industry-level. As a final critique, the word computerisation' is a weasel word. It does not identify what type of technology might replace what jobs. The paper suggests the term includes ML and mobile robotics but fails to specify if it includes further IT substitution.

Brynjolfsson et al. (2018) argue Machine Learning (ML) can circumvent Polanyi's Paradox. The technology allows for new automation because non-routine work does not need a procedure verbatim. Rather ML models use inputs and outputs to map functions. To test this, they construct the Suitability to ML measure (SML). For each Direct Working Activity (DWA), seven to ten knowledgeable respondents fill out the 21 questions ranking each based on eight criteria. The questions are ordinal, allowing respondents to answer a '1' (strongly disagree) until a '5' (strongly agree). The higher the score, the more suitable the DWA to ML. Here a '3' corresponds to a neutral expose to ML. There are two additional questions where respondents fill out DWA for the eighth criteria, which is the physically intensive activities. Here the scores are reversed, so the lowest score represents the highest physical activity and thus lowest suitability to ML.

Brynjolfsson et al. (2018) have three points of critiques about the metric. Firstly, the rubric focuses on technical feasibility and omits economic, organisational, legal, cultural and societal factors. Secondly, the rubric focuses on short term opportunities, where Frey and Osborne (2016) focus on long term results. Thirdly, the paper only looks at implications for the US labour force. There should be further investigation into other countries to rule out other explanations. Despite this, we select the SML metric. The SML directly addresses the "non-routine" tasks of the model of ALM-03. SML assess how much tasks will be affected by ML. Therefore we select SML, because it is based on the same conceptual model as RTI, and the critiques do not negatively affect this research.

Finally, Felten et al. (2019) proposes a new measure: Artificial Intelligence Occupational Impact (AIOI). Like the other papers, it uses the O*NET database. The study uses the crowd-sourced platform to fill 52 O*NET abilities. This paper only predicts automation caused by AI, where Frey and Osborne (2016) considers all automation. It looks back at advances in AI between 2010 to 2015. For forward-looking analysis of question three, this eliminates AIOI.

We considered three ML potential metrics. The SML metric by Brynjolfsson et al. (2018) suits this research best. As a final note, we again only analyse the US. New forms of survey-based data, like the crowdsourced database, such as Crowdflower and mTurk, are not yet applied to other OECD countries.

3.3.1 Suitability to Machine Learning

After downloading the occupation-level SML data set[2], we find 966 occupations indexed by SOC 2010. This is is the same classification as the OES Matrix data set. Table 8 shows the frequency for occupation-level scores. Table 5 shows the summary statistics of the dataset. The calculated maximum (3.90) and minimum (2.78) are significantly far from the theoretical maximum (5) and minimum(1). Tasks show higher variation than the occupation aggregated values. The mean value 3.47 for occupations is interpreted as slightly more ML potential than indifferent.

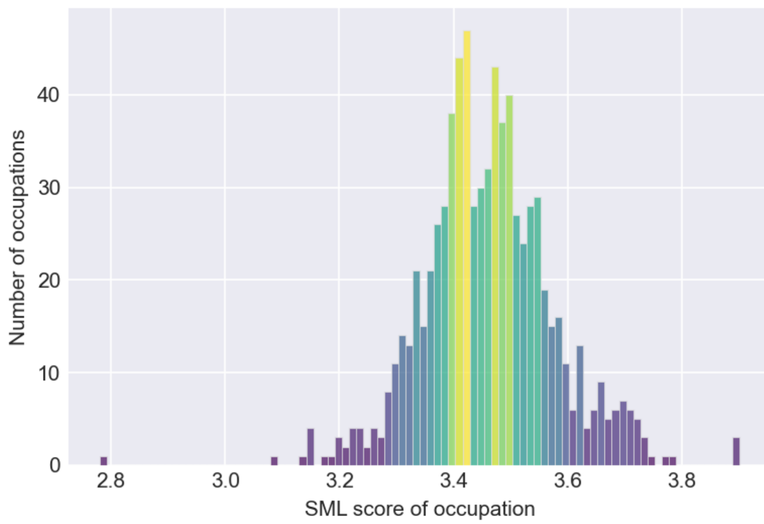


Figure 8: Histogram of frequency of occupation score of SML

Table 5: Description statistics of the SML data set used in the paper by Brynjolfsson et al. (2018).

	Occupation	Task
Count	966	19,612
Mean	3.47	3.47
Std. Dev. of SML	0.11	0.31
Minimum SML	2.78	2.38
25th Percentile SML	3.40	3.25
75th Percentile SML	3.50	3.68
Maximum SML	3.90	4.48

[2]Data set available for download at `https://www-aeaweb-org.eur.idm.oclc.org/articles?id=10.1257/pandp.20181019`

3.4 Crosswalk data - OES Matrix

For research questions two and three, we use the technological potential metrics, RTI and SML, to quantitatively analyse at the industry-level. The metrics are at the occupational-level, so we have to aggregate them. For the aggregation of occupational scores of RTI_k and SML_k, we rely on the OES Matrix provided by the BLS [3]. The data contains 65,531 occupations for 432 industries (indexed for NAICS 2007). Furthermore, the dataset contains the share employees of different occupations within industries for the US in 2019. We would have preferred to use the employment data of 1977 for RTI and 2016 for SML, respectively. However, earlier employment data is publicly unavailable. The industries contain line and summary items, such that industries can be aggregated using grananular industries. The OES Matrix data that we use consists of:

- Occupation code (& title) in SOC 2010
- Industry code (& title) in NAICS 2007
- 2019 Percent of Industry ($w_{i,k}$) – This number represents the employment share of an occupation k in industry i in 2019.

For our analysis, we use the 61 industries of the US KLEMS data set. Each industry of the 61 industries is labelled with a number $i \in \{1, ..., 61\}$. Note that some industries have more than one NAICS code and therefore differ in digit depth. A new data frame `df` is made for 61 industries by filtering on the NAICS values. `df` consists of 88 industries with a total of 24,652 occupations. Each job is classified by SOC 2010 and appears multiple times in the dataset. For example, occupations such as Chief Executives work in most industries such as construction and air transportation. The share (w) of Chief Executives differ for each industry because some industries have more Chief Executives than others. So $w_{i,k}$ is different for each occupation k and industry i.

The next step is to find a weighted average technological potential score for each of the industry. Formula 2 shows the weighted average technology score (T_j) for the 88 industries. Set J include 88 industries where with number $j \in 1, .., 88$. The 88 industries are matched to the 61 industries of the US KLEMS dataset. For example, industry 1 'Farms' is equal to $i = 1$ and $j \in 1, 2$. And so is industry 2 'Forestry, fishing, and related activities' equal to $i = 2$ and $j \in 3, 4, 5$.

$$T_j = \sum_{k}^{n_j} T_{j,k} * w_{j,k} \tag{2}$$

Where T_j is the weighted average of technology potential for occupation k in industry j. T_j can be RTI_j or SML_j. Here n_j is the share of occupations of the US economy in 2019 in industry j.

[3] The data set is downloadable at `https://www.bls.gov/emp/tables/industry-occupation-matrix-occupation.htm`

Here we have weight $w_{j,k}$. At this point, we have the weighted average technology potential score for 88 (NAICS) industries. We want to convert the average technology scores to the 61 industries score. Some industries only have one technological score such as 'Oil and gas extraction' with $i = 3$ and $j = 6$. Next, we calculate the weighted average for industry i classification. We use formula 4 to find the average score for industries that have more than one NAICS match. This is done in two steps. First, we use Formula 3 to find total average percentage representation of occupations in industry i represented by the dataset after merge.

$$p_i = \frac{1}{z_i} \sum_{k=1}^{n_i} w_{i,k} \tag{3}$$

Variable z_i is the unique number of occupation codes (the number of j's) for industry i. And $w_{i,k}$ is the share of occupation k in industry i. Here n_i is the sum of shares of occupations represented in the dataset for the US economy in 2019 of n_j for industries j matched to industry i. Then, using formula 4 we find the weighted average of the technology score ($T_{i,WA}$) for each industry i. Here $\sum_{j \in J_i}$ means it is the sum of all industries in set J_i that are equal to industry i.

$$T_{i,WA} = \frac{\sum_{j \in J_i} w_{j,k} T_j}{p_i} \tag{4}$$

Because we aggregate to industry values, we evaluate 3. It is deemed satisfactory if p_i is above 90% or more for most industries. We do not find 100% matching for each industry, but very close to it. Appendix C, table 14, shows the aggregation results after we matched RTI and SML to the OES Matrix for 61 industries. The summary statistics are shown here in Table 6. We find technology potential scores for all 61 industries.

Table 6: Summary statistics of SML and RTI industry scores.

	SML % of Industry	SML_i	RTI % of Industry	RTI_i
Count	61	61	61	61
Mean	97.01	3.482	97.01	1.168
Std. Dev.	2.91	0.038	2.91	0.734
Minimum	84.05	3.396	84.05	-0.229
25th Percentile	96.8	3.453	96.80	0.792
50th Percentile	98.10	3.477	98.10	1.232
75th Percentile	98.5	3.515	98.50	1.576
Maximum	99.7	3.549	99.70	3.859

Notes: Columns one and three are the results for p_i reported in percentages. Columns two and four are the results for $T_{i,WA}$.

4 Methodology

4.1 Measuring Productivity

To study the effects of technology on aggregate labour productivity growth, we require a measure of productivity. In its simplest form, productivity is the volume of output divided by the volume of inputs. A long body of literature discusses how these inputs and output are measured and what must be included for measuring the direct effect of technological change. This subject could be a thesis, but we summarise the topic to justify our decision to use labour productivity growth for the analysis.

The OECD provides a compendium of the most frequently used productivity measures. Here we discuss the arguments for using either the labour productivity (LP) or the Total Factor Productivity (TFP) for the analysis. The connection between technological change and technological progress is not straightforward.

LP is the real output per labour hour. It measures partial productivity and reflects the influence of a host of factors, including technological progress. For example, consider a car factory that builds 20 cars per hour. Now, management modernises the factory equipment and trains workers to use the new technology. With the new machinery, productivity performance increased to 30 cars per hour. This is a 50 % productivity increase, but the car company does not have that much demand, so management reduces the number of workers to achieve 25 cars per hour. Capital, technology, and market demand are all factors in this example. Therefore LP is not equal to technological change but a key part of it.

TFP is a productivity measure intends for disentangling of the contributions to growth of labour, capital, and technology (Schreyer, 2001). TFP growth is often referred to as Solow's residual. This measures the contributions to GDP growth that cannot be explained by the inputs labour and capital. In "Technical Change and the Aggregate Production Function," Solow (1957) observed between 1909 - 49, 87% of gross output per capita was attributable to technological change. The rest was attributable to human and physical capital. This observation is frequently misinterpreted as 'TFP growth is technological change', which is not the case OECD (2019). Solow's model does show strong evidence that technological progress determines long-run productivity growth. Among academics, there is further debate about metrics and their adequacy for measuring technological change.

Murray (2016) argues why a partial productivity measure, such as LP, is better suited for capturing technological change in productivity. Technologies that are embedded in products are excluded from TFP and therefore fail to capture the technological change. The technological improvements substitute capital and labour, allowing for cheaper inputs. Thus, TFP growth does not account for all technological progress.

In chapter 2, we reviewed Gordon (2016) who argues the pace of innovation is decelerating. For the analysis, he used TFP to make his argument. Mokyr (2018) criticises Gordon for this and so far as to state: "students of contemporary technological progress should wean themselves of TFP-fetishism; aggregate measures such as GDP (the basis for TFP calculations) were designed for a wheat-and-steel economy, not for an information and mass-customisation economy in which the service economy accounts for 70–80% of value-added". In other words, Mokyr strongly disagrees with Gordon because TFP mismeasures the rate of technological progress. Mismeasurement is the negligence of inputs and has gained has considerable attention from academics, as briefly discussed in section 2.3.1.

The time constraint of the thesis means we can only do one and choose to use LP. The main reasons are: Firstly, Schreyer (2001) argues LP reflects the efficiency of labour and is a good starting point for the analysis of factors. Secondly, for research question two, we consider task automation such that hours worked should be reduced in progressive industries. This makes LP more interpretable because hours worked is the denominator in LP. Thirdly, Solow's residual (TFP growth) is an important measure for productivity influenced by factors including technological change. However, the literature disagrees about its interpretation of technological change. Further research could be done using TFP.

4.2 Preliminary Variables

We rely on the methodology provided by Eldridge et al. (2020), who constructed the US KLEMS data set. The authors refer to Jorgenson et al. (2006). In section 3.1 Table 2 are the inputs we use to do our analysis. Table 7 show the preliminary steps for the analysis. The notation in the thesis is as follows; we use only upper-case Roman letters to indicate we use the quantity index. The lower-case letter in front of it can be the following:

- w - weight
- s - share
- l - level
- n - nominal values (notation also used in table 2.

Table 7: Calculated variables dictionary using US KLEMS data set, using the variables of table 2

Symbol	Description	Calculation
$sB_{i,t}$	Share of intermediate inputs	$B_{i,t}/X_{i,t}$
$wB_{i,t}$	weight of intermediate inputs	$(sB_{i,t} + sB_{i,t-1})/2$
$wV_{i,t}$	weight of value-added	$(sV_{i,t} + sV_{i,t-1})/2$
$gB_{i,t}$	Growth rate of intermediate inputs	$\ln(qB_{i,t}) - \ln(qB_{i,t-1})$
$gX_{i,t}$	Growth rate of gross output	$\ln(qX_{i,t}) - \ln(qX_{i,t-1})$
$gV_{i,t}$	Real value-added growth	Formula 5
$lV_{i,t}$	Level value-added	Algorithm 2 on page 66
$lA_{i,t}$	Level of labour productivity	$lV_{i,t}/H_{i,t}$
τ	length of time period	$t_{end} - t_{begin}$

Notes: All nominal variables are in current US dollars.

4.3 Labour Productivity Growth

To analyse past productivity growth, we use the annualised labour productivity growth denoted by $gLP_{i,t}$ for each industry i in year t. This is not readily available in the US KLEMS data set; therefore we use the variables of Table 2 to construct it. To do so we rely on the methodology provided by Eldridge et al. (2020), who are referring to Jorgenson et al. (2006). Firstly, we calculate the real value-added growth in equation 5, where intermediate steps for the growth rates and weights are in Table 7:

$$gV_{i,t} = \frac{gX_{i,t} - wB_{i,t} * gB_{i,t}}{wV_{i,t}} \tag{5}$$

To find the real level of value-added, we first need to set the base year (here 2009). The real value-added is measured against goods and services, where nominal is the real dollar value. We choose to set the real value-added level in 2009 equal to 100. The next step is to recursively and iteratively find the level of value-added ($lV_{i,t}$). This is done using Algorithm 2, in Appendix A.2 on page 66. To find the level of labour productivity, we divide the level of value-added by the hours ($H_{i,t}$):

$$lA_{i,t} = \frac{lV_{i,t}}{H_{i,t}} \tag{6}$$

Finally we find the annualised labour productivity growth (a_i, t, τ) for the chosen length τ, which is by default 1 using Formula 7.

$$a_{i,t,\tau} = \frac{\ln(lA_{i,t}) - \ln(lA_{i,t-\tau})}{\tau} \tag{7}$$

4.4 Fixed Shares Growth Rate

In the literature review, section 2.4, we discussed the Growth Disease as tested by Nordhaus (2008). We rely on the methodology of Nordhaus (2008) and Nordhaus (2004) to measure the Growth Disease effect. That is, the reduction of aggregate productivity growth due to stagnant industries. Nordhaus (2004) outlined three ways to measure productivity growth. The paper presented an alternative method for measuring productivity and determining the underlying factors. That is, how the share of stagnant and progressive sectors affected the aggregate productivity growth.

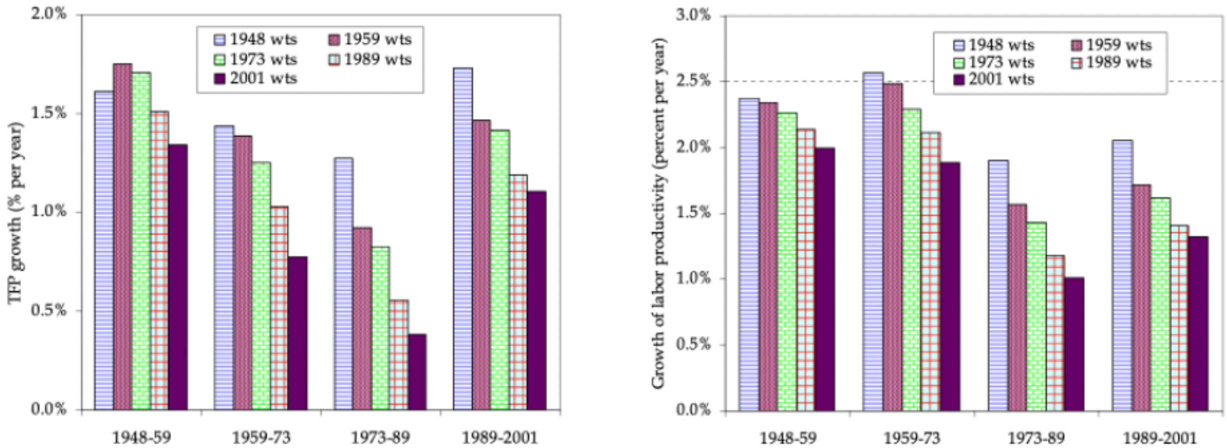
The first method is a classical approach and studies the difference in growth rates. This standard method does not account for the structural change of the economy. In this approach, we measure productivity growth.

The second method, the *welfare-theoretic measure*, multiplies the weighted average of productivity using the nominal output shares of a given year. The third approach, *the fixed-weight measure*, 'fixes' the nominal output shares for different based years as weight. Using the average of productivity growth rates, we get multiple fixed-share growth rates. The differences between the welfare-theoretic and fixed weight methods are called the Fixed Shares Growth Rate analysis (FSGR). Nordhaus (2008) uses the growth rates for different periods with different fixed years, to capture a complex set of factors, including the Growth Disease. The hypothesis is that changing nominal output shares of industries will decrease the aggregate FSGR of the US for later years. As the stagnant industries, those with low productivity growth, grow in nominal shares, the aggregate US growth decelerates.

Therefore, we rely on the FSGR methodology by Nordhaus (2004) and Nordhaus (2008). Firstly, we find the annualised growth rate $a_{i,t,\tau}$ for all 61 industries in the US KLEMS dataset over period T. $a_{i,t,\tau}$ is constructed as described in section 4.3 using Formula 7, where τ is the length of the period. Nordhaus does not detail how he finds $a_{i,t,\tau}$. Therefore, we considered using the either long log growth (Eldridge et al., 2020) or the geometric means (Hartwig and Krämer, 2019). Because the long log growth rate is consistent with the US KLEMS data, we chose this over the replication technique proposed by Hartwig and Krämer (2019).

The next step is to construct the weights ($W_{i,Y}$) for 'fixed years' (Y). We chose the chosen fixed years to be the beginning and end of each period as Nordhaus (2008) did. Formula 8 shows how nominal shares of output $W_{i,Y}$. Here $X_{j,T}$ is the nominal gross output of industry j (or i) and $B_{j,T}$ is the nominal intermediary input of industry j (or i).

$$W_{i,t,Y} = \frac{X_{i,t} - B_{i,t}}{\sum_{j=1}^{n} (X_{j,Y} - B_{j,Y})} \tag{8}$$



(a) Total Productivity Factor. Figure 6 from Nordhaus (2008).

(b) Labour Productivity. Figure 7 from Nordhaus (2008)

Figure 9: Fixed share growth rate for two measures of productivity for different base years and periods.

Using $a_{i,\tau}$ and $W_{i,Y}$, we find the aggregate labour productivity growth for each period and each fixed year (Y) as shown in Formula 9. For example, if we have four periods, and five fixed years, we find twenty FSGR's.

$$FSGR(Y) = \sum_{i=1}^{n} \hat{a}_{i,t,\tau} W_{i,t,Y} \tag{9}$$

Nordhaus reports the following results. Figures 9a and 9b shows the fixed shares growth rate for both TFP and labour productivity growth of the US economy over the period 1948-2001. Both figures are constructed similarly for different outputs. Each figure plots a histogram for four different periods. Each bar corresponds to one of five different weights (1948, 1959, 1973, 1989, 2001) for a given period. TFP drops from 1.27% with 1948 industry weights to 0.38% with 2001 industry weights. Therefore, rising shares of low growth industries, relative to high growth industries, reduce the US economy's aggregate growth.

Nordhaus (2008) creates a summary statistic to compare the linear difference of shift of composition of output. He subtracts the productivity growth of two base years ($Y_{t2} - Y_{t1}$) for one period and divides that number by the length of the period (τ). We call this the *Growth Disease effect*, and it allows for comparison for different period lengths. Based on his results, he concludes that the changing composition of the US economy over the 1948-2001 period reduced the annual productivity growth by 64 basis points per year. Thus the Growth Disease effect, is slightly more than 1 basis points per year: 64 basis points / 53 years = 1.20 basis points per year.

4.4.1 Periodization

The Nordhaus (2008) paper analysed the growth disease over 1948 - 2001. He divided the data set based on two criteria according to (Nordhaus, 2004). The periods are of approximately equal length and start and end at the peak of economic cycles. The fixed weights are based on the nominal output shares of industries at these peak years. He arrives at four samples 1948–1959, 1959–1973, 1973–1989, and 1989–2001. The weights years are subsequently 1948, 1959, 1973, 1989, 2001.

The US KLEMS data set spans 1963 until 2016. The period 1948-1962 is therefore excluded from the analysis. The US KLEMS data adds 15 more years, but introduces the challenge of choosing periods that are both equal in length and from peak to peak. Table 8 shows the periods in the US KLEMS set when the US economy had negative business cycles and their characteristics.

Table 8: Economic downturns between 1960 until 2020 according to NBER (2021).

Period	**Time since previous downturn**
Apr 1960 - Feb 1961	2 years
Dec 1969 - Nov 1970	8 years 10 months
Nov 1973 - Mar 1975	3 years
Jan 1980 - Jul 1980	4 years 10 months
Jul 1981 - Nov 1982	1 year
Jul 1990 - Mar 1991	7 years 8 months
Mar 2001 - Nov 2001	10 years
Dec 2007 - Jun 2009	6 years 1 month
Feb 2020 - Apr 2020	10 years 8 months

For example, The Great Recession of 2007/08, significantly impacted industries such as construction and finance. If we chose 2007 as a fixed year, it would produce biased results right after a big downturn. It is biased in the sense that some industries, such as construction, have smaller nominal value-added output shares. Ideally, we look at the steady-state of the economy (which does not exist). The characteristic of the last ten years in the US KLEMS data set, is that 2007 shows the most significant GDP decline. However, 2007 makes it hard to make statistically coherent breaks. The economic repercussion has been severe, even in the years after the recession. Most crucially, it affects the fixed weights. If the number of years between fixed weights is small, it is likely more affected by the shocks in 2001 and 2007, than structural change (Nordhaus, 2004).

Thus we arrive at a periodization, that extends Nordhaus (2008): 1973-1989, 1989-2001, 2001-2016, with fixed weights 1973, 1989, 2001, 2016. Just like Nordhaus, the fixed weights are based on the start and end dates of the periodizations. For completeness, we add the period 1963-1973 and weight 1963 even though it is not a business cycle peak. As a robustness check, test for an additional periodization. In this periodization, the average business cycle is shorter than the *extended* periodization. We choose: 1973-1979, 1979-1989,1989-2001, 2001-2007, 2007-2016. Here each period is six to eleven years. Let this be called 'Robustness short'. This periodization can be affected by the shocks mentioned above.

4.5 Correlation Analysis of Productivity Growth and Technological Potential

4.5.1 Ordinary Least Squares Regression

To estimate the predictive power of IT potential, we conduct a cross-industry regression using an Ordinary Least Squares (OLS) model. The model is of the form $y = X\beta + \epsilon$. Here y is the dependent variable, X are the independent variables. β is a k x 1 vector of unknown parameters and ϵ is a n x 1 vector of unobserved disturbances. We estimate β's with $b = (X'X)^{-1}X'y$, such that it minimises the sum of squares of the residuals. To do a Least squares estimation, we take the following three steps.

Firstly, the **choice of the variables**. Here we regard the RTI metric (RTI_i), as discussed in section 3.2.2, as the assessment of expectation of IT automation potential. The variable is inadequate for a time-series test because it is constant over time for industries. Therefore, we argue to use growth of investments into IT and software capital, defined as $gITK$, to exploit the potential and carry it into practice. We assume that technological potential drives IT investments, so we use interaction term to capture this. The chosen dependent variable is the annualised growth of labour productivity $gLP_{i,t}$ using the long log difference of five years. The number five is chosen because we assume that the rewards should be measurable in a relatively short period for investments to make sense.

Secondly, we **collect the data**. As described in chapter 3, we use variables of 2 of the US KLEMS data set to find dependent variables, the annualised labour productivity with and explanatory variable $gITK$. gLP_{it} and $gITK_{it}$ are both defined as long differences in the log of the respective variable: $gLP_{i,t} = \ln\left(\frac{LP_{it}}{LP_{i,t-\tau}}\right)/\tau$ and $gITK_{i,t} = \ln\left(\frac{lITK_{i,t}}{LP_{i,t-\tau}}\right)/\tau$, where τ is the length of the time period (the default is $\tau = 5$). For the assessment of the expected of IT potential we use the aggregated values of RTI, as described in section 3.2.2. Here $LP_{i,t}$ is equal to $a_{i,t,1}$. Table 9 shows an overview of variables in the regression.

The regression tests the following hypothesis: Industries that display high automation potential and make the necessary investments display high labour productivity growth. We specify a model with interaction terms to test the hypothesis:

Table 9: Variables overview for regression.

Symbol	Description	Calculation
$LP_{i,t}$	Annualised labour productivity in year t	$\ln(lA_{i,t})$
$LP_{i,t-\tau}$	Annualised labour productivity in year $t-\tau$	$\ln(lA_{i,t})$
RTI	Industrial-level Routine Task Intensity	See section 3.2.2
$lITK$	Level of sum investment in IT and Software capital	See section 4.5.2
gK	Growth of sum investment in IT and Software capital	Formula 15
$gITK$	IT growth capital	See section 4.5.2
$RTI \cdot gITK$	Interaction term of RTI and $gITK$	$RTI \cdot gITK$
τ	length of time period	For regression equal to 5

$$gLP_{i,t} = \beta_0 + \beta_1 \cdot RTI_i + \beta_2 \cdot gITK_{i,t} + \beta_3 \cdot RTI_i \cdot gITK_{i,t} + u_{i,t} \tag{10}$$

Thirdly, we **compute the estimate** based on the assumptions. To compute the multiple regression, we briefly discuss the statistical properties. Some do not hold, and this means we need to adjust the model. The seven assumptions, according to Heij et al. (2004), of OLS are:

1. Fixed regressors
2. Random disturbances (ϵ), with a zero mean
3. Homoskedascity
4. No Correlation
5. Constant Parameters
6. The data generated processes is a linear model
7. The disturbances ϵ are jointly normally distributed

The model violates assumptions 3 and 4 of an OLS model, such that we need to adjust the model. This model shows auto-correlation such that we have two challenges:

- The long log difference introduces at correlation of adjacent years.
- The RTI variable is constant over time, such that we observe clustering. Clusters exist because RTI is repeatedly observed.

In Python we cannot control for both [4]. Therefore we consider using Newey-West standard errors to control for serial correlation of growth rates or Clustered Standard Errors for constant RTI scores.

Serial correlation occurs when there is a relationship between consecutive residuals, common for time-series regression. The annualised long log growth rates introduce serial and auto-correlation. The growth rates overlap because they are constructed with equal values. Newey-West standard errors use weighting kernels, known as lags, to adjust for heteroskedasticity and auto-correlation. For more information see Heij et al. (2004).

Moreover, we consider clustering over industries because RTI is constant over time. For each year of industry i, RTI_i is equal with 100 % correlation. We have 54 observations that are equal for 61 industries in the case of RTI. On the opposite we have 54 observations with overlapping averages, however, the correlation between them is smaller due to the rolling window of five years. So there is a higher correlation for two adjacent years (4 out of 5 values are the same). Going ahead five years ahead in time for the same industry, these observations do not overlap anymore. Therefore we argue to use clustered standard errors [5].

4.5.2 Explanatory variables

The US KLEMS data set provides nominal and quantity indices of IT and Software for 61 industries. For the analysis, we use those, using the following equations provided by Eldridge et al. (2020) who follow Jorgenson et al. (2006), to construct the growth rate of the combined capital types for each industry i at year t. We use the variables of the US KLEMS data set as shown in Table 2 on page 18.

Firstly, we find the share of Software (sS) using the total nominal invested capital in both IT (nIT) and Software (nS) in year t. For IT we to calculate the share of IT. This is show in Formulas 11 and 12.

$$sS_{i,t} = \frac{nS_{i,t}}{nS_{i,t} + nIT_{i,t}} \tag{11}$$

$$sIT_{i,t} = \frac{nIT_i}{nS_{i,t} + nIT_{i,t}} \tag{12}$$

Next, we find the respective growth rates of Software and IT using the quantity indexes for each industry i in year t as shown in Formulas 13 and 14.

$$gS_{i,t} = \ln(qSi,t) - \ln(qSi,t-1) \tag{13}$$

[4] See documentation: `https://www.vincentgregoire.com/standard-errors-in-python/`

[5] We cluster industries in Python3, see "OLS Coefficients and Standard Errors Clustered by Firm or Year "`https://www.vincentgregoire.com/standard-errors-in-python/`

$$gIT_{i,t} = \ln(qIT_{i,t}) - \ln(qIT_{i,t-1}) \tag{14}$$

Then, find the growth rate of IT capital, thus the sum of Software and IT, with Formula 15. Using Algorithm 2, in Appendix A.2, we use gK to find the level of ITK capital ($lITK$). Then by dividing by the shifted, $\tau = 5$, annualised labour productivity growth ($LP_{i,t-\tau}$), we find the $gITK$ dependent variable of the OLS estimation.

$$gK_{i,t} = sS_{i,t} \cdot gS_{i,t} + sIT_{i,t} \cdot gIT_{i,t} \tag{15}$$

4.5.3 Correction of the model

Furthermore, there are a few adjustments made to the model to ensure interpretation and correctness. Firstly, RTI is centred by standardising all 61 values. To standardise a variable is to subtract the mean and dived by the standard deviation. After the variable is centred, β_2 is the effect of $gITK_{i,t}$ on $gLP_{i,t}$ for the industry that has "average" RTI_i. If an industry has an average RTI score, then the model reduces to:

$$gLP_{i,t} = \beta_0 + \beta_2 \cdot gITK_{i,t} \tag{16}$$

Similarly, we centre $gITK_{i,t}$ around the mean, by subtracting it. We do not standardise because this is a growth rate over time, whereas for RTI_i is an industry score. If an industry has an average $gITK$ score, then the model reduces to:

$$gLP_{i,t} = \beta_0 + \beta_1 \cdot RTI_i \tag{17}$$

When an industry has an average RTI_i score and average $gITK_i, t$, the model becomes:

$$gLP_{i,t} = \beta_0 \tag{18}$$

4.5.4 Periodization

In section 4.4.1, we discussed the considerations of different periods to analyse the growth disease of the US economy. In the RTI regression, these conditions still hold, such that we study the period 1989 until 2016. In the literature review we discussed that labour productivity growth was high over the period 1994-2004. However, we prefer to analyse the period 1989-2001 over 2002-2016. This period is consistent with the Fixed Shares Growth Rate analysis.

4.6 Correlation Analysis of IT and ML potential

Finally, we investigate industries that show the highest potential for ML. We use the aggregated data described in section 3.3.1. Furthermore, we analyse if the expectation of ML potential is different from IT. In section 3.2.1 and 3.3.1, we discussed the measures are based on the RBTC hypothesis, such that ”routine” tasks can be automated. In the assessment of ML, some type ”non-routine” task can be automated. Therefore we test if the assessment of expectation of ML is correlated with RTI. We analyse the correlation relationship between the SML and RTI metric as shown in equation 19. Where SML_i and RTI_i are the technological potential scores at the industry-level for industry i. We also introduce a constant β_0 and an error term u_t. Furthermore, we assume all seven assumptions of OLS hold.

$$SML_i = \beta_0 + \beta_1 \cdot RTI_i + u_t \tag{19}$$

5 Results

This chapter discusses the results to answer the three research questions. The chapter is outlined as follows:

Firstly, in section 5.1 we analyse Baumol's model of unbalanced growth of industries for the US over the period 1963-2016. We test if the stagnant industries show increasing nominal output shares and if these are concentrated in service-providing industries. We then analyse if the rising output of low productivity growth industries negatively affected the labour productivity growth in the US, using the methodology of the Nordhaus (2008) paper.

Secondly, in section 5.2 we test the explanatory power of the IT potential metric RTI. We use the industry-level values, according to the data transformation of chapter 3.2.2. This allows us to test if industry productivity growth was higher in industries where the automation potential by computers was also higher.

Thirdly, in section 5.3, we analyse the expectation of ML-enabled technology. We investigate in what industries ML potential is concentrated and if the expectation of ML potential is different from the IT potential.

5.1 Is the Growth Disease effect still present in the US economy?

In this section, we take the following steps:

- Validate the structural shift of the US economy towards more service-providing industries using the US KLEMS data set.
- Reproduction and extension of test 6 of Nordhaus (2008) analysis, the Fixed Shares Growth Rate (FSGR) of labour productivity growth.
- Perform a robustness check of the results obtained in the previous step. This step is to validate the results for different base years and periods.

5.1.1 From goods-producing to service-providing economy

In "Macroeconomics of Unbalanced Growth" (1967), Baumol makes the assumption that most of the economy can be grouped into two groups. One is known as *progressive*, where technological innovation, capital accumulation and economies of scales create substantially more output while reducing labour input. As discussed in the Literature Review, these industries are typically goods-producing because human labour is not part of the product. Second is the *stagnant* industry, where the nature of the activity makes it difficult to use technological progress to reduce human labour. By expectation of Baumol's model of unbalanced growth, it is categorised as a service-providing industry.

By the definition of the NAICS classification, one can divide the economy into two types of industries: goods-producing and service-providing. These consist of eight aggregated industries called 'super-sectors'. In the goods-producing industries, we have "Agriculture, Forestry, Fishing, Hunting, Mining", Construction and Manufacturing. By the assumptions of the Baumol, we expect these goods-producing sectors to have declining nominal shares and growth rates above the aggregate productivity growth of the US. In the service-producing industries, we have five super-sectors: Trade, Transportation, Warehousing, and Utilities, Information, "Finance, Insurance, Rental and Leasing" (FIRL), and "Other Services". The last one encompasses business services, education, health care, and leisure. Similarly, by Baumol's model, we expect these sectors to show rising nominal output shares and lower than aggregate productivity growth.

The shift of nominal output shares of goods-producing industries to service-providing is also known as tetriazation. In the US, tetriazation did evidently occur, as shown in figure 10. The NAICS defined goods-producing industries nominal output shares declined by nearly half from 43.7 % to 22.7 % . This observation is coherent with the literature (Schettkat and Yocarini, 2006). A complete overview of the shift of nominal output shares for all Super Sectors is shown in figure 16 in appendix D.

Figure 10: Nominal Value Added shares of the US economy Super sectors. The left pie chart shows period 1947 - 1963 and the right pie chart shows shares for period 2007-2016

We further investigate how the assumptions of the model of Unbalanced growth of industries hold up empirically. Figure 11 shows the the 31 service-providing industries according to the NAICS classification. We expect, according to Baumol's model, for all industries to have below the industry average (1.78%) annual labour productivity growth rates and all to have a rising share of nominal output over the period 1963-2016. We find that 18 out of 31 industries fit this assumption. The remaining 13 industries also show above-average annual productivity growth rates or declining shares. The above-average annual productivity growth rates is expected, as Oulton (2001) argued not all service industries are stagnant. Especially industries 29, 34, 36,37,38, 42,43, and 56 show progressive growth with rising shares of growth.

Consider industry 56, 'Social assistance', which is a labour-intensive industry and is inconsistent with the argument of Baumol. However, we argue that technology did affect the industry substantially because it affected the US demographics and social norms. The average life expectancy in the US has increased from 70 years old in 1960 to 79 years old in 2015 (Vollrath, 2020). The technological progress of medicine means that people today are getting older, and society needs facilities such as elder care. Therefore technological progress increased demand for elder care, even though the product bought is the attention and care of the nurses. Furthermore, research by Bailey (2010) shows the significant effects of the contraceptive pill on the labour market. The pill gave women the freedom to pursue careers. Gordon (2016) argues that before that, without technologies such as the washing machine, taking care of the household required a full workweek. Because technologies freed up time and cultural norms changed, women entered the workforce. With both parents at work, it implies that the 'child care' industry has increasingly grown in size and productivity. Therefore, we argue that technological advancements indirectly affected the growth of the 'social assistance' industry.

indnum	Industry Description	LP growth	Share change
27	Wholesale trade	3.52%	-7.71%
28	Retail trade	2.12%	-23.19%
29	Air transportation	3.21%	98.31%
30	Rail transportation	2.76%	-81.73%
31	Water transportation	2.67%	-38.48%
32	Truck transportation	1.28%	-20.42%
33	Transit and ground passenger transportation	-0.47%	-41.58%
34	Pipeline transportation	3.92%	22.96%
35	Other transportation and support activities	-0.10%	-10.17%
36	Warehousing and storage	2.44%	33.49%
37	Publishing industries, except internet (includes software)	3.43%	48.27%
38	Motion picture and sound recording industries	2.10%	37.45%
39	Broadcasting and telecommunications	4.92%	-0.07%
40	Data processing, internet publishing, and other information services	1.07%	316.28%
41	Federal Reserve banks, credit intermediation, and related activities	1.72%	68.82%
42	Securities, commodity contracts, and investments	3.87%	443.53%
43	Insurance carriers and related activities	2.15%	100.64%
44	Funds, trusts, and other financial vehicles	-4.87%	709.96%
45	Real estate	0.46%	22.04%
46	Rental and leasing services and lessors of intangible assets	1.65%	33.13%
47	Legal services	-0.60%	106.40%
48	Computer systems design and related services	0.11%	886.82%
49	Miscellaneous professional, scientific, and technical services	1.56%	210.71%
50	Management of companies and enterprises	1.50%	31.68%
51	Administrative and support services	1.17%	308.04%
52	Waste management and remediation services	0.18%	18.56%
53	Educational services	0.93%	111.97%
54	Ambulatory health care services	-0.49%	206.89%
55	Hospitals and Nursing and residential care	0.35%	184.00%
56	Social assistance	2.10%	371.54%
57	Performing arts, spectator sports, museums, and related activities	1.68%	126.91%
58	Amusements, gambling, and recreation industries	0.46%	16.16%
59	Accommodation	1.74%	60.83%
60	Food services and drinking places	0.13%	33.61%
61	Other services, except government	-0.29%	-22.80%

Figure 11: Service-providing industries according to NAICS.

5.1.2 Testing the Growth Disease with US KLEMS data

Figure 12 shows the FSGR plot over 1963-2016 using the fixed shares of years: 1963, 1973, 1989, 2001, 2016. Given that we use the methodology of Nordhaus (2008) and extend his timeline, it is crucial to verify the correctness and limitations of our results. Here periods 1973-1989 and 1989-2001 overlap with the Nordhaus (2008) analysis. There are two periods to compare with the fixed shares of 1973, 1989 and 2001 with Nordhaus results to verify our results. In the 1973-1989 period, the results are equal up to the one decimal point accuracy. However, the growth rates in 1989-2001 are roughly 50 basis points higher than with Nordhaus. However, the relative change between the fixed shares for the second period is roughly equal to the results presented here. The variation can be due to three reasons. Firstly, Nordhaus (2008) uses a BEA dataset for 67 industries, whereas the thesis uses the US KLEMS data for 61 industries. Secondly, we excluded poorly measured industries (government), whereas Nordhaus is vague if he includes them or not. Thirdly, Nordhaus did not specify the technique used to calculate $a_{i,t,\tau}$. Our method was consistent with the methodology of Eldridge et al. (2020). Our calculation method can therefore be different from the Nordhaus (2008) analysis and explain some of the differences. Because we used a different data set than Nordhaus and the results are not identical, we cannot make a direct comparison to the Growth Disease effect of the Nordhaus (2008) analysis.

Table 10: Fixed Shares growth rate of labour productivity growth for different base years and periods for the 'extension' periodization.

	1963-1973	**1973-1989**	**1989-2001**	**2001-2016**	**1963-2016**
1963	2.23	1.49	2.35	1.71	1.89
1973	2.24	1.56	2.33	1.70	1.90
1989	2.00	1.45	2.25	1.61	1.78
2001	1.81	1.40	2.23	1.48	1.69
2016	1.73	1.29	2.09	1.48	1.61

Notes: The results of the FSGR analysis, according to the methodology of test 6 of Nordhaus (2008). Values are reported in percentages. The periodization is roughly equal, with minimally 10 to maximally 16 years. The annualised labour productivity growth rates over a period (column) for 61 industries are multiplied by the weights (nominal output shares) of the industries for five fixed years. The last column is the annualised growth rates over the whole period (53 years) multiplied with weights of five fixed years.

Consider the final column in table 10. This shows the annualised labour productivity growth rate over the complete period (not shown in the figure). If we use fixed shares 1963, the average labour productivity growth would be 1.89 %. Using the fixed shares of 2016, this would be reduced to 1.61 %, equivalent to a 28 basis points drop per year over 53 years is a 0.51 basis points decline.

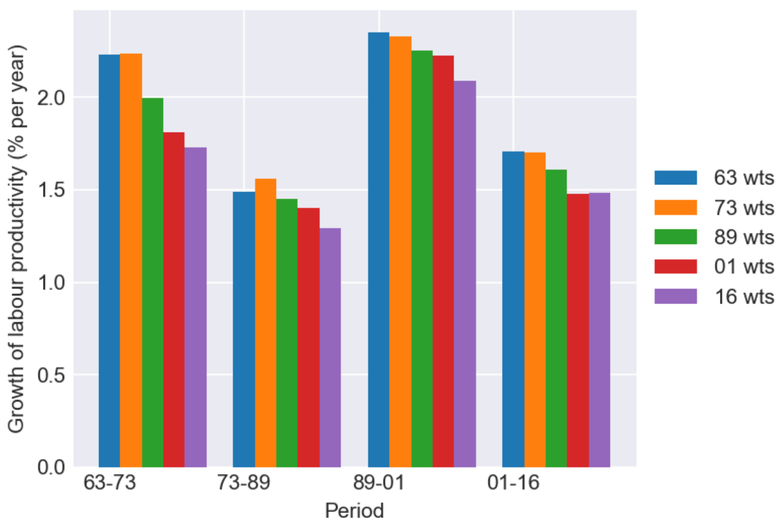


Figure 12: Fixed Shares Growth Rates analysis of labour productivity growth (% per year) extended with period 2001-2016.

We conclude that Growth Disease still persists in the US economy.

However, in the period 2001-2016 we find no change between the fixed years 2001 and 2016 as both are equal to 1.48 %. The Growth Disease effect is equal to zero for the extended period. We find small differences between the fixed weights of 1963 and 1973. That is 2.23 % compared to 2.24 % in period 1963-1973. One might conclude that the change for fixed weight in the earliest period is so small, like in the latest period for the respective weights, that cannot conclude the Growth Disease effect is declining. However, in the Nordhaus (2008) analysis, there was a significant difference for 1959-1973 with weights of 1959 and 1973. We discussed that our data set is different and the first period are different. Therefore we further analyse the dynamics of the last period with weights 2001 and 2016 to find the Growth Disease effect in the new millennium. Furthermore, Figure 16 in Appendix D on page 71 shows tetriazation from 1995-2000 to 2007-2016 continued towards service-providing industries. We conclude that US aggregate productivity growth is unaffected by the structural shift towards service-providing industries.

5.1.3 Robustness

In Methodology 4.4.1, we discussed the challenges of choosing a period. To summarise, we use the Nordhaus periodisation with extension, but due to the new data perform a robustness check (robustness short) to verify the effect of the growth rates in the new millennium.

The 'Robustness Short' results are shown in appendix F, in figure 18 and table 15. In figure 18, period 1979-1989 and 1989-2000 clearly show a declining output growth. However, for the later periods, the effect of the weights on output growth is significantly smaller, showing a flat pattern.

We observe, over the whole period 1973-2016, the FSGR declines from 1.82 % for fixed year 1973 to 1.58 % for fixed year 2016. This shows that the composition of the output of industries lowered the labour productivity growth by 24 basis points per year over the period 1973-2016 period. Put differently, the changing shares lowered the productivity growth by 0.55 basis points per year.

We again compare the fixed weights of nominal output shares for the years 2001 and 2016 for period 2001-2007 and 2007-2016. In the first period, the FSGR increases from 2.25 % to 2.26%, and in the second period, FSGR increases from 0.96% to 0.97%. This is consistent with the observations of the previous section. The increase is further evidence that the Growth Disease effect has run its course since 2001.

5.1.4 Conclusions

In this section, we have taken three steps to analyse how US labour productivity growth by the shift of goods-producing to service-providing industries. Firstly, we found that the US economy has shifted further from a goods-producing to a service-providing economy. However, within the service-providing industries 8 out of 31 are shown above-average annual labour productivity growth and rising nominal shares over the period 1963-2016. We focused on the 'social assistance' industry to show that technology has an indirect effect on industries and can create labour productivity growth, even if the industry is very labour-intensive and difficult to automate.

In step two, we showed that over the period 1963-2016, the US annualised labour productivity growth was decelerated by the sectoral shift towards low productivity industries. In all four periods, the labour productivity growth was lower for the later industry composition. However, we found that in the last period, 2001-2016, that the US industry composition of 2001 to 2016 was unaffected by the continued tetriazation between 2001 and 2016.

In step three, we did a robustness check to verify if the results of step two. We found when comparing the weights of 2001 and 2016 for the periods 2001-2007 and 2007-2016 that the annualised labour productivity growth was higher for the latest fixed years.

5.2 Did the expectation of IT potential predict productivity growth in the US over the period 1989-2016?

In this section, we test if the selected IT potential metric predicted past productivity performance. In that way, we test if high RTI_i corresponds to high labour productivity growth, such that the expectation corresponds to Baumol's *progressive* sectors. On the other hand, low RTI_i corresponds to constant productivity growth, such that it is a *stagant* sector. Table 14, in appendix C, shows the 61 industries from the US KLEMS data sets with the corresponding RTI industry values. Except for industries 21 and 44, all industries are represented by over 90 % of the occupations. In other words, the matching of occupational-level RTI to the OES Matrix data set was successful enough to have a high corresponds of the industry. The median matching success of industries is 98.1 %. This uses two strong assumptions. Firstly, missing occupations are equal to the mean of occupational scores for (higher-level) broad categories in the data set. The missing percentages represent occupations that belong to higher-level groups without an RTI score. Secondly, we assume that the industry composition of occupations is constant. This is a very strong assumption, considering the Fixed Shares Analysis studies the change of industry structure, and we now assume that no change occurred for 27 years within industries.

5.2.1 Correlation analysis of past productivity growth and IT potential

Table 11 shows the results for the regression (as described in chapter 4). The table shows three periods, where the first is the total of models two and three. This periodisation corresponds to the business peak cycles between 1989 until 2001 and 2002 and 2016 (the end of the data set). The dependent variable $gLP_{i,t}$ is the annualised growth rate of labour productivity for industry i at time t. We have a constant that is significant for all three models and three explanatory variables:

- RTI : The Routine Task Intensity for industry i.
- $gITK$: the IT capital stock of software and IT for industry i.
- $RTIxgITK$: The interaction term of the previous two.

Firstly, model 1 shows no significance in any explanatory variables, although all have positive coefficients. Due to a lack of statistical explanatory power, we conclude that the expectation of computers, by AD-13's formulation, fails to predict sustained long-run productivity growth. Furthermore, the investment into IT capital also fails to create statistically significant growth. Therefore the assessment of the expectation of IT technology did not predict sustained long-term labour productivity growth for industries.

Table 11: Regression results of three periods with dependent Variable: gLP. Between brackets is the reported standard errors.

Variable	**Model 1** 1989 - 2016	**Model 2** 1989-2001	**Model 3** 2002 - 2016
C	0.0192***	0.0181***	0.0203***
	(0.001)	(0.002)	(0.001)
RTI	0.0008	0.0006	-0.0005
	(0.001)	(0.002)	(0.001)
gITK	0.0089	0.0298***	-0.0187
	(0.007)	(0.010)	(0.012)
RTI x gITK	0.0070	0.0239**	-0.0073
	(0.006)	0.009	(0.005)
N	1708	793	915
R^2	0.003	0.034	0.009

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Secondly, Model 2 is over the first half of period model 1, that is 1989-2001. This period is between the peak cycles of 1990 and the 2001 dot-com recession. This model has statistical significance for $gITK$ and the interaction term, at 1% and 5%, respectively. The period is characterised by the acceleration of productivity growth in several sectors such as wholesale trade, retail trade and the finance industry (Remes et al., 2018). However, RTI_i is statistically insignificant with a very small positive coefficient.

Figure 13, on page 49, shows the relation between gLP and $gITK$ for different values of RTI, according to the coefficient results of model 2. We find for $RTI = 0$, the investment in IT and Software does not create any additional labour productivity growth in an industry. If $RTI = 1$, $gITK$ is increasing and positive for values higher than $gITK = -45\%$. If $RTI = -1$, we see an almost flat line that is increasing. In this setup, $gITK$ to be the better predictor of productivity than aggregate RTI value. The results of $gITK$ are consistent with the observations made by Jorgenson et al. (2010). He argued industries that show high investment in IT equipment and software tended to report higher productivity and faster growth rates than low IT and software investment industries.

Model 3, again, holds no predictive power except for the constant. Furthermore, all explanatory variables show negative coefficients. We, therefore, conclude using the US KLEMS macro variables and the aggregated RTI scores using the 2019 OES Matrix data, that the expectation of IT holds no predictive performance of past productivity growth over the 1989-2016 period.

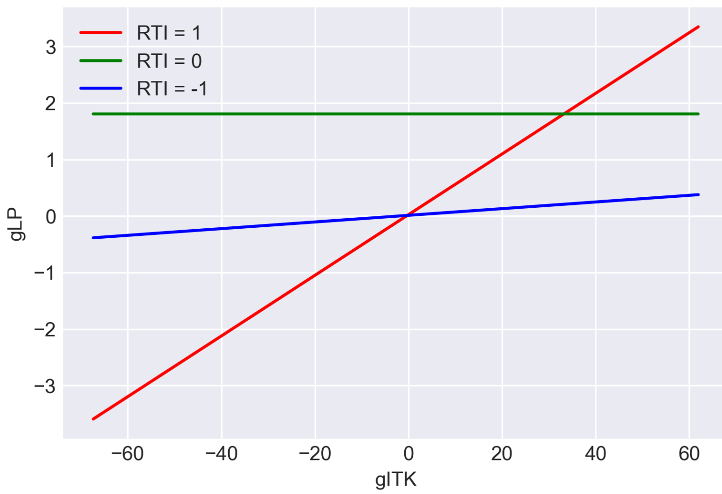


Figure 13: Coefficient effect of $gTIK$ for different values of RTI on dependent variable gLP. All values are reported in percentages.

5.2.2 Conclusions

To answer research question two: Did the expectation of IT potential predict productivity growth in the US over the period 1989-2016? No, our measure of IT potential, or the industry-level aggregated Routine Task Intensity, performed poorly.

The poor predictive performance can be explained by poor data quality is poor. Firstly, we made very strong assumptions of constant occupation structure within industries. If the BLS shared the occupation structure of the US over time, the RTI would become more variable over time. Secondly, our data set uses macro variables that are relatively poor measures. Recent literature, such as Raj and Seamans (2018) argues for the need for firm-level data. The paper argues it would allow the researcher to investigate under what conditions ML is a substitute for labour. Thirdly, in the literature review, we explained that service industries are often poorly measured (Triplett and Bosworth, 2004).

However, if these results are correct, this show that the expected potential of IT never materialised, and that we expect too much of IT technologies. However, during the COVID pandemic, applications of IT quickly diffused, such as remote work through video conferencing software or online education at universities. These applications were technologically feasible before the pandemic, but it took economic incentive, organisational change and social acceptance to happen. These factors are not part of the part of the RTI score, but are well-documented drivers of productivity growth (Dieppe, 2020; Brynjolfsson et al., 2017).

Furthermore, that applications are technologically feasible does not mean that it will happen. It takes ingenuity and deep understanding to use technology such that it creates productivity growth (Brynjolfsson et al., 2017). In the literature review, we discussed the example of the potential of nuclear energy that never materialised. Further research could investigate if the tasks, as described by O*NET 1977, were automated using IT technology. This tests if technological potential was achieved.

5.3 Is the expectation of automation of ML concentrated in historically stagnant industries?

This section answers the third research question and relates the answers to the first and second research questions. The following steps are taken:

- Analyse the distribution of the expectation of ML potential in industries.
- Investigate the correlation between the industry-level RTI and SML.

We investigate the SML_i scores for 61 industries of the US KLEMS data set. After the data matching of section 3.3.1, we find two industries (21,44) that have an employment representation below 90 %. This is like RTI satisfactory for the analysis. However, when we consider the variation of aggregate SML scores, it is considerably lower than the variation of the tasks. This was expected since occupation also showed low variation. Therefore, the results of aggregation suggest that the data should not be trusted at face value.

5.3.1 Historically stagnant industries

Table 12 show the distribution of industries for historic growth rates and the industry-level SML. The values reported are the number of industries with the nominal output share of the combined industries in 2016. The average SML_i is equal to 3.48. We find 26 industries with historically above-average annualised labour productivity growth rates (1.78%) over the period 1963-2016. We expect 14 industries, which a combined 28% shares of nominal output in 2016, to show technologically progressive growth. Moreover, the most ML potential is expected in the stagnant industries with 16 industries and 36 % total nominal output shares in 2016. Notice that 64 % of the nominal output shares of the industries show historically below average annualised labour productivity growth rates. Similarly, 64 % of the nominal output shares of the industries shows higher than average expectation of ML potential. Thus, above-average SML potential is expected to occur in a significantly larger part of the US economy than the below-average SML potential industries.

We focus on industries with a lower than average labour productivity growth rate and above-average SML_i in the lower left quadrant. Figure 14 shows the 16 industries, of which 4 industries are goods-producing industries and 12 are service-providing industries. All service-providing industries show an increased change of share over the period 1963-2016. This result shows that the potential of ML learning is concentrated in historically stagnating industries and are 36% of the nominal output shares of US output. Even industry 57, which includes violinists, is expected to benefit from the technological advancements in ML. This is an important result because this goes against the model of unbalanced growth of industries. Because in this model, historically stagnant industries are expected to continue to record relatively low productivity growth because the work is difficult to automate. Therefore, we also test the correlation between RTI and SML to determine if the same industries' technological potential is expected. If the potential of ML-enabled technology is realised, as these results show, then the model of unbalanced growth of industries has run its course.

Table 12: Distribution of historically progressive and stagnant industries versus value of SML.

	$SML_i > 3.48$	$SML_i < 3.48$	Total
Progressive	14 (28%)	12 (8%)	26 (36%)
Stagnant	16 (36%)	19 (28%)	35 (64%)
Total	30 (64%)	31 (36%)	61 (100%)

Notes: Progressive industries have a annual labour productivity growth rate over the period 1963-2016 above 1.78%, whereas stagnant industries have a annual labour productivity growth rate over the period 1963-2016 below 1.78%.

indnum	Industry Description	LP growth	Share change	SML	Share in 2016
6	Utilities	0.65%	-31.76%	3.49	1.77%
11	Fabricated metal products	1.27%	-58.59%	3.49	0.91%
16	Other transportation equipment	0.88%	-60.20%	3.48	0.80%
23	Printing and related support activities	1.46%	-62.22%	3.51	0.24%
40	Data processing, internet publishing, and other information services	1.07%	316.28%	3.54	0.75%
41	Federal Reserve banks, credit intermediation, and related activities	1.72%	68.82%	3.53	3.30%
44	Funds, trusts, and other financial vehicles	-4.87%	709.96%	3.54	0.30%
45	Real estate	0.46%	22.04%	3.53	14.02%
46	Rental and leasing services and lessors of intangible assets	1.65%	33.13%	3.53	1.26%
47	Legal services	-0.60%	106.40%	3.53	1.51%
48	Computer systems design and related services	0.11%	886.82%	3.52	1.72%
49	Miscellaneous professional, scientific, and technical services	1.56%	210.71%	3.52	4.94%
50	Management of companies and enterprises	1.50%	31.68%	3.53	2.21%
53	Educational services	0.93%	111.97%	3.49	1.27%
57	Performing arts, spectator sports, museums, and related activities	1.68%	126.91%	3.51	0.64%
58	Amusements, gambling, and recreation industries	0.46%	16.16%	3.49	0.54%

Figure 14: Industries with below average annual labour productivity growth rates (1.78%) over the period 1963-2016 and above average SML (3.48).

5.3.2 Correlation analysis of RTI and SML

We cannot predict if the expectation of SML_i accelerates growth, but we can compare it to RTI_i. In section 5.2 we concluded that our selected measure of IT potential was a poor predictor of labour productivity growth over the period 1989-2016. Figure 14 in Appendix C shows the SML and RTI values for the 61 industries of the US KLEMS data set. These values are used for the correlation analysis of SML and RTI, as discussed in section 4.6.

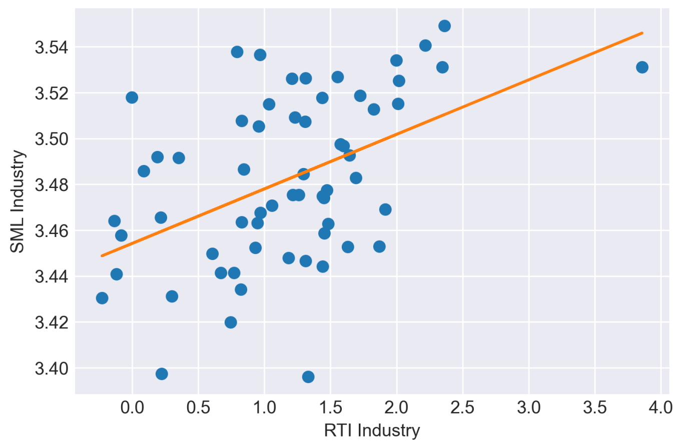


Figure 15: Scatterplot of 61 industries with SML and RTI scores.

$$SML_i = 3.454 + 0.023 \cdot RTI_i \tag{20}$$

The scatter plot in figure 15 provides the graphical relationship between SML_i and RTI_i. Each plotted point represents an industry with its respective SML and RTI value. The orange line is equal to the OLS regression with coefficients values as shown in equation 20. The relation between the two is positive and increasing. The correlation is low, and the positive relationship shows that industries with higher RTI scores will have higher SML scores. Notice that the outlier at (3.859, 3.531) is legal services. The correlation R^2 between the two variables for 61 industries is 0.22. This shows that RTI and SML are very different metrics. RTI is based on the likelihood that computer-enabled technology can substitute for routine work done based on task description from O*NET in 1977. SML measures the likelihood that ML-enabled technology can substitute human work for both routine and non-routine tasks in 2016. Furthermore, the two measures do not have the same results for measuring the 'routineness' of tasks because the survey are different despite being based on the same model, and the years of recording it are years apart. This shows that ML-enabled potential is expected to be different from IT-enabled potential.

5.3.3 Conclusions

To answer research question three: Is the expectation of automation of ML concentrated in historically stagnant industries? Yes, the higher potential for ML is concentrated in the majority share of the US (64 %). Here above-average potential for ML is concentrated in 36 % share of US nominal output is expected in historically stagnant industries. Furthermore, the expectation of ML potential is very different from the expectation of IT potential with only a 22 % correlation. Based on our data, ML potential affects different industries than the previous wave of technology (IT potential). Furthermore, the high concentration in stagnant industries means Baumol's model of unbalanced growth will be tested over the next few decades. The potential shows that growth can occur in previously hard-to-automate industries.

6 Conclusion

6.1 Main results

The third wave of automation led to disappointing productivity growth rates. This is known in the literature as the productivity paradox. Although it is indisputable that IT has changed our daily lives, we fail to see any acceleration of productivity growth. Rather the productivity growth has decelerated since the start of the third Industrial Revolution. Still, techno-optimists are hopeful that the fourth wave of automation can bring the US economy back to the historical growth rates of 2% and higher. Many argue ML is key to achieving this. This thesis analysed this claim, and asked: Does data support the expectation of acceleration of productivity growth through ML?

We considered four explanations for the productivity paradox. We chose to further investigate Baumol's model, because of the assumption that technological automation determines if an industry is stagnant or progressive. This allows for a direct test if ML technology is able to automate tasks within stagnant industries.

Our first question was: Is the Growth Disease effect still present in the US economy? This test is one of the six consequences of Baumol's model of unbalanced growth as identified by Nordhaus (2008). We relied on his methodology to test if the increasing shares of low growth industries reduced the aggregate US productivity growth. Our results show that the structural shift of the US economy reduced labour productivity growth by 28 basis points between 1963 until 2016. Thus higher productivity growth industries were a larger share of the US economy in 1963 than in 2016 as measured by the nominal output share. However, the aggregate US labour productivity growth showed a 0 basis point difference for the period 2001 to 2016. Although the US economy shifted further towards service-providing industries, as shown by Figure 16 in Appendix 16.

After we established the Growth Disease effect is still present, we investigated the assumption of technologically progressive and hard-to-automate stagnant industries. In chapter 3 'Data' we explained how we developed a methodology that aggregates occupational-level of existing assessments of IT and ML to industry-level. Prior research investigates the impact of IT and ML on occupations (Autor and Dorn, 2013; Brynjolfsson et al., 2018). However, none test the effect it has on industries productivity growth. That is, are the expectations of technological potential concentrated in the industries of high productivity growth industries.

The second question was: Did the expectation of IT potential predict productivity growth over the period 1989-2016? To answer this question, we used the Routine Task Intensity (RTI) of Autor and Dorn (2013). This scales all occupations in the data set as likelihood to automation by computers. We chose this metric as our data set for IT potential. RTI was aggregated to industry-level and used as explanatory variables in an Ordinary Least Squares regression. Over the period 1989-2016 we tested the explanatory power of RTI and IT capital growth for the dependent variable labour productivity growth. We found no statistical significance for RTI. Considering labour productivity is 'disappointing' while computers are everywhere, we argue this is a logical result. Furthermore, we found in the period 1989-2001 that IT capital growth was significant. This is consistent with the results of Jorgenson et al. (2010), who found industries with high IT investment significantly outperformed industries with low IT investments.

The third question was: Is the expectation of automation of ML concentrated in historically stagnant industries? We used the occupational data by Brynjolfsson et al. (2018) as a measure for ML potential. The paper created the 'Suitability to Machine Learning' (SML) metric to analyse the effect of ML on occupations. We found that ML potential is concentrated in historically stagnant industries. For 36% of the total nominal output share of 2016, industries with annualised labour productivity growth rates below average (1.78%) had the highest industry-level SML scores.

Furthermore, RTI and SML are both measures of technological potential. Therefore we investigate if the expectations of IT and ML are similar. We found that the industry-level SML has a low correlation (22%) with industry-level RTI. This result means the expectations of the technological potential of ML is very different from IT. The combination of these two results implies that the assumption of technologically stagnant industries has run its course. In Baumol's model, it is assumed that industries are stagnant because it is very difficult to automate tasks. However, these results show ML can automate these difficult tasks, showing high SML scores in, especially service-providing industries.

We conclude that the expectation of ML potential will affect different sectors than automation by IT. However, IT alone did not predict the productivity growth of industries. To turn potential into growth, firms must innovate and invest. Both measures of technological potential omit economic, organisational, legal, cultural and societal factors. If ML potential is achieved, the fundamental assumption of Baumol's model of unbalanced growth has run its course. We expect ML to turn a large share of the US economy from stagnant to progressive. However, it takes more than just computers and algorithms.

6.2 Policy Recommendations

Today we live in an age of paradox. Although recent productivity growth rates may appear disappointing, we have achieved enormous wealth in less than 250 years. The average workweek has decreased from over 70 hours in the 1800s to 40 hours today (Vollrath, 2020). One is more likely to die from obesity than starvation (Pinker, 2018). Furthermore, we can provide food, shelter, clothing and free entertainment (through YouTube) to most citizens in advanced economies. However, we cannot escape the fact that the cost of essential services, such as education and healthcare, are increasing dramatically.

Let us, therefore, consider two scenarios. In the first scenario, technology or a different driving factor creates sustained long-term productivity growth above the 2% threshold. Then we will be able to afford the ever-increasing essential services and help the less affluent members of our countries and the rest of the world. This is a continuation of the trend of the 20th century.

In the second scenario, productivity growth stops, and productivity remains equal. Here policymakers should be aware of the negative effects of the Cost- and Growth Disease. As long as technology fails to accelerate the productivity growth in the stagnant industries, which grow in relative size in the US economy, costs for essential services are expected to rise continually (Baumol, 2012). The thesis concludes that we can be hopeful about the future. However, we do not know how long it will take for the ML technology to fully diffuse such that they are recorded in the US productivity statistics. Until that happens, we have to assume scenario two and plan for increased costs in essential services. We argue that even though the costs of essential services are rising, we can afford them. Progressive industries will create goods and services at lower costs, such that our budget can pay for the services. Knowing the dynamics of the Growth Disease, we must protect the less affluent of society. Especially because the third Industrial Revolution lead to an increase in inequality and wage polarisation (Autor and Dorn, 2013). The jury is still out if ML will have the same negative effects (Brynjolfsson and Mitchell, 2017).

To achieve high productivity growth, we must make sure society is ready for ML technologies. That means the supporting environment should adapt quickly to the emergence of breakthrough technologies. Organisations will require new management techniques, workers need to be re-educated, and policy should incentivise firms to innovate. Finally, government officials also require training to make sure they plan ahead instead of reacting. When Facebook testified for congress in 2018, senators failed to comprehend what the then 14 years old company did (Stewart, 2018). This makes it hard for lawmakers to regulate. For the next wave of automation, we should all be ready.

6.3 Limitations

The aim of the thesis is to analyse future productivity growth. We relied on the expectations of technology to answer our main research question. The claim that ML can accelerate productivity growth is based on technological feasibility and disregards drivers of productivity growth such as physical capital and human. We only briefly discussed the importance of investments, but other literature show that it is essential for realising technological potential (Jorgenson et al., 2010; Brynjolfsson et al., 2017). Furthermore, we agree with the observations of Dieppe (2020) and Gordon (2016) about human labour. The post-war economy of the United States enjoyed a surge in educated workers (Vollrath, 2020). However, this trend reversed as the baby-boomer generation retires, and fertility rates are falling.

Furthermore, we disregarded the effect of supporting environments such as institutions. Dieppe (2020) argues these can impose regulations that incentivise firms to invest in acquiring technological innovation. But it can also create inefficient competition leading to market power abuse. Supporting environments such as policy can also reduce output for industries. Consider Industry 24 ' Petroleum and coal products', largely focused on fossil energies. With the US signing the Paris agreement, the US seeks to decrease carbon emissions to 50% by 2030 (Detrow, 2021). In that sense, if efficiency improves through technology but the output decreases, productivity can still decline. This also shows productivity growth should not be a mindless pursuit. If historically progressive industry 24 disappeared, US productivity growth would decline, but so would the emissions.

Moreover, for the analysis of technological potential, we made strong assumptions. For the aggregation of the occupational-level to industry-level RTI we assumed that employment share within industries did not change. This is strictly false because the composition of occupations changed within industries (Autor, 2015). Our solution is to aggregate occupation data that is transformed from 1990 to 2010. This 2010 occupation data is then aggregated by using the employment shares of the US in 2019. In a perfect scenario, we would like to aggregate the 1990 occupation data based on a US employment dataset from 1990, but this was not possible because such a data set does not exist publicly.

Finally, we assumed that all these jobs have overlapping tasks. Consider the crosswalk example of section 3.4. The complete crosswalk of occupation from Census 2000 to SOC 2010 is shown in Table 13 in Appendix 13. The Bureau of Labour Statistics regularly updates occupations classifications. This leads to occupations descriptions becoming more granular due to the changing of tasks within occupations and to better reflect the occupations in the US economy. Therefore, it is false to assume that the four granular occupations that stem from 'Computer scientists and system analysts' occupation have equal values for RTI.

6.4 Future Work

The US KLEMS by Eldridge et al. (2020), is a fantastic step towards a more harmonised data set for all industries. In chapter 3, we discussed using 61 industries of the second period (1963-2016) in the US KLEMS data set. The timeline can be expanded using the first period (1947-1963) in a follow-up paper. Furthermore, when the data set is updated, the analysis of the thesis could be expanded for the latest years until the COVID-19 recession. Thereby creating a good break as the data set then end at a business peak cycle.

This analysis used the value-added labour productivity growth rates to measure the effect of the Growth Disease and historical growth rates of industries. It is common in the literature to analyse productivity growth using the Total Factor Productivity (TFP), as discussed in section 4.1 'Measuring Productivity'. Furthermore, in section 4.4 we discussed that Nordhaus analysed the Growth Disease effect using both TFP and labour productivity. Because TFP is widely used in the literature, this thesis could be replicated using the TFP as a complement to the results of labour productivity presented in the thesis.

Furthermore, it warrants further research if upcoming economies such as China and Vietnam experience the Growth Disease. On the one hand, the declining manufacturing industry in the US is due to labour-saving automation. On the other hand, the Asian countries produce many of the articles due to globalisation. It warrants further research if these countries show a reversed Growth Disease effect, where the economy is growing due to a shift from agriculture to manufacturing. The analysis of Nordhaus started in 1948, when most of the US workers had already shifted from agriculture to goods-producing and service-providing industries. Using the newer data of upcoming economies, we can better investigate the Growth Disease effect.

Another point is that we based the industry averages on the employment composition of the US in 2019. This is constant over time, which is a gross oversimplification when considering that we tested for the shift of industries. Due to lack of availability of the data, this was the best considerable option. Consider if one would have OES Matrix data set for years $t \in 1989, ..., 2016$. Then one could construct the IT potential, RTI, with variation over time, such that RTI_i becomes $RTI_{i,t}$.

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Appendices

A Algorithms

All code for the thesis is written using Python 3.

A.1 Algorithm for Real Value Added

Algorithm 1: level of real value-added

Result: list of level real value-added values over 1963-2016 for industry i

Create an empty list $list_i$ for industry i, and store 100 as the first element.

for *t = 2009, .., 1963* **do**

  $y = y * e^{-gV_{i,t+1}}$

  append y to $list_i$

end

Reverse list, so the first value is the real value-added growth in 1963

for *t = 2010, .., 2016* **do**

  $y = y * e^{-gV_{i,t}}$

  append y to $list_i$

end

Return $list_i$ containing lV_i, t for $t \in \{1963, ..., 2016\}$

A.2 Algorithm for level of IT and Software investment

Algorithm 2: level of IT and Software investment

Result: list of $lITK$ values over 1963-2016 for industry i

Create an empty list $list_i$ for industry i, and store 100 as the first element.

for t = *2009, .., 1963* **do**

  $y = y * e^{-gK_{i,t+1}}$

  append y to $list_i$

end

Reverse list, so the first value is the real value-added growth in 1963

for t = *2010, .., 2016* **do**

  $y = y * e^{-gK_{i,t}}$

  append y to $list_i$

end

Return $list_i$ containing $lITK_i, t$ for $t \in \{1963, ..., 2016\}$

B Full table of RTI crosswalk

Due to the size of the table, it is broken up into two parts

Table 13: Crosswalk match for 'Computer scientists and system analysts' from Census 2000 to SOC 2010.

Census 2000	**Census 2000 Title**	**Census 2002**	**Census 2002 Title**	**SOC 2000 code**
100	Computer scientists and system analysts	1000	Computer scientists and system analysts	15-101
100	Computer scientists and system analysts	1000	Computer scientists and system analysts	15-105
100	Computer scientists and system analysts	1000	Computer scientists and system analysts	15-105
100	Computer scientists and system analysts	1000	Computer scientists and system analysts	15-109

SOC 2000 code	**SOC 2000 title**	**SOC 2010 code**	**SOC 2010 title**	**RTI**
15-101	Computer and Information Scientists, Research	15-1111	Computer and Information Research Scientists	-0.95
15-105	Computer Systems Analysts	15-1121	Computer Systems Analysts	-0.95
15-105	Computer Systems Analysts	15-1143	Computer Network Architects	-0.95
15-109	Computer Specialists, All Other	15-1199	Computer Occupations, All Other	-0.95

C Aggregation of industry for technology metrics

Table 14: Aggregation of the SML and RTI industry scores. To make sure the table fit on the page, the column names were shortenend. 'Ind.' is the industry number according to the BEA file. NAICS is the NAICS 2007 code. SML% and RTI % is the total conversion rate of occupations to industries. Finally SML_i and RTI_i are the respective technology potential metrics for a given industry.

Ind.	**Industry Description**	**NAICS**	**SML%**	SML_i	**RTI %**	RTI_i
1	Farms	111, 112	99.7	3.441	99.7	-0.12
2	Forestry, fishing, and related activities	113, 114, 115	96.833	3.397	96.833	0.222
3	Oil and gas extraction	211	98.0	3.463	98.0	0.946
4	Mining, except oil and gas	212	98.5	3.434	98.5	0.821
5	Support activities for mining	213	98.2	3.42	98.2	0.745
6	Utilities	22	98.3	3.487	98.3	0.845
7	Construction	23	97.4	3.441	97.4	0.669
8	Wood products	321	99.3	3.444	99.3	1.44
9	Nonmetallic mineral products	327	98.1	3.448	98.1	1.182
10	Primary metals	331	99.7	3.474	99.7	1.451
11	Fabricated metal products	332	98.7	3.493	98.7	1.644
12	Machinery	333	98.4	3.497	98.4	1.6
13	Computer and electronic products	334	98.3	3.505	98.3	0.957
14	Electrical equipment, appliances, and components	335	98.2	3.483	98.2	1.693
15	Motor vehicles, bodies and trailers, and parts	3361, 3362, 3363	96.733	3.469	96.733	1.914
16	Other transportation equipment	3364, 3365, 3366, 3369	92.8	3.485	92.8	1.296
17	Furniture and related products	337	98.9	3.463	98.9	1.482
18	Miscellaneous manufacturing	339	98.5	3.497	98.5	1.576
19	Food and beverage and tobacco products	311, 312	98.25	3.453	98.25	1.871
20	Textile mills and textile product mills	313, 314	93.3	3.515	93.3	2.011
21	Apparel and leather and allied products	315, 316	84.05	3.519	84.05	1.725
22	Paper products	322	98.4	3.459	98.4	1.455
23	Printing and related support activities	323	98.8	3.513	98.8	1.829
24	Petroleum and coal products	324	98.0	3.452	98.0	0.93
25	Chemical products	325	98.0	3.475	98.0	1.259

26	Plastics and rubber products	326	98.7	3.453	98.7	1.631
27	Wholesale trade	42	93.9	3.507	93.9	1.309
28	Retail trade	44, 45	97.8	3.525	97.8	2.017
29	Air transportation	481	93.1	3.492	93.1	0.19
30	Rail transportation	482	96.0	3.43	96.0	-0.229
31	Water transportation	483	89.3	3.458	89.3	-0.084
32	Truck transportation	484	98.6	3.431	98.6	0.3
33	Transit and ground passenger transportation	485	98.7	3.464	98.7	-0.136
34	Pipeline transportation	486	94.2	3.441	94.2	0.769
35	Other transportation and support activities	487, 488, 492	96.467	3.464	96.467	0.828
36	Warehousing and storage	493	98.7	3.396	98.7	1.331
37	Publishing industries, except internet (includes software)	511, 516	98.8	3.536	98.8	0.967
38	Motion picture and sound recording industries	512	96.8	3.515	96.8	1.034
39	Broadcasting and telecommunications	515, 517	98.2	3.509	98.2	1.232
40	Data processing, internet publishing, and other information services	518, 519	98.2	3.538	98.2	0.792
41	Federal Reserve banks, credit intermediation, and related activities	521, 522	95.4	3.534	95.4	1.997
42	Securities, commodity contracts, and investments	523	99.1	3.531	99.1	2.345
43	Insurance carriers and related activities	524	98.1	3.549	98.1	2.363
44	Funds, trusts, and other financial vehicles	525	86.9	3.541	86.9	2.218
45	Real estate	531	98.0	3.527	98.0	1.552
46	Rental and leasing services and lessors of intangible assets	532, 533	95.4	3.526	95.4	1.209
47	Legal services	5411	99.1	3.531	99.1	3.859
48	Computer systems design and related services	5415	98.4	3.518	98.4	-0.003
49	Miscellaneous professional, scientific, and technical services	5412-5414, 5416-5419	97.714	3.518	97.714	1.436
50	Management of companies and enterprises	55	96.8	3.526	96.8	1.311

51	Administrative and support services	561	93.5	3.477	93.5	1.472
52	Waste management and remediation services	562	97.7	3.471	97.7	1.056
53	Educational services	61	97.1	3.486	97.1	0.088
54	Ambulatory health care services	621	99.1	3.475	99.1	1.214
55	Hospitals and Nursing and residential care	622, 623	98.05	3.45	98.05	0.607
56	Social assistance	624	98.2	3.466	98.2	0.216
57	Performing arts, spectator sports, museums, and related activities	711, 712	97.35	3.508	97.35	0.828
58	Amusements, gambling, and recreation industries	713	96.5	3.492	96.5	0.351
59	Accommodation	721	98.5	3.468	98.5	0.969
60	Food services and drinking places	722	99.3	3.447	99.3	1.313
61	Other services, except government	81	96.8	3.475	96.8	1.441

D Tertiarization

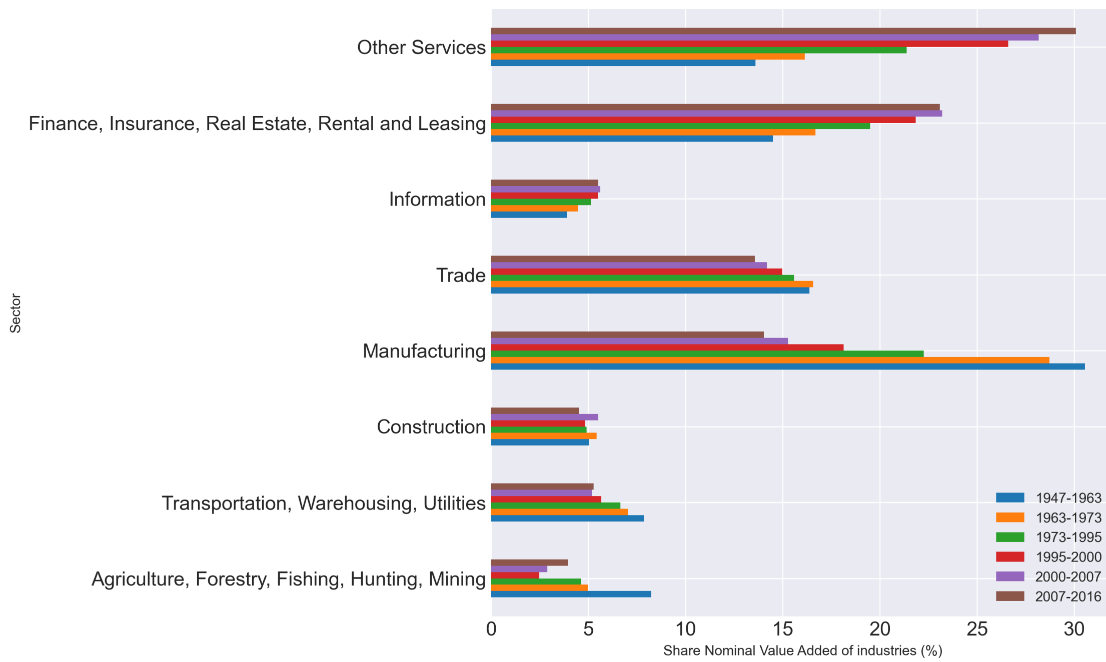

Figure 16: Change of nominal output shares of the US economy for eight super sectors between 1947-2016. Data from Eldridge et al. (2020).

E Stagnant and Progressive industries over period 1963-2016

The following table shows the annualised growth rates for the period 1963-2016, the RTI and SML. If growth is above the average (1.78%) the colour is blue, and we claim this is a high growth industry (progressive). Otherwise it is orange. Also, RTI and SML are coloured. When the value for a given industry is above the average of all industries, the colour is blue. Otherwise (when lower) it is orange. The RTI and SML average are 1.12 and 3.48, respectively. Finally the share change is over the period 1963-2016, and is red for negative values and green for positive values.

indnum	Industry Description	1963-2016	Share change	RTI	SML
1	Farms	5.36%	-75.33%	-0.12	3.441
2	Forestry, fishing, and related activities	-0.53%	-32.52%	0.222	3.397
3	Oil and gas extraction	-0.54%	-5.69%	0.946	3.463
4	Mining, except oil and gas	2.19%	-45.34%	0.821	3.434
5	Support activities for mining	0.79%	9.93%	0.745	3.42
6	Utilities	0.65%	-31.76%	0.845	3.487
7	Construction	-0.70%	-4.33%	0.669	3.441
8	Wood products	1.23%	-64.88%	1.44	3.444
9	Nonmetallic mineral products	1.14%	-69.31%	1.182	3.448
10	Primary metals	1.88%	-85.67%	1.451	3.474
11	Fabricated metal products	1.27%	-58.59%	1.644	3.493
12	Machinery	2.29%	-65.06%	1.6	3.497
13	Computer and electronic products	12.70%	-2.76%	0.957	3.505
14	Electrical equipment, appliances, and components	2.55%	-71.86%	1.693	3.483
15	Motor vehicles, bodies and trailers, and parts	2.28%	-66.27%	1.914	3.469
16	Other transportation equipment	0.88%	-60.20%	1.296	3.485
17	Furniture and related products	1.53%	-63.54%	1.482	3.463
18	Miscellaneous manufacturing	2.81%	-25.77%	1.576	3.497
19	Food and beverage and tobacco products	1.49%	-56.54%	1.871	3.453
20	Textile mills and textile product mills	3.57%	-88.43%	2.011	3.515
21	Apparel and leather and allied products	2.86%	-95.22%	1.725	3.519
22	Paper products	1.51%	-69.68%	1.455	3.459
23	Printing and related support activities	1.46%	-62.22%	1.829	3.513
24	Petroleum and coal products	7.67%	98.98%	0.93	3.452
25	Chemical products	2.41%	-4.83%	1.259	3.475

indnum	Industry Description	1963-2016	Share change	RTI	SML
26	Plastics and rubber products	1.94%	-42.53%	1.631	3.453
27	Wholesale trade	3.52%	-7.71%	1.309	3.507
28	Retail trade	2.12%	-23.19%	2.017	3.525
29	Air transportation	3.21%	98.31%	0.19	3.492
30	Rail transportation	2.76%	-81.73%	-0.229	3.43
31	Water transportation	2.67%	-38.48%	-0.084	3.458
32	Truck transportation	1.28%	-20.42%	0.3	3.431
33	Transit and ground passenger transportation	-0.47%	-41.58%	-0.136	3.464
34	Pipeline transportation	3.92%	22.96%	0.769	3.441
35	Other transportation and support activities	-0.10%	-10.17%	0.828	3.464
36	Warehousing and storage	2.44%	33.49%	1.331	3.396
37	Publishing industries, except internet (includes software)	3.43%	48.27%	0.967	3.536
38	Motion picture and sound recording industries	2.10%	37.45%	1.034	3.515
39	Broadcasting and telecommunications	4.92%	-0.07%	1.232	3.509
40	Data processing, internet publishing, and other information services	1.07%	316.28%	0.792	3.538
41	Federal Reserve banks, credit intermediation, and related activities	1.72%	68.82%	1.997	3.534
42	Securities, commodity contracts, and investments	3.87%	443.53%	2.345	3.531
43	Insurance carriers and related activities	2.15%	100.64%	2.363	3.549
44	Funds, trusts, and other financial vehicles	-4.87%	709.96%	2.218	3.541
45	Real estate	0.46%	22.04%	1.552	3.527
46	Rental and leasing services and lessors of intangible assets	1.65%	33.13%	1.209	3.526
47	Legal services	-0.60%	106.40%	3.859	3.531
48	Computer systems design and related services	0.11%	886.82%	-0.003	3.518
49	Miscellaneous professional, scientific, and technical services	1.56%	210.71%	1.436	3.518
50	Management of companies and enterprises	1.50%	31.68%	1.311	3.526
51	Administrative and support services	1.17%	308.04%	1.472	3.477
52	Waste management and remediation services	0.18%	18.56%	1.056	3.471
53	Educational services	0.93%	111.97%	0.088	3.486
54	Ambulatory health care services	-0.49%	206.89%	1.214	3.475
55	Hospitals and Nursing and residential care	0.35%	184.00%	0.607	3.45
56	Social assistance	2.10%	371.54%	0.216	3.466
57	Performing arts, spectator sports, museums, and related activities	1.68%	126.91%	0.828	3.508
58	Amusements, gambling, and recreation industries	0.46%	16.16%	0.351	3.492
59	Accommodation	1.74%	60.83%	0.969	3.468
60	Food services and drinking places	0.13%	33.61%	1.313	3.447
61	Other services, except government	-0.29%	-22.80%	1.441	3.475

Figure 17: Annualised labour productivity growth rates for 61 industries over 1963-2016 period.

F Robustness Short for Fixed Shares Growth Rate Analysis

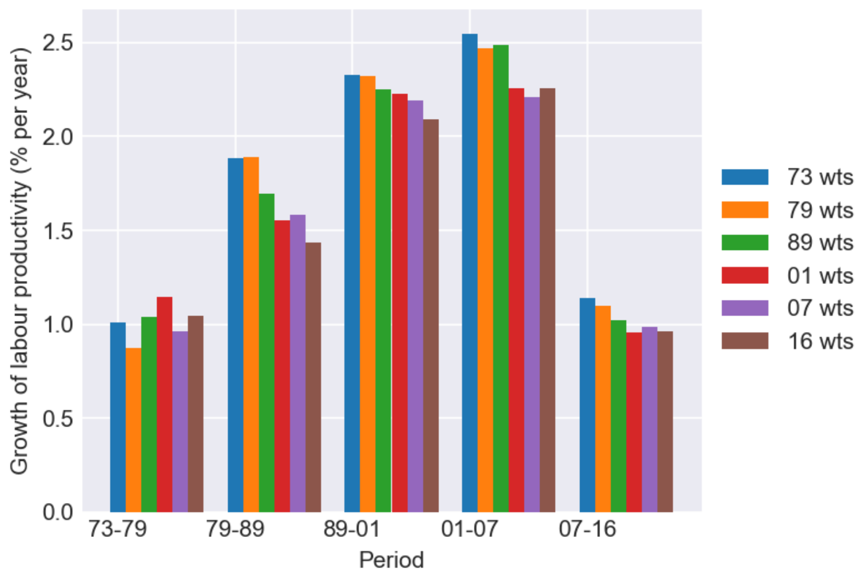

Figure 18: Fixed Shares Growth Rate Analysis for 'short' periodization.

Table 15: Fixed Shares Growth Rate Analysis for 'short' periodization

	1973-1979	**1979-1989**	**1989-2001**	**2001-2007**	**2007-2016**	**1973-2016**
1973	1.01	1.89	2.33	2.55	1.14	1.82
1979	0.88	1.89	2.32	2.47	1.10	1.78
1989	1.04	1.70	2.25	2.49	1.02	1.73
2001	1.15	1.55	2.23	2.25	0.96	1.73
2007	0.96	1.58	2.19	2.21	0.98	1.62
2016	1.05	1.44	2.09	2.26	0.97	1.58

Notes: This is an robustness check for the results of the FSGR analysis, according to the methodology of test 6 of Nordhaus (2008). Values are reported in percentages. The periodization is roughly equal, with minimally 6 to maximally 11 years. The annualised labour productivity growth rates over a period (column) for 61 industries are multiplied by the weights (nominal output shares) of the industries for six fixed years. The last column is the annualised growth rates over the whole period (43 years) multiplied with weights of six fixed years.