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IMPACT OF THE COVID-19 PANDEMIC FIRST WAVE ON QUARTERLY LABOUR PRODUCTIVITY OF US LISTED TECHNOLOGY COMPANIES

Bachelor's Thesis

Programme Applied Economics, specialization in Finance and Accounting

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Tallinn 2020

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TABLE OF CONTENTS

SHORT SUMMARY 4
INTRODUCTION 5
1. PRODUCTIVITY AND INNOVATION IN PREVIOUS THEORETICAL AND EMPIRICAL LITERATURE 7
1.1. Economic growth 7
1.2. Productivity 9
1.2.1. Measures of productivity 9
1.2.2. Determinants of labour productivity 10
1.2.3. Role of innovation in productivity growth 12
2. DATA AND METHODOLOGY 15
2.1. Data and variables 15
2.2. Descriptive statistics 18
2.2. Relationships between variables 19
2.4. Analysis methodology 20
3. ECONOMETRIC ANALYSIS 22
3.1. Modeling the labour productivity determinants and Covid-19 pandemic first wave effect 22
3.2. Analysis results and conclusions 26
SUMMARY 28
REFERENCES 30
APPENDICES 35
Appendix 1. Correlation matrix 35
Appendix 2. Fixed-effects model with robust (HAC) standard errors 36
Appendix 3. Non-exclusive licence 37

SHORT SUMMARY

This bachelor's thesis focuses on quarterly labour productivity in the United States (US) listed technology companies over the period of the fourth quarter of 2017 through the third quarter of 2020. The goal of this paper is to observe the association between quarterly labour productivity and its determinants. Additionally, this paper seeks to find whether the Covid-19 pandemic first wave had an effect on companies' labour productivity. Labour productivity in this paper is measured as turnover per employee.

To reach the goal of this paper, an econometric model is conducted in the open-source statistical package Gretl, using unbalanced panel data. The data includes the dependent variable, labour productivity, as well as independent variables such as age, return on assets, intangible assets, leverage, fixed assets growth and cash flows. To see the effect of the Covid-19 pandemic first wave, a dummy variable COVID is included that takes the value of 1 for periods in which the pandemic is present and 0 for all other periods under observation. Some variables such as labour productivity, intangible assets and cash flows are transformed to a logarithmic form and a lag of one is taken from all independent variables to deal with the endogeneity problem. The final model is a fixed-effects model with robust standard errors in which age, intangible assets, cash flows and COVID are significant. The model includes 1,583 observations for 199 companies.

The results of this paper show a significantly positive effect of age, cash flows and intangible assets on quarterly labour productivity. Additionally, the results show a significantly negative effect of Covid-19 pandemic first wave on quarterly labour productivity. The goal of this paper is achieved as the model describes the determinants of quarterly labour productivity in the US listed technology companies and shows a negative effect of the Covid-19 pandemic on quarterly labour productivity.

Keywords: labour productivity, technology companies, innovation, Covid-19 pandemic, econometric model

INTRODUCTION

In December 2019 the first cases of the coronavirus (Covid-19) disease were reported in Wuhan, China and have since created a worldwide pandemic, causing widespread infections and severe outcomes. While different countries have taken different measures to contain the virus, the world is strongly integrated and economic disruptions in the biggest countries can generate spill-over effects on the whole globe throughout the supply chains. According to the estimates by the World Bank, in 2019 the US accounted for 15.8% of the world's economy (The World Bank ... 2019), outperformed only by China. Due to the magnitude of the US economy, any economic shock it might experience can have an impact on the rest of the world. As of January 2nd, 2021, according to the data reported by the World Health Organization, the US is leading in the number of Covid-19 cases with a cumulative number of 59,148.22 cases per 1 million population and a cumulative number of 1,025.82 deaths per 1 million population of (WHO … 2020).

In order to prevent the spread of the virus, many governments set strict measures such as the mandatory lockdown policy to maximize social distancing, lowering the population mobility and preventing people from going to their offices and workplaces. It is presumable that a drop of such nature in population movability can lead to job losses and corporate bankruptcies. There's a link between a national economy and the stock market as stock prices influence business and consumer confidence and behaviour, which in turn affects the whole economy. Therefore, because the stock market companies are an important component of the national economy, the purpose of this paper is to address the impact of the Covid-19 pandemic first wave on US listed technology companies' labour productivity. The reason for choosing the US as the subject of analysis is that the US is one of the biggest economies in the world, as was mentioned above. Furthermore, the US stock market is the largest in the world with the New York Stock Exchange ranking first based on the market capitalization, accounting for more than 40% of the total stock market capitalization (Haqqi 2020).

The purpose of this paper is to observe the association between quarterly labour productivity and its determinants in the US listed technology companies and to find whether the Covid-19 pandemic first wave had an effect on quarterly labour productivity. The reason for choosing technology companies as subjects of observation is that technology companies often introduce new innovations that are an important part of productivity growth (Storey, Tether 1998). To reach the goal, three research questions were raised:

1. Which variables have an effect on the US stock market technology companies' quarterly labour productivity?
2. In which direction and how strongly those variables affect quarterly labour productivity?
3. Did the Covid-19 pandemic first wave have a statistically negative effect on US listed companies' labour productivity?

The author of this paper also raised three hypotheses:

- Higher level of intangible assets has a significantly positive effect on labour productivity
- Higher level of leverage has a significantly negative effect on labour productivity
- Covid-19 pandemic first wave had a significantly negative effect on US listed technology companies' labour productivity.

In order to solve the research problems an econometric analysis is performed, using the fixed-effects model with robust standard errors. The analysis is conducted in the open-source program Gretl and the model uses unbalanced panel data for the US listed technology companies during the period of the last quarter of 2017 to the third quarter of 2020. The pandemic emerged in the beginning of 2020 and, at the time of writing this paper, has been present for three quarters. Therefore, quarterly labour productivity is observed to better see the impact of the pandemic. The data includes a dependent variable, labour productivity, and various financial data, extracted from the Thomas Reuters Eikon database, as independent variables.

This thesis paper is divided into three chapters. The first chapter gives an overview of labour productivity. This includes the theories regarding economic growth, including exogenous and endogenous growth theory, and definitions of productivity and innovation. Additionally, the author outlines some of the previous empirical papers that have explained various determinants of labour productivity in the past. The second chapter presents the data that was used in writing this paper, including the methods for data cleaning and processing. The author gives an overview of the descriptive statistics and the linear relationships between the variables. Additionally, the analysis methodology is introduced. The third chapter gives an overview of the empirical modeling, the final model and analysis. Finally, the author presents the results and conclusions.

1. PRODUCTIVITY AND INNOVATION IN PREVIOUS THEORETICAL AND EMPIRICAL LITERATURE

The first chapter of this thesis gives an overview of the theories regarding economic growth, the definitions of productivity and innovation, and the determinants of labour productivity, including the role of innovation in labour productivity.

1.1. Economic growth

In the 1990s, the growth of gross domestic product (GDP) per capita in the US accelerated, causing a renewed interest towards the subject of economic growth. However, many other major economies of the Organization for Economic Co-operation and Development (OECD), such as Japan and Germany, suffered from economic growth slowdown, raising the question of what the determinants of economic growth are. (Bassanini, Scarpetta 2001; Ahmad *et al*. 2003) OECD (2014) defines GDP as the following: "GDP combines in a single figure, and with no double counting, all the *output* (or *production*) carried out *by all the firms, non-profit institutions, government bodies and households* in a given country during a given period, regardless of the type of goods and services produced, provided that the production takes place within the country's economic territory. In most cases, it is calculated quarterly or annually, but it can also be calculated monthly.“. In order to compare the economic growth-rates of different countries, the ratio of GDP to population is used (*Ibid.*). In history, there have been several economists that have proposed different theories for economic growth (Solow 1956; Swan 1956; Romer 1986; Lucas 1988).

Exogenous growth theory is a neoclassical growth model theory developed in the 1950s independently by economists Robert Solow (1956) and Trevor Swan (1956) explaining the determinants of long-run economic growth. The model starts with the assumption of a standard neoclassical production function, often specified to be the Cobb-Douglas production function (1) with decreasing returns to capital (Sredojević *et al.* 2016).

$Y=F(K,A,L)$ (1)

where

Y- production (gross domestic product),

A- technology,

K- physical capital,

L- amount of work.

One of the key standpoints of this theory is the importance of physical capital accumulation as a key driver of economic growth in the short run. In the long run, however, a crucial determinant of economic growth is technological advancement. (Solow 1956*)* An important extension of this model was proposed by Mankiw *et al*. (1992) who argued that physical capital accumulation should be complemented with human capital accumulation, so that the model could also be applicable to data on multiple countries.

Even though the model considers technological advancement as a key factor of long-run economic growth, the model also assumes that technological progress is an exogenous component in the production function as opposed to being an internal and interdependent one. This means that policymakers cannot affect long-term economic growth with a nation-wide technology policy, and that technological progress is independent of economic forces. (Solow 1956; Swan 1956)

In the 1980s, a new theory emerged called endogenous growth theory (Romer 1986; Lucas 1988). The theory was formulated as a result of critique against the exogenous growth theory, specifically the fact that technological progress is an exogenous component, and therefore it is impossible for policymakers to affect growth *(Ibid.)*.

Endogenous growth theory states that long-term economic growth is the result of internally driven changes as opposed to factors from outside of an economic system. The core of this theory is that long-term economic growth is greatly impacted by investments in human capital and knowledge, which leads to greater innovation inside the system. The theory stresses the importance of policy measures to incentivize investments in education and research and development (R&D). (Romer 1986; Lucas 1988) Innovation inside the system causes spill-over effects meaning that innovation carried out by one company can also benefit their competitors between industries or within industries (Yoo *et al.* 2019).

1.2. Productivity

Productivity is an economic indicator which, in the most general terms, measures output relative to input (Demeter *et al*. 2011). There is a broad consensus among economists that productivity plays a key role in economic success and is one of the main drivers of per capita growth in the long run (Krugman 1994; Bassanini, Scarpetta 2001; Sakamoto 2018). It has been found that there are similarities between the growth rates of GDP per capita and labour productivity (Marattin, Salotti 2011). On a microeconomic level, labour productivity is an important source of business success and therefore on an aggregate level it contributes to the national income (Demeter *et al*. 2011).

Krugman (1994) states: "In the long run, the only way to sustain or improve the standard of living of a country is through productivity growth." He explains that essentially there are three options to raise the total output per capita:

a) Increase labour productivity so that there is more output per worker;
b) Raise the percentage of working people per population;
c) Instead of using current output as savings for the future, use it for current consumption.

Realistically, option c) is only a short-term solution as eventually, economies would exhaust available output for consumption. Similarly, option b) is not a long-term solution as there is a set number of people in a country that can be hired as workforce and workforce cannot be grown indefinitely. Due to these reasons, productivity growth is the only way to accomplish sustained and long-term growth. *(Ibid.)*

1.2.1. Measures of productivity

There are various ways of measuring productivity and it can be viewed on different levels of the economic system. On a macroeconomic level, this can be calculated as a ratio of real GDP to hours worked (Sakamoto 2018). For instance, on a macroeconomic level, the conditions for productivity growth can be a country's economic and social policy. On a microeconomic level, these are external factors. To raise productivity, companies need to engage in the regulating factors of productivity, which impact the level and dynamics of the companies' productivity. (Kalle 2004)

Broadly, productivity measures can be classified as single factor productivity measures or multi-factor productivity measures. Single factor productivity measures, such as labour or capital productivity, relate a measure of output to a single measure of input. Multi-factor productivity (MFP) measures, such as capital-labour MFP, relate a measure of output to a bundle of inputs. Growth in productivity means that for the same amount of relative work more goods and services are produced. (Bassanini, Scarpetta 2001)

Labour productivity is most often calculated either based on gross output or value added (Bassanini, Scarpetta 2001). The simplest way of measuring labour productivity is measuring output per hour of labour input (Mansfield *et al*. 1980). From the variety of different input types, labour productivity plays an important role as it includes in itself several effects of capital productivity and labour productivity growth absorbs a large part of capital productivity growth. One example would be the high impact of information and communications technology (ICT) investments on labour productivity growth. (Pilat *et al*. 2002) Gust and Marquez (2004) also find that the combination of information technology (IT) and the less regulated labour market has a potential of a higher increase in productivity growth. Based on the discussion above, the current thesis focuses on the study of labour productivity.

1.2.2. Determinants of labour productivity

Labour productivity as most of the other economic indicators is influenced by various factors that have complex interactions among each other and that are explained further in the following chapter. Since the development of the neoclassical growth theory, the discussion of technology's role in productivity growth has grown popularity amongst economists (Kumar *et al*. 2016). Technological advancement has reduced working hours and improved working conditions (Mansfield *et al*. 1980). As such, one of the most common determinants of growth and productivity in previous literature is investments in ICT (Chen *et al*. 2016). For example, since 1995 the manufacturing sector has been a significant contributor to economic growth in Europe. In the manufacturing sector, the electrical machinery sector is one of the biggest contributors. It is noteworthy that it is also the sector covering all the industries that use ICT. (Timmer *et al*. 2007)

In the 1990s, the US enjoyed rapid rates of productivity growth. It is argued that one contributor to productivity growth was the growth in ICT usage. Since there was a labour productivity gap between the US and other developed countries, governments in such countries as the UK, Germany and Japan started to incentive ICT investments in order to reach the US productivity levels, but without success. A paper by Fukao and his colleagues (2009) found that one of the reasons was a low multi-factor productivity growth in services using ICT. Additionally, they find that increase in intangible capital accounted for 27% of the labour productivity growth in the US in the late 1990s and 2000s, however, the contribution of intangible capital to labour productivity growth in Japan was negative in the early 2000s. (Fukao *et al.* 2009)

Furthermore, there is a significant link between ICT usage and intangible capital. It has been found that intangible capital has a greater effect on growth if it is complemented by ICT investment. It is necessary to draw attention to the fact that not all intangible assets are complementary to ICT investment: for instance, organisational structures, and R&D are complimentary but such other assets as design or market research are not. (Chen *et al*. 2016)

One way of investing in knowledge by enterprises can be through employee training programs. Bartel (1994) found in the manufacturing sector that new employee training programs contributed significantly to short-term labour productivity growth on the organizational level. Two ways of impacting labour productivity through knowledge are: (1) having a stronger emphasis on the integration of human capacities; and (2) finding ways to make use of already existing know-how within the organisation and passing it along for further adoption. (*Ibid.*)

Borgo *et al*. (2012) show intangible assets' importance in labour productivity growth even further. The research finds that for the UK during the period 2000-2008, investment in knowledge or intangible assets accounted for 23% of labour productivity growth in market sector value added per hour. This contribution was larger than for example computer hardware (12%) and other intangible investments (18%). The largest contribution with 40% was total factor productivity. They also found that in 2008 investments in knowledge were greater than investments in tangible assets and that the most intangible-intensive industries were as manufacturing and financial services. (*Ibid.*)

There have also been some opposing researches in history. Robert Solow (1987) stated: „You can see the computer age everywhere but in the productivity statistics." This has been a point of a discussion for many economists over time. It has caught the name of „productivity paradox" or Solow paradox, meaning that with more investments made in IT, labour productivity might become lower rather than higher. The belief stemming from that in the early 1970s US productivity started to slow down, but even after accounting for factors such as changed oil prices, researchers found it challenging to explain the drop in productivity. However, the US experienced a rapid growth in the use of IT, bringing many scholars to believe that IT has either not helped with the US productivity growth or has even had a counter-effect on productivity. (Brynjolfsson 1993)

In addition to ICT and intangible assets, there have been found other determinants of labour productivity, such as company age. Coad *et al.* (2013) found that older firms experience higher levels of productivity and profits, lower debt ratios, and higher equity ratios. Their analysis indicated that younger firms tend to be smaller and less productive, however, in the first years of operating they face higher sales, and productivity and profit growth. As companies get older, the equity ratio becomes a more important financial source than external financing sources. (*Ibid.*) A study on French manufacturing markets found that the first few years of a new company, a learning effect undertakes, meaning that the growth of productivity is usually higher than the industry average. However, eventually, productivity growth will slow down and converges towards what is average in the industry. (Bellone *et al.* 2008) Alon *et al.* (2018) also found that firm's age has a significant effect on the firm's productivity growth. They studied the nonfarm business sector in the US during the time period of 1996 to 2002. They found that during the first 5 years of operating, firms' productivity growth was about 20%. After 5 years of entering the market, productivity growth slowed down to near zero. (*Ibid.)*

Another factor of labour productivity is leverage. Avarmaa *et al.* (2011) find that for companies that do not excessively rely on leverage, an increase in leverage has a positive effect on labour productivity. After a while, however, the effect of leverage on labour productivity becomes negative. The effect of leverage on labour productivity is different for local and multinational companies. For local companies, leverage has a greater effect on labour productivity than on multinational companies. The authors concluded that the reason for that could be that multinational companies have easier access to external financing, and debt does not play a significant role in companies investment activities. (*Ibid.*)

1.2.3. Role of innovation in productivity growth

The purpose of the current thesis is to observe the associations between quarterly labour productivity and its determinants in US stock market technology companies. It is argued that technology companies are in the front line of product and service innovation, and they are responsible for a country's economic growth as several innovations come from technology-intensive sectors (Storey, Tether 1998). It is found that labour productivity is positively impacted by technological innovation. Moreover, the organizational innovation plays a crucial role in labour productivity levels. (Martin, Nguyen-Thi 2015) Therefore, it is crucial to explain the role of innovation in productivity growth further.

Innovation is a concept that has through history had many different definitions. Schumpeter (1942) defined innovation as "process of industrial mutation, that incessantly revolutionizes the economic structure *from within*, incessantly destroying the old one, incessantly creating a new one". In his framework, he described how new ways of production cause more inefficient competitors of innovative companies to lag behind or even bankrupt *(Ibid.)*.

Drawing from Schumpeter's idea, innovation can help businesses to find new ways of maintaining their market position when new firms enter the market, but also help new entrants survive with developing strategies that have not been used before (Cefis, Marsili 2006). One example of an innovative activity would be R&D which has an important role in fostering innovation (McGuirk *et al.* 2015).

There is not only one conventional way to measure innovation. Therefore, it is considered as an on-going challenge (McGuirk *et al.* 2015). Such different proxies as patents and trademarks are used for measuring innovation. However, the concern may arise in two ways: (1) many innovations may not be registered; and/or (2) some patents may not be inventions. (OECD 2011) Another measure of innovative activity is R&D spending. Both patents as well as R&D spending are mostly linked to technological innovation and therefore such measures are not that well suited for companies in for example the services sector. However, the benefit of R&D spending as a measure of innovation is that it is observed in nominal values, making it monetarily comparable. (Hall 2011)

There are also some constraints of innovation that firms might face. For example, innovative firms often hold large amounts of intangible assets that are related to R&D. Those assets could be for instance patents or knowledge. Therefore, they are not accepted as collateral. However, R&D activities require large investments partly because they are uncertain and high in risk. Due to the lack of collaterals, this might impose a high risk of being constrained by finance as they might find it more difficult to finance their activities, for example through bank loans. (Brown *et al*. 2009)

When compared with fixed capital, intangible capital requires more time and firm-specific investments. Research has found that if a firm wishes to undertake an innovative project, then the constraints are bigger on smaller firms due to the risks accompanying an innovative project. This has for example been proven in a study made on 120,000 Chinese firms for the period of 2000-2007 where financial constraint, in particular internal finance availability, was a strong constraint on the firms' innovation activities. The study also stressed that financial constraint had the biggest negative effect on smaller private firms. (Zhang, Zheng 2020)

A study composed by Brown *et al.* (2012) on different firms across 16 European economies found that there is a weak link between financing and R&D activities. Then, the authors controlled for endogenous R&D smoothing. The findings showed that access to internal and external equity finance mattered a lot for R&D, especially for firms that faced financing constraints. Additionally, the paper finds that the stock market is an important part of financing R&D. This helps to explain in part the fact of R&D-intensity in young firms that are being publicly traded in the UK as well as Sweden. (*Ibid.*)

In spite of the constraints of innovative activities, those activities can help companies navigate in difficult times. Bristow and Healy (2018) looked at different European regions and their rates of recovery from the economic crisis of 2007 to 2008. Their empirical results showed that there was a strong link between the capacity for innovation of a region and its resilience to the economic shock. Furthermore, the regions with the lowest innovation capacity were the least able to respond to the economic crisis. (*Ibid.*)

A study composed by Obrenovic *et al.* (2020) looked into different contemporary case studies and previous theoretical literature. They drew some aspects of companies that managed to survive or even thrive in previous crises. They found that some of the key elements were for example distributed leadership team, adaptive workforce, workplace culture, and decentralized decision-making. They also concluded that the companies that were most successful in economic shocks were the ones that leveraged ICT usage the most, combined with different online communication platforms to help maintain strong bonds with their employees, customers and stakeholders. (*Ibid.*)

2. DATA AND METHODOLOGY

The second chapter of this thesis gives an overview of data used, methods for data cleaning and processing including descriptive statistics and the linear relationships between the variables. The author then proceeds with introducing the analysis methodology.

2.1. Data and variables

In order to observe the associations between quarterly labour productivity and its determinants in the US listed technology companies, various financial data are extracted. The data on companies' financials is taken from the Thomas Reuters Eikon database which provides financial information on companies in 130 different countries. The database covers various data for real-time trading, financial analysis, market news, company fundamentals and more (Refinitiv 2020). The companies under observation are ones that by The Refinitiv Business Classification (TRBC) are operating in the economic sector of technology. TRBC sectors cover more than 250,000 securities in 130 countries. They can be divided by economic or business sectors, industry groups, industries or activities (The Refinitiv 2020). The seven variables under observation are companies' labour productivity as the dependent variable, age, return on assets, intangible assets, leverage, fixed assets growth, and cash flow as independent variables. Additionally, a dummy variable was included that takes the value of 1 for all quarters of 2020, indicating the presence of the Covid-19 pandemic, and a value of 0 for all quarters from 2019 through the third quarter of 2017, indicating the absence of the Covid-19 pandemic.

Labour productivity is an endogenous variable that in this paper is calculated by dividing quarterly sales revenues (or in other words company turnover) with the number of employees. In previous literature there are various ways of measuring labour productivity, such as turnover per employee or value added per employee (Avarmaa *et al.* 2011; Martin, Nguyen-Thi 2015). Data for companies' turnover and number of employees is taken from the Thomas Reuters Eikon database based on TRBC classification and technology sector. Labour productivity is calculated by dividing companies' turnover by the number of employees of that company.

Companies age is calculated as full years, subtracting the year of incorporation from current year. The author of this paper expects that age impacts labour productivity positively as older companies have more financial sources as well as knowledge to make their operations more productive. Previous literature has found contradicting results in terms of the relationship between companies age and productivity.

Return on assets (ROA) is a profitability performance indicator that shows the ability of a company to earn a profit (Selvam *et al.* 2016) and in this paper this is presented as a percentage return. In general, higher profitability can mean that the turnover is higher or cost of goods sold is lower. Higher number of employees raises the cost of goods sold; therefore, higher profitability usually means higher labour productivity.

Intangible assets can be assets such as patents, skilled workforce, software, know-hows, strong customer relationships, brands and unique organizational skills (Kumar 2016). There have been found strong links between labour productivity and intangibles and the author of this paper assumes a positive link between the two.

In this paper leverage is calculated as the ratio of total liabilities to total assets, similarly to previous studies (Greenaway *et al*. 2014). Previous literature has found a significant effect of leverage on labour productivity (Dimelis, Louri 2002). Based on previous literature, the author of this paper assumes a negative relationship between leverage and labour productivity.

Fixed assets growth is calculated as the percentage growth of fixed assets compared to previous period. Fixed assets in this paper are companies' property, plant, and equipment. The author of this paper assumes that companies with higher labour productivity invest more in intangible assets and that the investments to fixed assets are smaller. Therefore, the author of this paper assumes a negative effect of fixed assets growth on labour productivity.

Cash flow is the net amount of cash moving in and out of a company over a certain period of time. The author of this paper assumes a positive link between cash flow and labour productivity as positive cash flows mean that the company has more resources to invest in productivity-enhancing activities or innovative activities, that raise labour productivity.

Companies' labour productivity and the determining variables are observed with a Cobb-Douglas production function. This function is presented in formula 2:

$$\mathrm{Y}_{it} = \alpha + \beta_1 \cdot \mathrm{AGE}_{it} + \beta_2 \cdot \mathrm{ROA}_{it} + \beta_3 \cdot \mathrm{INT}_{it} + \beta_4 \cdot \mathrm{LEV}_{it} + \beta_5 \cdot \mathrm{FIX\_A}_{it} + \beta_6 \cdot \mathrm{CF}_{it} + \beta_7 \cdot \mathrm{COVID}_{it} + u_{it} \tag{2}$$

where

Y – labour productivity

AGE – companies age

ROA – return on assets

INT – intangible assets

LEV – leverage

FIX_A – fixed assets growth

CF – cash flow

COVID – dummy variable for the presence of COVID-19 pandemic

α – company-level fixed effects

u – disturbance

i – companies

t – quarters

$\beta_{1,2,3,4,5,6,7,8}$ – coefficients

The data used in this thesis paper is panel data which means that observations on a cross-section of companies is pooled over several time periods. Therefore, both cross-sectional as well as time series data on the same companies are observed. There are various benefits to panel data. For example, panel data includes a large amount of data points which increases the degrees of freedom. Collinearity among explanatory variables is reduced. Also, panel data permits analysing more complex economic questions that cross-sectional or time-series data sets would be unable to address. (Hsiao 2003) Initially, the data in this thesis paper covered the periods of the third quarter of 2017 through the third quarter of 2020. As there were missing observations for some companies, the data is unbalanced panel data.

2.2. Descriptive statistics

Initially, the sample data set consisted of 425 companies that were incorporated in the US and were trading on the US stock market. The data set covered the periods of the third quarter of 2017 through the third quarter of 2020. The author of this paper calculated the fixed assets growth, meaning that the last quarter of the dataset was excluded. Additionally, observations with missing data and data on companies whose number of employees were zero were excluded. For observations with missing data, the author used listwise deletion, meaning that if a single value from an observation was missing, the entire record was excluded from the dataset. Therefore, the final period coverage is the last quarter of 2017 through the third quarter of 2020. After the above-mentioned modifications, the author was left with data on 199 companies. The table 1 gives an overview of the descriptive statistics.

Table 1. Descriptive statistics

Variable	Mean	Minimum	Maximum	Standard deviation
Labour productivity (turnover/employees) (thousands USD)	99.34	1.87	881.26	80.36
Age	21.00	0.00	109.00	18.09
Return on assets	-0.01	-1.10	0.39	0.07
Intangible assets (millions USD)	2,511.69	0.05	124,236.00	12,330.56
Leverage	0.55	0.04	3.11	0.27
Fixed assets growth	0.06	-0.99	4.12	0.24
Cash flows (millions USD)	337.83	-4,977.00	16,538.00	1,508.46

Source: author's calculations using the open-source program Microsoft Excel

Labour productivity was highest for Franklin Wireless Corp in the third quarter of 2020 and lowest for Akoustis Technologies Inc in the second quarter of 2018. The oldest company in the dataset was International Business Machines Corp with the age of 109 years. Return on assets was highest for Leaf Group Ltd in the last quarter of 2017 and lowest for Super League Gaming, Inc. in the first quarter of 2019. Intangible assets varied largely and were highest for Verizon Communications Inc in the third quarter of 2020. Intangible assets were lowest for Kimball Electronics Inc in the second quarter of 2019. The leverage ratio was highest for Remark Holdings Inc in the first quarter of 2020 and lowest for Super League Gaming, Inc. in the first quarter of 2019. Fixed assets growth was highest for Riot Blockchain Inc in the first quarter of 2018 and lowest for Riot Blockchain Inc in the fourth quarter of 2018. Cash flows also varied extremely with the highest being in Microsoft Corp in the third quarter of 2020 and lowest in Centurylink Inc in the first quarter of 2019.

2.2. Relationships between variables

Table 2 gives an overview of the relationship between the variables. Correlation analysis (see Appendix 1) is a statistical method that helps to evaluate the strength and direction of the linear relationship between the variables. If the correlation coefficient (r) between two variables is positive, then there is a positive linear relationship between the variables. It means that with the increase in one variable, there is an average increase also in the other variable. If the correlation coefficient between two variables is negative, then it means the relationship between the variables is negative indicating that an increase in one variable results in an average decrease in the other variable. If the correlation coefficient is 0, then there is no linear association between the variables, whereas if the correlation coefficient is 1, then there is a perfect linear relationship between the variables (Sauga 2017).

Table 2. Correlation matrix

	Y	AGE	ROA	INT	LEV	FIX_A	CF
Y	**1.00**	0.01	0.15	0.16	0.12	-0.01	0.24
AGE	0.01	**1.00**	0.17	0.08	-0.03	0.07	0.15
ROA	0.15	0.17	**1.00**	0.05	-0.07	-0.02	0.15
INT	0.16	0.08	0.05	**1.00**	0.13	-0.02	0.56
LEV	0.12	-0.03	-0.07	0.13	**1.00**	-0.05	0.05
FIX_A	-0.01	0.07	-0.02	-0.02	-0.05	**1.00**	-0.01
CF	0.24	0.15	0.15	0.56	0.05	-0.01	**1.00**

Source: author's calculations using the open-source program Microsoft Excel

Looking at the absolute values of the correlation coefficients, the correlation matrix indicates the strongest relationship between intangible assets and cash flows. The correlation coefficient between those two variables is 0.56, indicating a moderate correlation. The weakest relationships are between age and labour productivity, fixed assets growth and labour productivity and fixed assets growth and cash flows. What is considered as a strong relationship or a weak relationship depends largely on the size of the sample, but often an r of less than or equal with 0.3 is considered a weak relationship; r that is between 0.3 and 0.7 is considered a moderate relationship and r that is more than or equal with 0.7 is considered a strong relationship (Sauga 2017).

2.4. Analysis methodology

The following chapter gives an overview of the methodology of analysis. As some of the independent variables range very largely, they should be transformed to a logarithmic form. Such variables in this paper are labour productivity, intangible assets and cash flow. For labour productivity and intangible assets, logarithms of the values were taken. Cash flow is a variable that can also take zero or negative values. As it is not possible to take a logarithm from zero or negative numbers, inverse hyperbolic function is applied for those (ASINH function in Excel) (Liping *et al.* 2017).

Table 3. Names, abbreviations, units and logarithms/asinh functions of variables

Variable	Abbreviation	Unit	Logarithm/ASINH
Labour productivity (turnover/employees)	Prod	Thousand USD	l_prod=ln(prod)
Age	AGE	Full years	-
Return on assets	ROA	Percentage	-
Leverage	LEV	Percentage	-
Fixed assets growth	FIX_A	Percentage	-
Cash flows	CF	Millions USD	ASINH_CF=asinh(CF)
Intangible assets	INT	Million USD	l_INT=ln(INT)
Covid-19 presence	COVID	Covid-19 presence = 1, no presence = 0	

Source: created by the author using the open-source program Microsoft Excel

In this paper, the author first used the Ordinary Least Squares (OLS) method to analyse labour productivity and its determinants in the US stock market companies. To observe the impact of the Covid-19 pandemic first wave, random effects model and fixed effects model were employed. The data modelling was conducted in the open-source statistical package Gretl. The data used in this thesis paper is unbalanced panel data, meaning that the number of observations differs among companies.

As the sample consists of unbalanced panel data, which also has a time dimension, before moving on to the regression analysis, a unit root test should be conducted to determine whether the time series variables are stationary or not. Stationary time series are time series that are independent of time and do not show any trends or seasonality (Baltagi 2005). As the panel data in this paper is unbalanced, it means there are missing observations for some companies. For such data, one of the options would be to conduct the Fisher-type unit root test as it does not require the panel to be balanced (*Ibid.*). The statistical package Gretl does not offer the option of the Fisher type ADF test. This should however not be a problem as Levin *et al.* (2002) showed that for microdata, if the number of observations is small and the number of subjects is big, the statistics are subject to normal distribution. Therefore, the potential for spurious regression can be overlooked.

The author of this paper created several models with different independent variables, using the OLS method. As the correlation matrix indicated a correlation of 0.56 between intangible assets and cash flow, the author first created separate models with either one of the variables and a third one with both INT and CF to see how the coefficients differ. To deal with the endogeneity problem, lags of one were added to every independent variable except for COVID.

3. ECONOMETRIC ANALYSIS

3.1. Modeling the labour productivity determinants and Covid-19 pandemic first wave effect

The purpose of this paper is to analyse the quarterly labour productivity determinants in US stock market technology companies and to see whether the Covid-19 pandemic first wave affected quarterly labour productivity. In order to do that, a dummy variable COVID was used that took the value of 1 for periods that showed the presence of Covid-19 and 0 for time periods that showed the absence of Covid-19. When working with panel data, there are essentially two ways of modeling the differences between two groups: fixed effects model (FE) and random effects model (RE). A fixed effect model examines individual intercepts of the subjects and the intercepts are time invariant. This model allows for heterogeneity among subjects. A random effect model assumes that the estimates error variance is specific to groups. It must be noted that the estimates of the random effect model are more efficient than the ones for fixed effects model but the estimates for the fixed effects model are always consistent (Gujarati, Porter 2004).

According to the correlation matrix the expected effects of INT and CF on labour productivity are positive. As the correlation between INT and CF was 0.56, meaning there might be multi correlation between the variables, the author created three models to see if the effects on quarterly labour productivity differ between the models. The first model (1) included all independent variables mentioned above except for INT. The model was significant on a level of 0.01 and indicated a significantly positive effect of CF on labour productivity. Second model (2) included INT but not CF. The second model was significant and indicated a significantly positive effect of INT on labour productivity. The combined model (3) with both INT and CF was significant and indicated positive effects of both INT and CF on labour productivity, INT being significant on a level of 0.01. As the signs of the coefficients didn't depend on whether the other variable was included, the author decided to proceed with a combined model of both INT and CF (3).

Table 4. First regression models

	Model 1	Model 2	Model 3
Constant	11.1027*** (0.0472)	9.9585*** (0.1501)	9.9875*** (0.1558)
AGE_{t-1}	-0.0018* (0.0010)	-0.0031*** (0.0010)	-0.0031*** (0.0010)
ROA_{t-1}	-1.9274*** (0.3850)	1.9974*** (0.3202)	1.8572*** (0.3786)
LEV_{t-1}	0.2743*** (0.0643)	0.1407** (0.0653)	0.1444** (0.0655)
FIX_A_{t-1}	-0.2194** (0.0936)	-0.2510*** (0.0914)	-0.2439*** (0.0920)
$ASINH\_CF_{t-1}$	0.0046*** (0.0014)	–	0.0010 (0.0014)
l_INT_{t-1}	–	0.0682*** (0.0083)	0.0661*** (0.0088)
COVID	0.0149 (0.0437)	0.0123 (0.0429)	0.0141 (0.0430)
Number of observations	1,583	1,583	1,583
R^2	0.0605	0.0926	0.0929
Adjusted R^2	0.0569	0.0891	0.0888
P-value	$5.22 \cdot 10^{-19}$	$1.55 \cdot 10^{-30}$	$6.66 \cdot 10^{-30}$

Source: author's calculations using the open-source statistical package Gretl

Notes: Statistical significance is indicated by asterisks as follows:

a) *** statistically significant on a level of 0.01;
b) ** statistically significant on a level of 0.05;
c) * statistically significant on a level of 0.1.

Each of these models were tested for collinearity with VIF (Variance Inflation Factors) test. The results showed that none of these three models indicated multicollinearity as the values of each variable were less than 10. Also, the effects of intangible assets and cash flows on labour productivity were always positive, therefore, the author of this paper decided to proceed with model 3, including the variables AGE, ROA, LEV, FIX_A, CF, INT and COVID.

The author of this paper created both random and fixed effects model in order to see which one should be chosen. For random effects models (4), a Breusch-Pagan test was conducted, and the p-value was p<0.05, meaning that random effects model should be preferred over pooled model. In this model, return on assets, leverage and intangible assets were significant on a level of 0.01. For fixed effects models (5), the p-value for test for differing group intercepts was 0, meaning that the null hypothesis can be rejected, and fixed effects model should be preferred over pooled model.

The model was significant on a level of 0.01 and all independent variables except for fixed assets growth were also significant in this model. In order to choose between fixed effects model and random effects model, a Hausman test was conducted which indicated that a fixed effects model should be used.

Table 5. First random effects and fixed effects models

	Model 4 (RE)	Model 5 (FE)
Constant	8.8586*** (0.2080)	7.3657*** (0.2721)
AGE_{t-1}	0.0014 (0.0027)	0.0704*** (0.0093)
ROA_{t-1}	0.4543*** (0.1615)	0.4703*** (0.1595)
LEV_{t-1}	-0.1518*** (0.0552)	-0.2295*** (0.0571)
FIX_A_{t-1}	-0.0105 (0.0301)	-0.0270 (0.0295)
$ASINH\_CF_{t-1}$	0.0008 (0.0006)	0,0013** (0.0006)
l_INT_{t-1}	0.1293*** (0.0108)	0.1322*** (0.0122)
COVID	0.0040 (0.0142)	-0.0774*** (0.0172)
Number of observations	1583	1583
LSDV R^2	–	–
Within R^2	–	–

Source: author's calculations using the open-source statistical package Gretl
Notes: Statistical significance is indicated by asterisks as follows:
a) *** statistically significant on a level of 0.01;
b) ** statistically significant on a level of 0.05;
c) * statistically significant on a level of 0.1.

For heteroskedasticity a Wald test was performed on model 5 and the p-value of the Wald test was 0, meaning that heteroskedasticity is present in the model. Heteroskedacity in a model results in consistent estimates of the regression coefficients, but these estimates are not efficient. Additionally, the standard errors of the estimates are biased. (Baltagi 2005) Therefore, robust standard errors should be used to correct for heteroskedasticity. The results for fixed-effect Arellano robust standard errors model (6) are shown in table 6. The final model (7) is presented in table 6, where all variables with a p-value above 0.1 were excluded. In the final model, age, cash flow, intangible assets and Covid were significant.

Table 6. First fixed-effect model with robust standard errors and final fixed-effects model with robust standard errors

	Model 6 **Fixed-effects with robust (HAC) standard errors** **Dependent variable: l_prod**	**Model 7** **Fixed-effects with robust (HAC) standard errors** **Dependent variable: l_prod**
Constant	7.3657*** (0.5920)	7.3391*** (0.6249)
AGE_{t-1}	0.0704*** (0.0113)	0.0615*** (0.0132)
ROA_{t-1}	0.4703 (0.3690)	–
LEV_{t-1}	-0.2295 (0.1437)	–
FIX_A_{t-1}	-0.0270 (0.0327)	–
$ASINH\_CF_{t-1}$	0.0013 (0.0010)	0.0022** (0.0010)
l_INT_{t-1}	0.1322*** (0.0335)	0.1365*** (0.0376)
COVID	-0.0774*** (0.0214)	-0.0740*** (0.0215)
Number of observations	1,583	1,583
LSDV R^2	0.9279	0.9263
Within R^2	0.1509	0.1321

Source: author's calculations using the open-source statistical package Gretl

Notes: Statistical significance is indicated by asterisks as follows:

a) *** statistically significant on a level of 0.01;
b) ** statistically significant on a level of 0.05;
c) * statistically significant on a level of 0.1.

Therefore, the final formula is the following:

$$\underset{(0.6249)}{Y_t = 7.3391} + \underset{(0.0132)}{0.0615} \cdot AGE_{t-1} + \underset{(0.0010)}{0.0022} \cdot CF_{t-1} + \underset{(0.0376)}{0.1365} \cdot INT_{t-1} - \underset{(0.0215)}{0.0740} \cdot COVID_t \quad (4)$$

where

Y_{it}– labour productivity

AGE_{it-1}– companies age

CF_{it-1}– cash flow

INT_{it-1}– intangible assets

COVID– dummy variable for the presence of COVID-19 pandemic

The author also tried a fixed-effects robust standard errors model where all independent variables except for COVID had a lag of 2. However, as the explanatory power of the model decreased and the signs of the coefficients became illogical, the author of this paper decided to consider model 7 as the final model.

All of the variables in the final model are statistically significant. Companies age, intangible assets and Covid-19 were significant on a level of 0.01. Companies cash flows were significant on a level of 0.05. All variables except for Covid-19 had a positive coefficient, meaning a positive impact on quarterly labour productivity.

3.2. Analysis results and conclusions

The purpose of this paper was to observe the associations between quarterly labour productivity and its determinants in US stock market technology companies and to see whether Covid-19 pandemic first wave had an impact on quarterly labour productivity. At the beginning of this paper the author made three hypotheses:

1) Higher level of intangible assets has a significantly positive effect on labour productivity;
2) Higher level of leverage has a significantly negative effect on labour productivity;
3) Covid-19 pandemic first wave had a significantly negative effect on US stock market companies' labour productivity.

In the final model, leverage was insignificant and therefore it is impossible to either confirm or reject the second hypothesis. It is however possible to confirm hypotheses one and three as intangible assets and Covid-19 were significant in the final model. There is plenty of research done on the relationship between intangible assets and productivity and the author of this paper assumed a positive relationship between the two. The model confirmed this hypothesis and with a 1% change in intangible assets there is a 0.14% increase in labour productivity.

Another hypothesis of this paper was that the Covid-19 pandemic first wave had a negative effect on firms' labour productivity, and this was also confirmed by the model. The presence of Covid-19 first wave decreased labour productivity by approximately 7.90%. There can be various reasons for this. For instance, the uncertainty about the consequences as well as the duration of the pandemic might have hindered investment activities in the companies under observation.

Labour productivity also had a statistically significant relationship with age and cash flows. Labour productivity had a statistically insignificant relationship with return on assets, leverage and fixed assets growth.

Labour productivity had a significantly positive relationship with age on a level of 0.01. The author of this paper assumed a positive relationship between age and labour productivity, as older firms should have more resources to invest in capital that could make production processes more productive as well as more know-how on how to better operations. Therefore, the model confirmed the author's assumption. Previous findings have been contradicting with some papers finding a positive link between labour productivity and some a negative link.

The significant positive relationship between labour productivity and cash flows also confirmed the author's assumption. With 1% increase in cash flows, labour productivity increases 0.002%. For many companies, especially smaller companies, undertaking innovative activities is accompanied by financial constraints. More productive companies often hold more intangible assets that are not accepted as collateral. Greater cash flow means more available resources for the company to spend on technology or costly innovative activities that would help to raise labour productivity.

SUMMARY

The purpose of this paper is to observe the association of quarterly labour productivity and its determinants in the US listed technology companies and to find whether the Covid-19 pandemic first wave had an impact on quarterly labour productivity. The data used in this thesis paper includes financial data on the US listed technology companies over the period of the last quarter of 2017 through the third quarter of 2020. The reason for quarterly labour productivity is that the pandemic has only been present since the first quarter of 2020. The data is unbalanced panel data, meaning that at least one company was not observed every period.

This thesis paper seeks to solve the following research questions:

1. Which variables have an effect on the US stock market technology companies' quarterly labour productivity?
2. In which direction and how strongly those variables affect quarterly labour productivity?
3. Did the Covid-19 pandemic first wave have a statistically negative effect on US listed companies' labour productivity?

Based on previous theoretical and empirical literature on this subject, the author of this paper raised three hypotheses:

- Higher level of intangible assets has a significantly positive effect on labour productivity.
- Higher level of leverage has a significantly negative effect on labour productivity.
- Covid-19 pandemic first wave had a significantly negative effect on US stock market technology companies' labour productivity.

This thesis paper failed to reject the first and third hypotheses. It occurred that higher level of intangible assets had a significantly positive effect on labour productivity. Also, the Covid-19 pandemic first wave had a significantly negative effect on the US stock market technology companies' labour productivity. Based on the final model of this paper, it was impossible to either

confirm or reject the second hypothesis as leverage was excluded from the final model due to its insignificance.

The subject under observation was labour productivity which is one of the most common measures of productivity next to capital productivity and total factor productivity. Labour productivity was measured as turnover per employee. The independent variables under observation were age, return on assets, intangible assets, leverage, fixed assets growth and cash flows. To observe the impact of the Covid-19 pandemic first wave, a dummy variable COVID was used that took the value of 1 for periods in which the pandemic was present and 0 for periods in which the pandemic was not present. Based on the data published by the World Health Organization, the first cases of Covid-19 were found in the US at the end of the first quarter of 2020 and therefore all three quarters of 2020 showed the presence of the Covid-19 pandemic.

As some of the variables varied largely, different transformations were performed. The variables that were transformed were the dependent variable labour productivity and independent variables cash flow and intangible assets. Additionally, to deal with the endogeneity problem, lags of one were added to every independent variable except for COVID. To reach the goal of the paper, the author conducted econometric analysis, using the fixed-effects model with robust standard errors. The number of observations in the final model was 1,583 with 199 individual companies. The analysis was conducted in the open-source statistical package Gretl.

The goal of this bachelor's thesis paper was achieved as two hypotheses out of three were successfully confirmed. In the final model, intangible assets and COVID were statistically significant on a level of 0.01. Intangible assets had a significantly positive effect on labour productivity and COVID had a significantly negative effect on labour poductivity. The model also showed significantly positive effects of age and cash flows on labour productivity. The author of this bachelor's thesis finds that further research should be done on this subject when more time has passed from the outbreak of the pandemic. Additionally, as this paper only included technology companies, other types of companies should be observed as well as the pandemic might have different impact on companies in different industries and sectors.

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APPENDICES

Appendix 1. Correlation matrix

Y	AGE	ROA	INT	–
1.0000	0.0087	0.1532	0.1567	Y
–	1.0000	0.1716	0.0811	AGE
–	–	1.0000	0.0503	ROA
–	–	–	1.0000	INT
LEV	FIX_A	CF	–	–
0.1205	-0.0083	0.2403	Y	–
-0.0314	-0.0683	0.1486	AGE	–
-0.0679	-0.0247	0.1464	ROA	–
0.1343	-0.0232	0.5608	INT	–
1.0000	-0.0506	0.0494	LEV	–
–	1.0000	-0.0114	FIX_A	–
–	–	1.0000	CF	–

Source: author's calculations using the open-source statistical package Gretl

Appendix 2. Fixed-effects model with robust (HAC) standard errors

Fixed-effects, using 1,583 observations Included 184 cross-sectional units Time-series length: minimum 1, maximum 11 Dependent variable: l_prod Robust (HAC) standard errors					
	coefficient	std. error	t-ratio	p-value	–
Const	6.80415	0.759553	8.958	$3.75*10^{-16}$	***
AGE_1	0.0888660	0.0237404	3.743	0.0002	***
ASINH_CF_1	0.00216215	0.000935604	2.311	0.0219	**
l_INT_1	0.134874	0.0379657	3.553	0.0005	***
COVID_1	-0.117042	0.0349965	-3.344	0.0010	***
dt_2	-0.0161999	0.0271273	-0.5972	0.5511	–
dt_4	-0.0366733	0.0325661	-1.126	0.2616	–
dt_5	-0.0280331	0.0219725	-1.276	0.2036	–
dt_6	-0.0360680	0.0169696	-2.125	0.0349	**
dt_7	-0.0624445	0.0186128	-3.355	0.0010	***
dt_9	0.0319075	0.0229548	1.390	0.1662	–
dt_10	0.0219128	0.0252822	0.8667	0.3872	–
dt_11	-0.0261926	0.0261601	-1.001	0.3180	–

Source: author's calculations using the open-source statistical package Gretl

Notes: Statistical significance is indicated by asterisks as follows:

a) *** statistically significant on a level of 0.01;
b) ** statistically significant on a level of 0.05;
c) * statistically significant on a level of 0.1.

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