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IMPACT OF INNOVATION AND MANAGEMENT PERFORMANCE ON CORPORATE FINANCIAL RETURNS EXEMPLIFIED BY THE US RESEARCH AND DEVELOPMENT SECTOR FIRMS BEFORE AND DURING THE COVID-19 PANDEMIC

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Introduction

Nowadays, the COVID-19 global pandemic is one of the most controversial discussion topics among economists and finance specialists. Once the World Health Organization declared the outbreak of a new virus on 30 January 2020, economists around the world arrived at the consensus that market volatility determined by restrictions and lockdowns imposed by governments around the world could lead to the biggest financial market crash in the 21st century. Thus, the global scientific community immediately responded with a substantial research and development (R&D) effort to fight against the SARS-CoV-2 virus.

Research and development is defined as the analysis and trials of new products and services by businesses. Moreover, R&D is the core business activity of any firm, and investment in R&D could be considered to be a key factor in firm's successful financial performance. Numerous international studies suggest that innovation-related investments in firms rise during the economic recovery and fall dramatically during the economic downturn, for

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example during the global financial crisis of 2008. However, there are various research studies suggesting the opposite: investments in innovation, firm characteristics, and different R&D management strategies can characterise firms' rapid growth during a crisis, such as the one caused by the COVID-19 pandemic.

Historically, there were only two similar pandemics: the Black Death occurring from 1347 to 1351 and the Spanish Flu from 1918 to 1919. Therefore, the choice for the topic of this study stems from the lack of empirical evidence on the potential and the actual impact of the global pandemic on the financial results of innovative companies. Since the United States is one of the leading countries in terms of the innovation sector's growth and development, and the US market is the best representative of innovation companies, the sample of this study consists innovation firms the US.

This paper aims to evaluate to what extent investments in R&D, firm innovation-related spending, firm characteristics, and management performance impacted the financial results of the US companies before and during the global COVID-19 pandemic. The main research question is whether the COVID-19 pandemic has a significant positive impact on the financial results of the US innovation-based companies. The main hypothesis of the research is that innovation-related investments, firm characteristics, and management performance have a significant positive impact on the financial results of the US innovation sector firms. Another hypothesis is that the COVID-19 pandemic has a significant impact on the successful financial performance of the US high-leverage innovation companies. Finally, it is expected that the greatest significance in the US innovation industry-level models is acquired by the healthcare and IT sectors.

The article presents empirical findings of numerous researchers proving that there is a significant impact of innovation-related investments, firm characteristics, and management performance on the financial performance of innovation-oriented firms. However, they are mainly using the best models that describe the relationship between the chosen variables according to some criteria. In this case the parameter estimates are conditioned based on the selected model and any imperfections are ignored. In contrast to the previous studies, the Bayesian model averaging (BMA) has been found to be a proper econometric model in the context of the current research. As a result, the parameters for all possible research models are firstly selected and then their estimates are combined based on the posterior probabilities.

1. Theoretical Approach

Initially, the importance of innovation was marginalised in different economic theories. Founders of classical economics such as David Ricardo, Jean-Baptiste Say, and Adam Smith focused on capital and labour, considering them as the main factors contributing to economic growth. However, they ignored the role of intellect and skills in economic growth. As a result, economists started to turn elsewhere in their research.

1.1. Exogenous growth model

In the 1980s recession, traditional capital and labour-based industries struggled with severe problems of excess capacity and falling profitability. This period marked the beginning of the third industrial revolution, the era of new computer technologies, and the potential of new information technologies (Harris 2001). Most importantly, the 1980s recession started the process of the knowledge-based economy (KBE), the dominant post-industrial economic paradigm. The most conventional contribution of the KBE is that knowledge (A) is another input to the production process, treated in the same way as capital (K) and labour (L) inputs. This has three important implications. First, knowledge creation is an investment, economic calculations of which are performed as any other kind of investment activity (Harris 2001). Second, the knowledge factor (A) contributes to the productivity of a capital factor input with non-diminishing returns: marginal returns to each additional investment do not decline. Third, knowledge accumulates over time, in the same way as capital K (Harris 2001). Altogether, knowledge accumulation and non-diminishing returns result in economic growth.

Therefore, Keynes's models for economic regulation were found to be inapplicable during the 1980s recession (Sundbo 1998). In response, Joseph Schumpeter developed the innovation theory, according to which innovation determines economic boom in a period of economic depression. He believed that healthy economy was not in equilibrium but constantly disturbed by innovations. According to Schumpeter and Nichol, there are five forms of innovations: the introduction of a new good, the introduction of a new method of production, the opening of a new market, the conquest of a new source of supply of raw materials or half manufactured goods, and the carrying out of the new organisation of any industry (1934). Moreover, innovations are essential for the potential expansion and future profits of individual companies. Thus, Schumpeterian growth model predicts that the turnover of an innovative firm will positively correlate with productivity growth (Schumpeter and Hausman 1994). This prediction implies that the entrepreneur's function is to innovate – to introduce the new processes for new outputs. Schumpeter even defined product development as the process of creating “new combinations” of factors (Schumpeter and Nichol 1934). As a result, entrepreneurship was defined as the growth factor of an economy (Schumpeter and Hausman 1994).

Schumpeter is also famous for his theory of the business cycle (Schumpeter 1939). According to this theory, innovation is the cause of ups and downs in business cycles. The cycle's recovery phase starts from the entrance of innovation into widespread use. The recovery ends with the end of technology's maturity and the diminishment of benefits arising from innovation, i.e. recession. This phase is followed by depression, after which a new wave of innovation (revival) will begin, replacing old institutional structures with new, more effective conditions for an impending recovery cycle. According to this concept also named as the “creative destruction”, more effective and innovative companies may emerge to replace those that are ineffective and fail (Schumpeter 1939). As a result, Schumpeter's theory of innovation is associated with the concept of competitive advantage.

Philippe Aghion further developed the concept of competitive advantage under the Schumpeterian paradigm (2018). Namely, he predicted that more competition should reduce monopoly in the innovation sector and thus would incentivise entrepreneurs to invest in innovations. Moreover, Aghion defined two types of firms in most sectors of the economy that react in a different way to increased competition. The first type includes “frontier firms”, i.e. firms that are close to the current technological frontier in their sector (Aghion 2018). These are currently active firms that make substantial profits from innovating. The second type includes “laggard firms”, i.e. firms that are far below the current technological frontier (Aghion 2018). These firms generate low profits and try to get closer to the technology frontier. In case of a new market entrant, the situation will be the following: frontier firms will innovate more to remain the leaders in their sector, whereas firms that are far from the technological frontier will be discouraged by the higher degree of competition; and as a result, innovate less (Aghion 2018). Overall, the effect of market competition on innovation and productivity growth is an inverted-U shaped figure, which reflects the positive escape competition effect (“frontier firms”) and the negative discouragement effect (“laggard firms”) (Aghion 2018).

Finally, the Schumpeterian growth model postulates that innovations generate growth, that entrepreneurs invest in innovations, which is motivated by the prospects of competition, and that innovations replace old technologies (creative destruction).

1.2. Endogenous growth model: Romer's theory

In the early 1980s, there was a widely held view among economists that productivity growth is exogenous. However, Paul Romer developed the endogenous growth theory, according to which technological change arises from efforts made by researchers and entrepreneurs who respond to monetary incentives (1986). Romer's theory originates from two models. The first one is a discrete-time model of growth that represents a competitive equilibrium without governmental intervention (Romer 1986). In this model the production function exhibits increasing returns to scale, where the main factors of production are knowledge, human capital, and research and development (Romer 1986). Romer emphasised that knowledge is assumed to be an intangible capital good and a fundamental input in the production function (1986). Thus, the discrete-time growth model demonstrates that the long-term endogenous growth is generated through the accumulation of new knowledge by forward-looking profit-maximising agents (Romer 1986). The second model is an infinite-horizon growth model, where Romer analysed the existence and characterisation of a social optimum (Romer 1986). He concluded that the social optimum could not be the same as a competitive equilibrium in the absence of government intervention (Romer 1986). Therefore, he discussed the existence and characterisation of the competitive equilibrium, showing that the economy represented in the model has a suboptimal (not Pareto) equilibrium. Overall, P. Romer (1986) emphasised the increasing returns and the importance of research and knowledge for the long-term economic growth rate.

Unlike his predecessors, who divided the world into capital and labour, Romer distinguished ideas (non-rival) and objects (rival) (Jones 2019). The main difference between objects and ideas is that objects are rivals, which means that only one person uses an object (Jones 2019). On the contrary, ideas are non-rival and can be used simultaneously by any number of people (Jones 2019). Overall, non-rival ideas together with other rival inputs give rise to increasing returns of economic growth.

In addition, in 1990 Romer developed models of imperfect competition created by Dixit and Stiglitz (1977) and Ethier (1982) (Jones 2019). A key finding which allowed the American economist to make these models applicable to the growth theory is that non-rival ideas are not pure public goods (non-rival and non-excludable) (Jones 2019). While non-rivalry depends on the economic environment, excludability depends on the decisions that institutions and societies make (Jones 2019). In other words, institutions earn the profits, a mark-up over marginal cost in the context of imperfect competition. Overall, the Romer model implies that entrepreneurs are motivated to search for new ideas because of the financial incentives received from innovating.

Another contribution of Romer to the endogenous growth theory is the linearity of the AK structure in the idea production function. To avoid the confusion between knowledge and capital, Romer denoted the stock of knowledge (A) and physical capital (K) (1990). According to Romer, increase in the number of ideas leads to positive knowledge spillovers, which boosts the productivity of future researchers (1990). Romer further denoted the fraction of the stock of the human capital dedicated to research. The stock of human capital is affected by taxes, research subsidies, patents, and other economic features, which influence the long-term growth rate within the market for entrepreneurs (Romer 1990). As a result, market equilibrium determines the value for the stock of the human capital, which is constant in the long run.

To summarise, in 1990 Paul Romer made three key contributions to the endogenous growth theory: he identified the non-rivalry of ideas, highlighted the role of imperfect competition and profit-maximising entrepreneurs, and derived the idea (AK) production function. These terms were found to be the most realistic in the modern endogenous growth theory literature for which Paul Romer was awarded the 2018 Nobel Prize in Economic Sciences.

1.3. Innovation drivers

The above-mentioned theories highlight that innovation is an important driver of improvements in productivity. However, it is also important to answer the question of what drives innovation itself.

Internal drivers

a) Size and age of firms

Young and small firms are usually perceived as the main drivers of innovation because they often come up with “ideas” that are new to the global market. On the other hand, unsuccessful innovative start-ups often run out of funding and exit the market. Thus, not only small companies generate the greatest number of innovations. Global corporations constantly invest in the production of new products and advanced technologies that are more difficult and costly to absorb and develop (EBRD 2014). Overall, small firms are motivated to innovate and make a profit, whereas larger firms rather develop their products to remain on the market.

b) Type of ownership

Another important firm characteristic is the type of firm's ownership. In general, companies with foreign ownership as well as firms that expand globally are expected to innovate more. Foreign firms do not necessarily have more knowledge compared to locally owned firms; they are rather likely to engage in the acquisition of knowledge from abroad.

Another type of ownership divides firms into the ones owned by the state and the ones owned by private individuals. State-owned firms are often less likely to introduce new products or processes (EBRD 2014). The reason is that entrepreneurs are motivated by the expected high profits from new products and processes. As a result, private firms have more financial incentives to innovate than state-owned firms.

c) R&D inputs and human capital

Investing in R&D significantly increases the probability of innovation happening and being successful. For instance, high-tech manufacturing sectors such as electrical equipment or pharmaceuticals have significantly high chances of introducing a new product (EBRD 2014). However, R&D is not always the introduction of new products or processes, but also their development through knowledge acquisition from elsewhere. Therefore, R&D investments in low-tech manufacturing sectors have a great impact on process innovation (EBRD 2014).

External drivers

d) Business environment

Firms' ability to innovate also depends on external factors such as the business environment. Such factors as corruption, weak legislation, certain customs, and trade regulations can substantially increase the cost of introducing new products and processes. Thus, innovation-based growth will be discouraged in environments with poor property rights protection or hyperinflation, as these will undermine firms' incentives and ability to innovate.

e) Economic openness

Innovative firms are more constrained by custom and trade regulations than non-innovative firms. Consequently, there is also a positive relationship between innovation and the financial openness of the economy. Trade openness creates opportunities such as free trade agreements, which generate foreign direct investments. Indeed, countries that are more open to international trade tend to attract significant amounts of investments from abroad.

1.4. The US research and development sector: main trends

Relying on the economic theory presented above, it is important to discuss general patterns of the US innovation sector, which is the sample of the present research.

In the post-war (World War II) period, the US developed one of the most effective national innovation systems in the world. It was a set of policies, including significant government investments in R&D, focused on maintaining a technological and military advantage over the main competitor – the Soviet Union (Atkinson 2020). However, when the Soviet Union dissolved, American policymakers focused on internal economic and social problems. This caused an innovation crisis in the 2000s, in which Americans lost over thirty percent of manufacturing jobs due to falling international competitiveness (Atkinson 2020). Moreover, the former trade surplus in high-technology products transferred into a USD 184 billion deficit in trade with China in 2017 (Atkinson 2020). As a result, challenges such as growing economic competition against China and the global pandemic prompted the US government and firms to actively invest in innovations.

From the conventional point of view, innovation sector is pure science and technology. In fact, it involves factors such as economy, politics, a financial system, tax policies, an educational system, culture, etc. All these factors form a national innovation system (NIS). There are three elements of an NIS: the business environment, the regulatory environment, and the innovation policy environment. As for the business environment, American companies are world leaders in the adoption of information and communications technologies. Thus, the US is on the fourth place in terms of cloud computing services usage globally (Atkinson 2020). Moreover, the United States pioneered and became the world leader in the venture capital (VC) industry. Numerous private VC firms across the States not only analyse and invest funds, but also serve on boards and advise on business strategy (Atkinson 2020). There are so-called "angel" funding deals initiated by wealthy private individuals who invest in high-growth innovation companies (Atkinson 2020). In this way, in 2019 the US innovation-based firms raised around USD 39 billion through initial public offerings (Ritter 2020).

While the business environment determines innovation success, government policies play a significant role in enabling innovations. The US system of regulations begins with Congress passing legislation and continues with its cost-benefit analysis conducted by the Office of Information and Regulatory Affairs (OIRA) at the White House (Atkinson 2020). This process is generally quite transparent and backed up by the rule of law. In general, the government supports innovation through macroeconomic policies[1], which usually rely on monetary policies such as the reduction of inflation. However, the 2008 American Recovery and Reinvestment Act and the 2020 COVID recovery packages suggest that fiscal policy is more efficient (Atkinson 2020). Therefore, there is an increasing pressure from Democrats to raise taxes on businesses, especially on large corporations.

Moreover, the United States is famous for its powerful regulatory system of IP protection, which applies to protection of copyrights, patents, and trademarks. The US government also does not intervene in picking industry standards. Instead, it lets the market competition and consumer choice to determine the suitable standard. Finally, the US government supports innovation sector by funding the federal labs for mission-oriented research (healthcare, military defence, etc.) and by funding universities for curiosity-directed research (software, apps).

It is worth mentioning that most scientists and researchers (including students and professors) in the US are immigrants. Numerous empirical studies have examined the role of immigrants in launching start-ups in the US, and all conclude that immigrants play a critical role in this process (Atkinson 2020). Indeed, 15 to 26 per cent of new companies in the US high-tech sector over the past two decades were established by immigrants (Atkinson 2020). This pattern results from the fact that innovators born outside are natural risk-takers and share their knowledge with their American colleagues.

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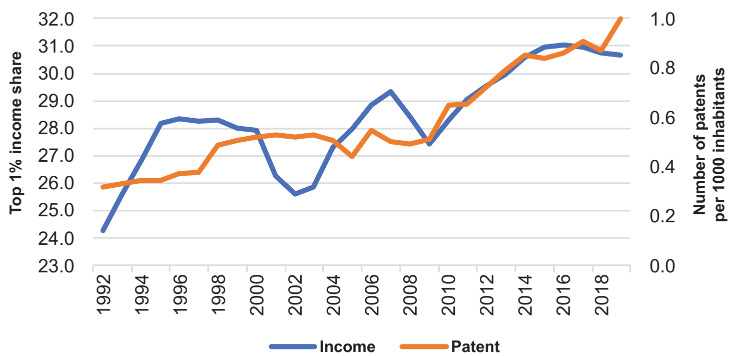
[1] For more on the role of macro policy see Beck 2011; Beck 2013; Beck 2014; Beck and Janus 2014; Beck 2020a.

According to the Global Innovation Index 2021 rankings, the US is in third place among the most innovative countries in the world (WIPO 2021). According to statistics, the US research and development sector has been experiencing a rapid increase in the share of gross GDP from 177,920 billion dollars in 1992 to 818,919 billion dollars in 2021 (FRED 2022). At the same time, developed nations (including the US) have experienced a rapid increase in income inequality caused by the fact that the top 1 % of their population captures an accelerated growing share of total income (Aghion 2018). Figure 1 illustrates the evolution of innovation (measured by the total number of patents per 1000 inhabitants) with income inequality (measured by the share of total net worth held by the top 1%) in the US between 1992 and 2020. There is a visible strong correlation, which results from causation between innovation and extreme inequality. Precisely, income from innovation leads to the increase in the share of income going to the top 99th to 100th wealth percentiles (Aghion 2018).

Figure 1

The top 1% income share and the annual patent flow in the US from 1992 to 2019

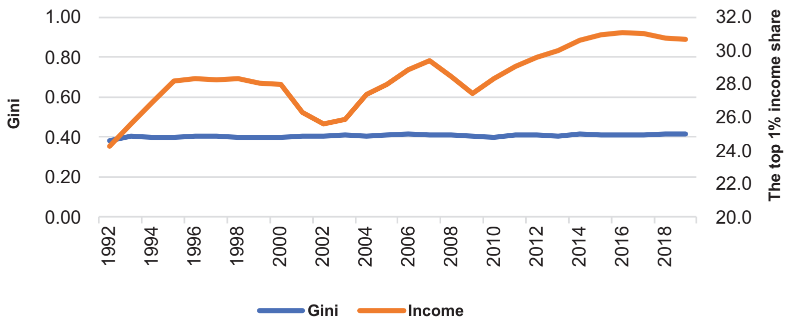


Source: FRED, 2022.

The observation that innovation contributes to the extreme income inequality highlights that innovation has features that the other sources of high income do not possess (Aghion 2018). First, as mentioned before, innovation is the main factor of economic growth. Second, the inequality brought by innovation is temporary. In this way, innovation creators and developers benefit from innovation in the short run. In the long term, returns from innovation dissipate due to imitation and Schumpeterian phenomena of creative destruction (Aghion 2018). Third, innovation connected with creative destruction generates social mobility, which allows new talent to enter the market and displace the firms that are there. However, the second graph shows no correlation between the top 1% income share and broader measurement of income inequality within a nation or a social group – the Gini coefficient.

Figure 2

The top 1% income share and the Gini coefficient in the US between years 1992 and 2019

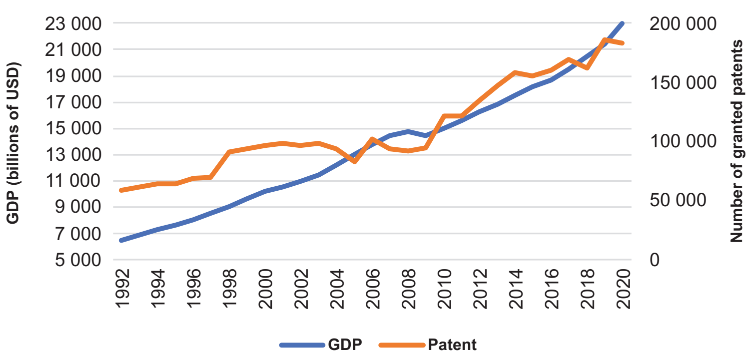


Source: FRED, 2022.

If all the above-mentioned factors are considered, it is possible to determine that innovation does not contribute to income inequality. However, innovations stimulate economic growth. Indeed, Figure 3 illustrates a strong positive correlation between innovation (measured by the total number of patents originating in the US) and GDP (measured in billions of USD) in the US since the year 1992.

Figure 3

GDP (billions of USD) and total patents originating in the United States since 1992



Source: FRED, 2022.

As a result, innovations do not cause income inequality, but generate overall economic growth.

2. Literature Review

Many researchers concluded that R&D investment is essential for the creation and development of knowledge. Thus, firms can not only generate new knowledge, but also develop patentable inventions to keep the competitive advantage derived from invention (Ceccagnoli 2009). In this way, Artz et al. (2010) suggested that continuous generation of innovations is crucial to improving profitability and maintaining the competitive advantage of a firm, having increasing levels of market competition and decreasing product life cycles. The impact of innovations on a firm's performance was measured by the return on assets (ROA) and sales growth (Artz et al. 2010). The research sample consisted of large R&D spenders in North America between 1986 and 2004 (Artz et al. 2010). Empirical results met the expectation of a positive relationship between patents and new product announcements. However, a negative relationship was found between patents and financial performance, which undermines the value of patents as a protection mechanism.

In 2014 Hasan Ayaydin and Ibrahim Karaaslan presented a model of endogenous firm performance where R&D investment is one of the main drivers of a firm's successful performance. The sample of their model was represented by manufacturing sector firms in Turkey between 2008 and 2013. The authors selected the Generalised Method of Moments, which produces unbiased and consistent estimates, controlling the endogeneity and firm-specific effects (Ayaydin and Karaaslan 2014). The empirical results proved that R&D intensity, firm size, investment in knowledge generation, and innovation make a strong contribution to the firm's financial performance (Ayaydin and Karaaslan 2014). At the same time, firm's liquidity and financial leverage were found to have a negative effect on the profitability of a company (Ayaydin and Karaaslan 2014).

In 2018, Jian Xu and Jae-Woo Sim studied the characteristics of corporate R&D investments in emerging markets between 2012 and 2016 (Xu and Sim 2018). Tobin's Q ratio was used to measure a firm's performance. The following variables were chosen to determine the relationship between R&D investment and firm performance: R&D intensity, total assets, total liabilities, financial leverage, debt maturity, internal cash flow, and sales growth from the previous year (Xu and Sim 2018). Empirical results indicated a negative relation between R&D and firm size, which can be explained by the fact that most R&D investment is carried out by medium and small-sized firms (Xu and Sim 2018). At the same time, debt maturity and cash reserves were identified as positive determinants of R&D investment (Xu and Sim 2018). Finally, empirical evidence proved that a firm's financial performance is positively associated with R&D investments (Xu and Sim 2018).

In 2021, the scholars: Jian Xu, Xiuhua Wang and Feng Liu published an article investigating the relationship between government subsidies, R&D investment, and innovation performance of pharmaceutical listed companies in China between 2009 and 2015. Xu et al. (2021) suggested that government subsidies play a notable role in motivating firms to invest in research and development (R&D). Innovation performance was measured by three indicators: the total number of patents, the number of invention patents, and the number of non-invention patents. The empirical results showed that government R&D subsidies could stimulate corporate R&D investment. At the same time, empirical evidence indicated that government subsidies had no significant impact on innovation performance. In addition, Xu et al. (2021) examined whether company ownership and executives' technological experience affect this relationship. The correlation between those two variables was found to be strongly positive. Overall, this study provided some insights for managers and policymakers in making effective innovation strategies.

In 2021, the researchers: Lujing Liu, Jian Xu, and Yue Shang analysed the determinants of financial performance of publicly listed agricultural companies in China between 2013 and 2018 (Liu et al. 2021). The financial performance of companies was measured by the following ratios: return on sales (ROS), return on assets (ROA) and return on equity (ROE) (Liu et al. 2021). The internal factors included the firm's size, current ratio, debt ratio, long-term liability ratio, sales growth rate, capital intensity, R&D intensity, export intensity, and the type of company ownership (private or state-owned) (Liu et al. 2021). The external factors were determined by GDP and consumer price index (CPI) growth rates (Liu et al. 2021). The econometric model selected for the analysis was the ordinary least square (OLS) regression. The empirical results indicated a positive relationship between the financial performance of a company and the following parameters: firm size, long-term liability ratio, and sales growth rate (Liu et al. 2021). At the same time, debt ratio, capital intensity, and export intensity were found to have a negative impact on corporate returns. In addition, empirical results indicated that external factors have no significant impact on the financial performance of a company. Overall, this study offered several practical implications: company size expansion does not always result in higher profitability; excess cash flow that is not invested cannot contribute to performance improvement; corporate managers should pay close attention to the capital structure, which is important to maintain financial sustainability; and most importantly, companies should increase investment in R&D and develop high-tech products through the use of advanced technology (Liu et al. 2021).

The above-mentioned literature exaggerates the influence of financial indicators when explaining the relation between innovation and a firm's profitability. By this, these studies overlook the management involved in the allocation of corporate resources, including R&D investments. Thus, in 2002 the researchers Vincent L. Barker III and George C. Mueller used qualitative measures of management performance and predicted their direct impact on corporate returns. The sample of their research was drawn from 172 firms that appeared in both the 1989–1990 Business Week 1,000 lists and Business Week's R&D Scoreboard special issues (Barker III and Mueller 2002). Researchers empirically examined how R&D spending of a firm depends on the characteristics of its CEO, even after controlling of the firm's corporate strategy (Barker III and Mueller 2002). The examined characteristics of a CEO were: CEO's tenure, CEO's age, CEO's stock ownership, CEO's career experience, and CEO's education (Barker III and Mueller 2002). Empirical evidence indicated surprising results: there was a significant increase in R&D spending associated with an undergraduate degree of a CEO (Barker III and Mueller 2002). This confronts the general assumption that a high level of education drives innovative attitudes. At the same time, empirical evidence showed that R&D spending positively reflects career experience and the number of technical degrees obtained by CEOs (Barker III and Mueller 2002). In this way, CEO's understanding of technologies and innovations results in the large amount of R&D spending. Moreover, researchers made an observation of relationship between the value of CEO's stockholdings and R&D spending (Barker III and Mueller 2002). This observation is consistent with agency theory, according to which CEOs are profit-maximisers from the shareholders' perspective. Finally, regression results revealed that CEO's age is the most significant determinant of R&D spending. Thus, empirical evidence pointed out the fact that long-term R&D investments are greater in value in firms with young CEOs, since CEOs close to the retirement age focus on short-term investments. Overall, this study positively answered the question whether individual characteristics of top managers and their decisions matter in innovation-based firms.

Moreover, there is a study worth mentioning due to its novelty and interesting methodological approach. In 1990 Noel Capon, John U. Farley, and Scott Hoenig analysed the determinants of a firm's financial performance using meta-analysis. Meta-analysis summarizes and compares the results of different studies in the literature on the determinants of firm and industry financial performance (Capon et al. 1990). Their research involved 320 empirical works published between 1921 and 1987 (Capon et al. 1990). In the selection process of studies for review, the researchers reviewed references in all 320 studies until they found no new studies in the list of references. All sample studies have almost the same variables used in their model estimations. The financial performance of a firm was usually measured by levels, growth, and variability in profit, whereas market value was assessed through assets, equity, cash flow, and sales. Most frequently regressions used in the literature included ordinary least squares (OLS), two-stage least squares (2SLS), 3-stage least squares (3SLS), generalised least squares (GLS), and a generalised linear model (GLM) (Capon et al. 1990). Capon et al. used two methods of meta-analysis: counting methodology and analysis of covariance (ANCOVA) methodology (1990). Empirical results from both models indicated positive relationships between the following notions: industry concentration and firm performance; growth in sales and financial performance; and most importantly, R&D spending and financial performance (Capon et al. 1990). At the same time, the size of a firm and capital investment intensity appeared to have no impact on the financial returns of a company. Overall, meta-analysis allows future researchers to sort through alternative explanations in the existing extensive literature, select variables, and choose the most appropriate model for estimation.

Finally, this chapter reviews the papers on the topic of innovation companies' performance during the global financial crisis, which allows for making assumptions about the potential impact of the financial crisis caused by the COVID-19 pandemic. The COVID-19 crisis has two significant similarities to the 2008–2010 global financial crisis, hereinafter referred to as GFC. First, both crises are sharp exogenous shocks, not business cycle fluctuations (Roper and Turner 2020). Second, both crises result in a sharp decline in liquidity of a firm (Roper and Turner 2020). In both cases, financial constraints will force firms to make quick strategic decisions about spending and potential savings.

Evidence obtained from the international research literature about the GFC indicates that R&D and innovation are highly pro-cyclical. Therefore, a sharp drop in a firm's development should be expected with slow recovery to previous level of innovation activity. Also, the GFC example suggests that firms that faced the COVID-19 crisis with strong cash positions may also emerge from it. Therefore, Joseph et al. (2020) used company-level data to examine if a firm's pre-crisis cash position is a reliable predictor for the potential foreign investments. According to the empirical results, continued investments matter to cash-rich companies that aim to gain a strategic advantage over financially resourced competitors during the recovery period. Moreover, empirical evidence suggests that strong cash position is highly important for young and small companies, which are more likely to experience financial difficulties during a crisis. A firm with a stable financial position would be also making other types of (more radical and riskier) investments than a firm with more limited financial resources (Roper and Turner 2020). This goes in alignment with previous research on this matter. Bruneel et al. (2016) empirically proved that firms with higher levels of financial reserves are prone to exploratory knowledge sourcing, which is the basis for radical innovation, while firms with low levels of financial reserves are more likely to make incremental innovation.

The GFC evidence also suggests that the impact of the crisis on innovation varies widely across sectors and regions (Roper and Turner 2020). For example, Delgado et al. (2015) examined the role of regional clusters in the United States. Empirical results indicated that strong clusters not only decrease a region's unemployment rate over time, but also increase the resilience of regional economies to downturns (Delgado et al. 2015). Perhaps less obviously, cultural factors may also play a role in determining how well firms in different countries overcome crises (Roper and Turner 2020). Therefore, an economy that has or develops a pro-innovation culture can perform better in the future despite experienced economic downturns (Petrakis et al. 2015). Overall, based on the example of the GFC, the researchers predicted the impact of innovations on financial performance of innovative businesses during the COVID-19 crisis.

To summarise, the literature review results in the conclusion that the financial performance of innovation-based companies is largely dependent on the firm's R&D intensity, government subsidies, and management performance. On the contrary, the impact of factors such as firm size and CEO education were found to be insignificant. As a result, the literature review helps to select the appropriate research methodology described in the next chapter.

3. METHODOLOGY

Econometric approach

Many research methods initially involve the best models that describe the relationship between the chosen variables based on some criteria. An analysis often proceeds with learning about the parameters of the selected model. However, in this case the parameter estimates are conditioned by the selected model, and any of its "imperfections' are ignored. A possible solution to the model selection problem is to utilise Bayesian Model Averaging (BMA), that is to compute a parameter's value in every possible model and take a weighted average of this parameter based on the according probability of those models (Wasserman 2000). In addition, in the presence of some evidence or belief in favour of some theory or parameter's value, a researcher can conveniently employ this prior knowledge while constructing a model utilising BMA (Beck 2019, 2023; Beck and Nzimande 2023).

The computation of the unconditional posterior distribution of a parameter β, i.e., estimation of a parameter's value not in a single model, but rather taking into consideration whole model space, is conducted as follows (Beck 2017, 2021a, 2021b):

$$P(\beta \mid y) = \sum_{j=1}^{2^K} P(\beta \mid M_j, y) * P(M_j \mid y), \tag{1}$$

where $P(\beta \mid M_j, y)$ indicates the probability distribution of a coefficient β conditional on a model M_j, and $P(M_j \mid y)$ is the Posterior Model Probability (PMP). The Bayes' rule allows to denote $P(M_j \mid y)$ in the following manner (Beck 2020b, 2021c, 2021d, 2022):

$$PMP = p(M_j \mid y) = \frac{l(y \mid M_j) * p(M_j)}{p(y)} = \frac{l(y \mid M_j) * P(M_j)}{\sum_{j=1}^{2^K} l(y \mid M_j) * P(M_j)}, \tag{2}$$

where $l(y \mid M_j)$ stands for the model-specific marginal likelihood, that is for the probability of the data given the model M_j, and $P(M_j)$ is the model-specific prior probability. The denominator $p(y) = \sum_{j=1}^{2^K} l(y \mid M_j) * P(M_j)$ allows to view (1) as a weighted average, where PMP is the weight of a specific model in the whole model space.

Overall, BMA has several advantages over other research methods: it reduces overconfidence regarding models and parameters; it results in optimal predictions and avoids all-or-nothing decision making; and it is relatively robust against model misspecification.

Research sample

The sample of current research is represented by the top largest publicly listed innovation companies in the US. The selected companies are based on the "2018 Global Innovation 1000 & What the Top Innovators Get Right" study conducted by PwC in October 2018. The main purpose of that study was to understand what drives innovation success of the global innovation companies. Since the main interest of the current study is the US innovation market, the list of global 1000 top innovation companies publicly provided by PwC was filtered (firms with missing data were deleted) and narrowed down to 281 US companies, which form a sample for the first model of the present research. The period of observation is the same as in the PwC study – from 2012 to 2018 with yearly frequency. The initial PwC study involved only the following variables: R&D expenses, total revenue, and R&D intensity of a company. For the complexity and relevance to the subject of the current research, the following variables are included in the first regression:

Regression (1)

- Headquarters – the location of companies' headquarters by state;
- Age – number of years that passed since a company's foundation date (current or specific year minus the year when a company was founded) (PwC 2018);
- The return on asset (ROA) – financial ratio that indicates how profitable a company is in relation to its total assets (Bloomberg 2022);
- Return on invested capital (ROIC) (RETURN ON INV CAPITAL) – a financial ratio that indicates how effectively a company uses the sources of capital invested in its operations (Bloomberg 2022);
- R&D intensity – the amount spent by a company on research and development divided by the firm's sales, in percentage (PwC 2018);
- Total assets (TOT ASSET) – the total of all short and long-term assets as reported on the firm's balance sheet, denominated in millions of the US dollars (Bloomberg 2022);

- Total liabilities (TOTAL LIABILITIES) – the sum of all current and non-current liabilities as reported on the firm's balance sheet, denominated in millions of the US dollars (Bloomberg 2022);
- Sales revenue turnover (SALES REV TURN) – the number of sales generated by a company after the deduction of sales returns, allowances, discounts, and sales-based taxes, denominated in millions USD (Bloomberg 2022);
- Market capitalisation (MARKET CAP), which measures total current market value of all a company's outstanding shares, denominated in millions USD (Bloomberg 2022);
- Tobin's Q ratio (Tobin Q) – the ratio of the firm's market value to the replacement cost of its assets (Bloomberg 2022);
- Property Plant & Equipment Net (BS NET FIX ASSET) – a measure of gross fixed assets less amounts of accumulated depreciation, in millions USD (Bloomberg 2022);
- RGDP growth, which measures growth of real GDP in the state where a company's headquarters is located, in percentage (Bureau of Economic Analysis 2022);
- Average Wages (Avg Wages) – a measurement of average wages and salaries in the state where a company's headquarters is located, in USD (Bureau of Economic Analysis, 2022);
- Primary and Secondary education (P&S educ. (%POP)), which measures the percentage of people enrolled in Primary and Secondary education out of the total population of the state where a company's headquarters is located (National Center for Education Statistics 2022);
- Post-Secondary Education (Post-Sec educ. (%POP)), which measures the percentage of people enrolled in Post-Secondary education out of the total population of the state where a company's headquarters is located (National Center for Education Statistics 2022);
- Expenditures per pupil (Exp per Pupil) – a measurement of expenditures per pupil in the state where company's headquarters is located, in USD (National Center for Education Statistics 2022);
- Pupil per teacher ratio (Pupil/Teacher ratio) – a ratio of the total number of pupils of the state to the total number of teachers in the state where company's headquarters is located (National Center for Education Statistics 2022);
- Unemployment – annualised unemployment in the state where a company's headquarters is located, in percentage (US Bureau of Labor Statistics 2022);

- Migration (%POP), which measures the volume of migration out of the state to other states out of the total population of the state where a company's headquarters is located, in percentage (US Census Bureau 2022);
- Government subsidies (LN of Gov Subs) – a natural logarithm of government subsidies to the industry that a company belongs to (Good Jobs First 2022);
- Population – total population of the state where a company's headquarters is located (US Census Bureau, 2022);

where quantitative variables such as the return on asset (ROA), the return on invested capital (ROIC), the return on common equity (ROE) and Tobin's Q ratio are used as indicators of financial performance of a company. In total, the first regression includes 59,010 observations.

The key finding of "Global Innovation 1000" study was that among 1,000 companies observed between 2012 and 2018, there were companies which outperformed their industry median and simultaneously invested less than the industry median in R&D as a percentage of sales (PwC 2018). These companies were identified as high-leverage innovators (HLIs). There are six main characteristics that differentiate HLI companies from regular companies: deep insight into the end-users of their products; strong culture of innovation; senior leadership closely involved in innovation agenda; business strategy and innovation strategy that are in alignment; rigorous innovation project selection process; and lastly, the ability to integrate all these characteristics (PwC 2018). The empirical evidence suggests that there is no long-term correlation between the amount of money a company spends on innovation and its overall financial performance (PwC 2018). Instead, it is important how a company uses that money and allocates its resources, such as quality of products and services, and company management (PwC 2018).

Thus, the second model includes variables specific for the analysis of HLI companies: R&D intensity, total assets, total liabilities, sales revenue turnover, market capitalisation, Tobin's Q ratio, net fixed assets, age of a company, percentage of women on board, financial leverage, number of executives, total intangible assets, overall company rating, CEO approval rating, positive business outlook rating, and the number of patents and trademarks owned by a company and the state subsidies to a company. The dummy control variable such as the ruling party (democratic or republican) in the state where companies' headquarters are located was also added to the second regression. Finally, the COVID-19 pandemic measured by the number of COVID-19 cases and the number of lockdowns in the respective state was used as a control variable to investigate its influence on the relationship between pro-innovation investments and the financial performance of HLI firms.

Regression (2)

- The return on asset (ROA);
- Return on invested capital (ROIC);
- Return on common equity (ROE) – a measure of corporation's profitability, how much profit a company generates with the money shareholders have invested, in percentage (Bloomberg, 2022);
- R&D intensity;
- Total assets (TOT ASSET);
- Total liabilities (TOTAL LIABILITIES);
- Sales revenue turnover (SALES REV TURN);
- Market capitalisation (MARKET CAP);
- Tobin's Q ratio (Tobin Q);
- Property Plant & Equipment Net (BS NET FIX ASSET);
- Age;
- Government subsidies (Gov Subs) – a measurement of government subsidies to the company, in USD (Good Jobs First, 2022);
- Women on board (WMN BRD) – a percentage of women on the board of directors as reported by the company (Bloomberg, 2022);
- Financial leverage (FNCL LVRG), which measures the average assets to average equity, in actual units (Bloomberg, 2022);
- Number of executives (No of EXEC) – the number of individuals on the management committee/board or executives as of the fiscal year (Bloomberg, 2022);
- Property Plant and Equipment (PP&E), which measures net fixed assets (Bloomberg, 2022);
- Total intangible assets (TOT INT ASSET), which measures the total of intangible assets as disclosed in the financial reports (Bloomberg, 2022);
- Overall rating (Overall) – a rating that consists of employees' assessment of company's culture & Values, Diversity & Inclusion, Work/Life Balance, Senior Management, Compensation and Benefits, and Career Opportunities; Scale – 0 to 5 (Glassdoor, 2022);
- CEO Approval, which measures the percentage of employees that approve CEO (Glassdoor, 2022);
- Positive Business Outlook (PBO), which measures the percentage of employees thinking that their company is getting better (Glassdoor, 2022);

- Patents Trademarks and Copyrights (PATENTS), which measures the carrying amount of patents, trademarks or copyrights owned by the company (Bloomberg, 2022);
- COVID-19 cases (Cov per 100k) – the number of COVID-19 cases in the U.S. per 100,000 people (Centers for Disease Control and Prevention, 2022);
- Lockdown – the duration of lockdown and stay-at-home orders in the state where a company's headquarters is located, in days (Ballotpedia, 2022);
- Democrats/Republicans (Dem –1 Rep – 0) – a dummy variable, where a Democratic state = 1, a Republican state = 0 in the state where a company's headquarters is located, dummy (Ballotpedia, 2022).

Finally, the third model groups companies from the first model into industries and analyses which industries are the top performers among the others and which variables impact on their success.

Regression (3)

Industries and industry groups determined by PwC in 2018:

- Global Industry – an industry (within a broad meaning) in which a company operates: Consumer Discretionary; Consumer Staples; Energy; Financials; Healthcare; Industrials; Information Technology; Materials; Telecommunications services;
- Industry – a specific industry in which company operates: Industrial Conglomerates; Healthcare Equipment and Services; Biotechnology; Information Technology; Electrical and Electronic Equipment, Instruments and Components; Miscellaneous Manufacturing; Tobacco; Internet and Direct Marketing Retail; Auto Components; Food Products; Diversified Telecommunications Services; Capital Markets; Pharmaceuticals; Leisure Products; Oil, Gas and Consumable Fuels; Household and Personal Products; Airlines; Chemicals; Aerospace and Defence; Automobiles; Beverages; Energy Equipment and Services; Hotels, Restaurants and Leisure; Household Durables; Media; Metals and Mining.

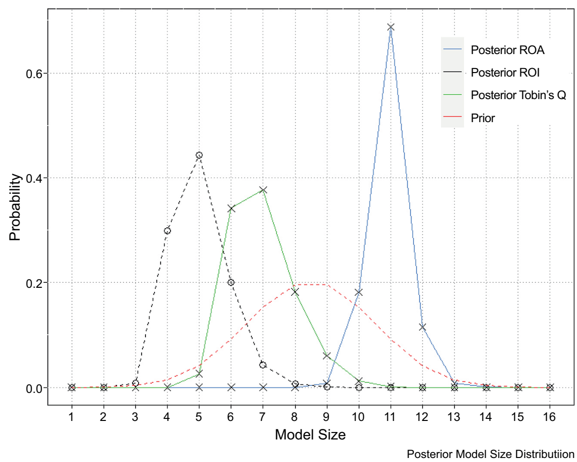
Overall, the regression models include variables such as a company's R&D intensity, age, total assets, total liabilities, sales revenue turnover, market capitalisation, Tobin's Q ratio, net fixed assets, and the government subsidies to a company. The following control variables were also added to the models: education, average wages, unemployment, migration level, population, and the real GDP growth in the state where the firm's headquarters is located.

4. Empirical findings

First, the performance of estimated models with different financial performance (FP) proxies (ROA, ROI and Tobin's Q) is evaluated. Models prior and g-prior used during estimation are default (Eicher et al. 2011b), being fixed and UIP accordingly.

Figure 4

Estimation of Posterior Model Sizes for Different FP Proxies

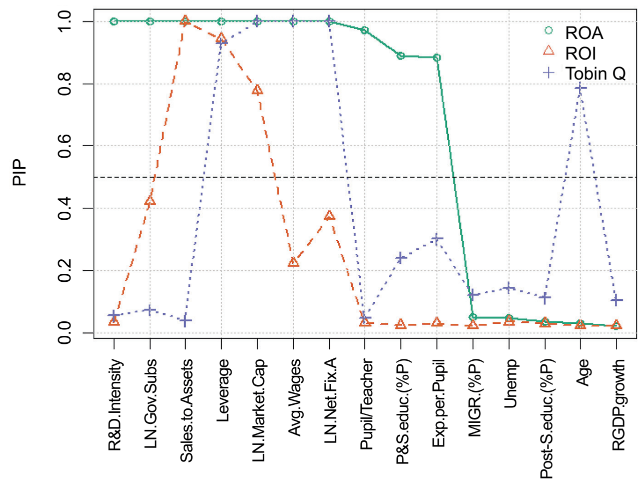


Source: author's own estimations.

The above figure (4) illustrates suggested (efficient) size of the models. Thus, in the model where ROA is the measure of the firm's financial performance, 10 to 12 of the selected variables are statistically significant, whereas the model with 11 variables is found to be the most probable. Figure 5 below illustrates these 11 variables with the best explanatory power regarding the innovation-based firm's ROA: R&D intensity, government subsidies, sales to assets ratio, financial leverage, market capitalisation, average wages, net fixed assets, pupil/teacher ratio, post-secondary education ratio, expenditures per pupil and migration. In the second model where, only 7 variables determining the financial performance of an innovative company measured by Tobin's Q ratio were found to be statistically significant, these are: financial leverage, market capitalisation, average wage, net fixed assets, post-secondary education, expenditures per pupil and the firm's age. The last model, where the company's financial performance is measured by ROI, was found to be small in its size, e.g. most of the variables are statistically insignificant.

Figure 5

PIPs of Regressors for Different FP Proxies

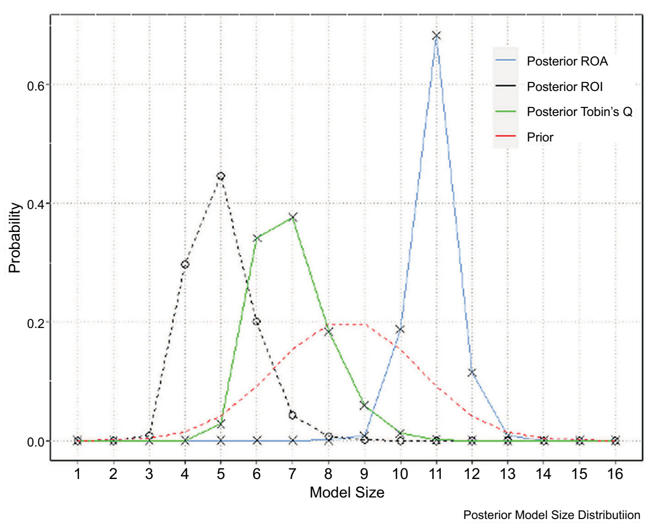


Source: author's own estimations.

Additionally, the data were standardised (Figure 6, Figure 7), and non-typical observations were excluded (Figure 8, Figure 9), however, explanatory power of unprocessed data was almost identical to those standardised for ROA (Figure 10, Figure 11, Figure 12).

Figure 6

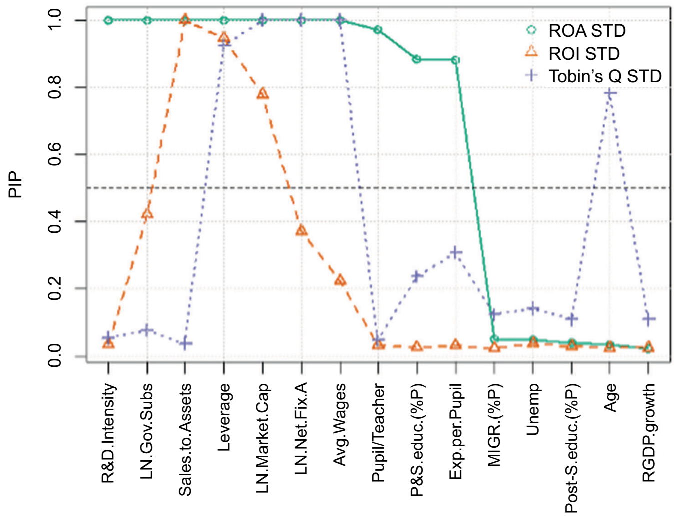
Estimation of Posterior Model Sizes for Standardised Models with Different FP Proxies



Source: author's own estimations.

Figure 7

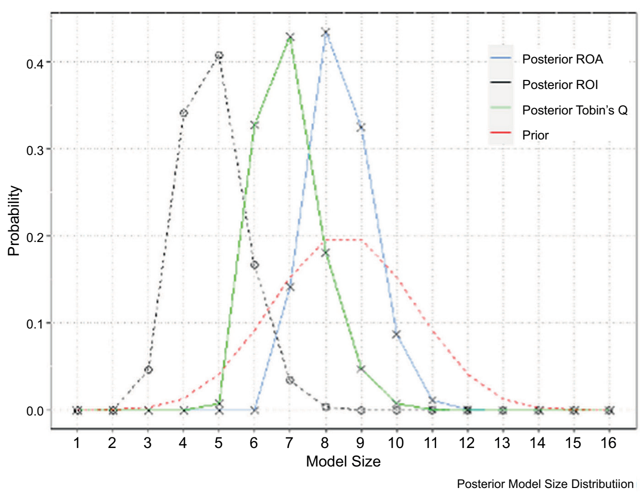
Comparison of PIPs of Standardised Regressors for Different FP Proxies



Source: author's own estimations.

Figure 8

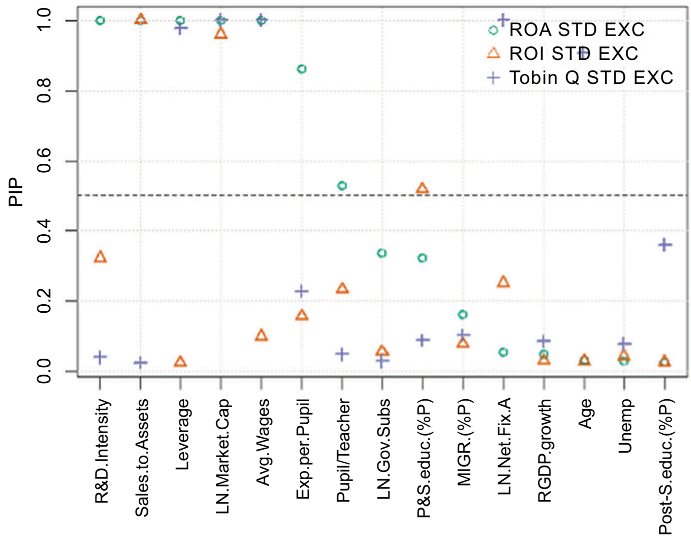
Estimation of Posterior Model Sizes for Standardised Models with Excluded Non-typical Observations with Different FP Proxies



Source: author's own estimations.

Figure 9

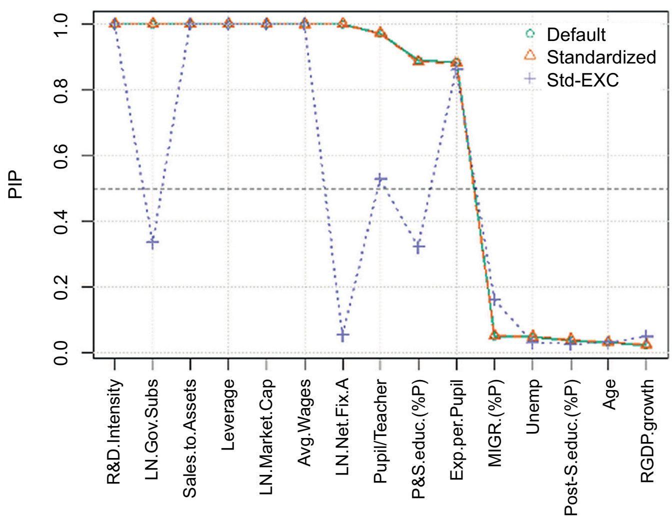
Comparison of PIPs of Standardised Regressors for Different FP Proxies



Source: author's own estimations.

Figure 10

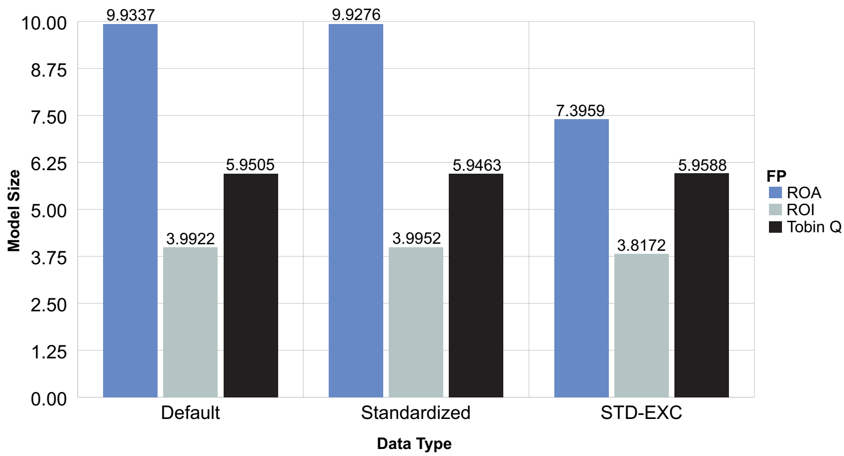
Comparison of PIPs of Regressors for ROA



Source: author's own estimations

Figure 11

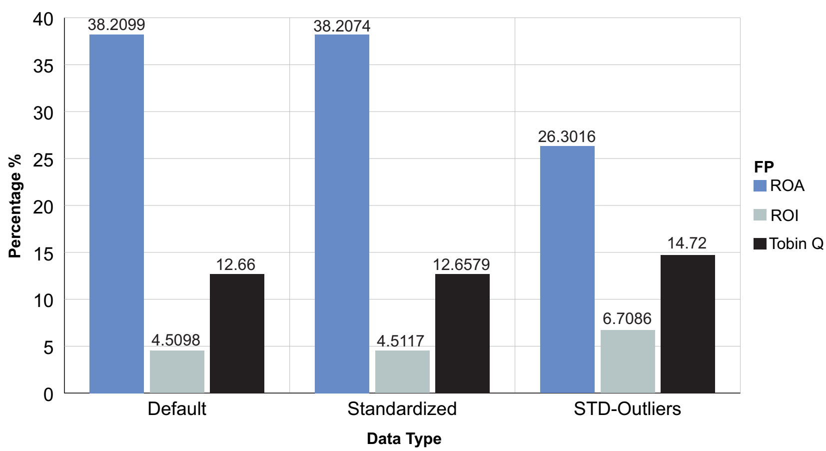
Comparison of Average Model Sizes



Source: author's own estimations.

Figure 12

Comparison of Pseudo-R^2



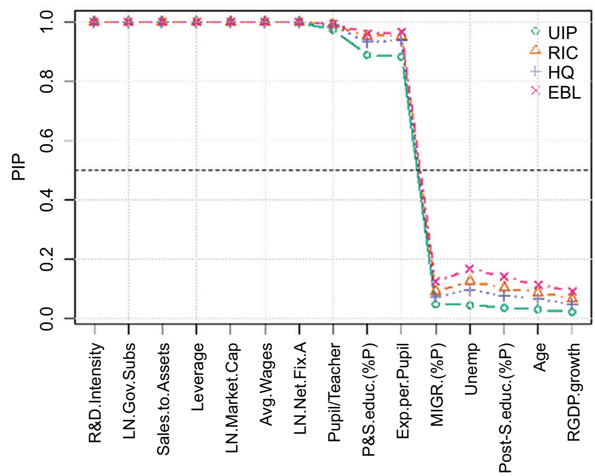
Source: author's own estimations.

Pseudo-R^2 of Tobin's Q and ROI models significantly increased from exclusion of non-typical observations; nevertheless, selected determinants appear to better account for the variability in ROA rather than in ROI and Tobin's Q. Thus, ROA was selected and used further in the research as the main proxy for financial performance.

Second, different g-priors and model priors were tested to determine which combination has the highest performance. Figures 13, 14, and 15 indicate EBL g-prior superiority in terms of PIPs.

Figure 13

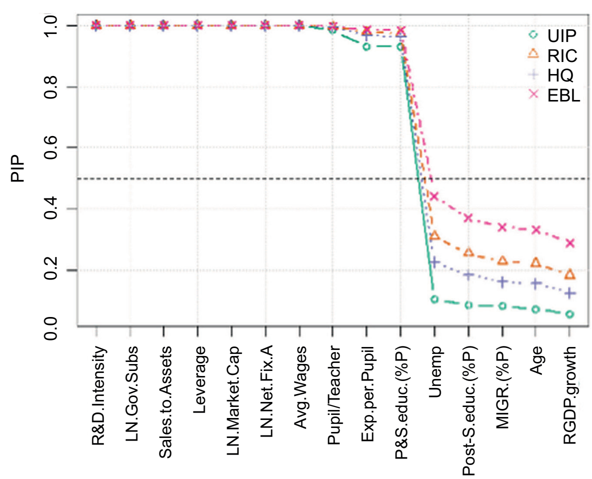
Comparison of Different g-priors under Fixed Model Prior



Source: author's own estimations.

Figure 14

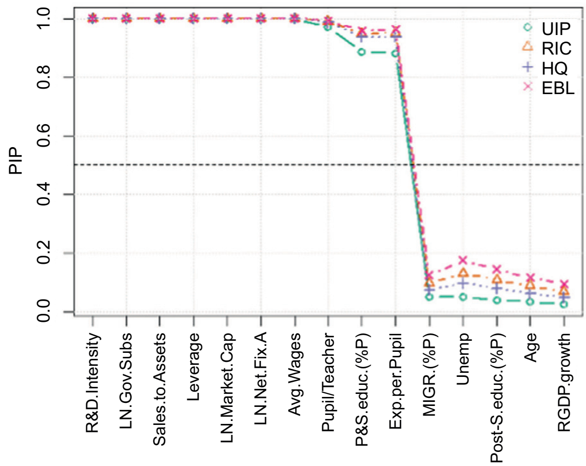
Comparison of Different g-priors under Random Model Prior



Source: author's own estimations.

Figure 15

Comparison of Different g-priors under Uniform Model Prior



Source: author's own estimations.

Nevertheless, Table 1 shows that EBL noticeably worsened goodness of fit, in contrast with RIC, which also produced second best results in average model size.

Table 1

Pseudo-R^2 Scores of Estimated Models

	UIP	RIC	HQ	EBL
Fixed	0.38210	0.38123	0.38188	0.37972
Random	0.38251	0.38161	0.38225	0.37981
Uniform	0.38208	0.38120	0.38189	0.37970
Fixed (%)	0.000	–0.228	–0.058	–0.623
Random (%)	0.107	–0.128	0.039	–0.599
Uniform (%)	–0.005	–0.236	–0.055	–0.628

Note: the upper part of the table represents pseudo R^2 scores, while the lower part indicates R^2 percentage differences; Fixed UIP is set as a benchmark.

Source: author's own estimations.

Taking into consideration the obtained information, RIC and Random Model Prior were chosen, which resulted in the final model estimation summarised in Table 2.

Table 2

The Results of BMA Estimation under RIC and Random Model Prior

	Posterior Inclusion Probability	Posterior Uncond. Mean	Posterior Uncond. SD	Uncond. |Mean/SD| Ratio	Posterior Cond. Mean	Posterior Cond. SD	Cond. |Mean/SD| Ratio	Cond. Positive Sign
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R&D.Intensity	1.0000	–0.0698	0.0096	7.2692	–0.1301	0.0179	7.2692	0.0000
LN.Gov.Subs	1.0000	1.4273	0.2163	6.5971	0.1223	0.0185	6.5971	1.0000
Sales.to.Assets	1.0000	10.1469	0.7268	13.9605	0.2874	0.0206	13.9605	1.0000
Leverage	1.0000	–15.7196	1.2237	12.8464	–0.2458	0.0191	12.8464	0.0000
LN.Market.Cap	1.0000	3.4719	0.3091	11.2339	0.3444	0.0307	11.2339	1.0000
Avg.Wages	1.0000	–0.0004	0.0001	4.7617	–0.1954	0.0410	4.7617	0.0000
LN.Net.Fix.A	0.9999	1.0936	0.2313	4.7288	0.1534	0.0324	4.7288	1.0000
Pupil/Teacher	0.9967	0.6314	0.1558	4.0534	0.1691	0.0417	4.0534	1.0000
Exp.per.Pupil	0.9788	0.0010	0.0003	2.9439	0.1663	0.0565	2.9439	0.9999
P&S.educ.(%P)	0.9743	–105.4055	36.8994	2.8566	–0.0825	0.0289	2.8566	0.0000
Unemp	0.3102	–0.0727	0.1498	0.4851	–0.0084	0.0174	0.4851	0.0047
Post-S.educ.(%P)	0.2556	–5.4960	14.4966	0.3791	–0.0049	0.0129	0.3791	0.0017
MIGR.(%P)	0.2283	–14.0408	45.2036	0.3106	–0.0045	0.0144	0.3106	0.0112
Age	0.2214	0.0014	0.0047	0.2972	0.0037	0.0125	0.2972	1.0000
RGDP.growth	0.1836	–1.3875	9.5971	0.1446	–0.0012	0.0083	0.1446	0.0042

Mean no. regressors	**Draws**	**Burnins**	**Modelspace 2^K**
11.1488	1.00E + 06	1.00E + 05	32768
% Topmodels	**Model Prior**	**Corr PMP**	**No. Obs.**
100	random / 7.5	1.0000	1967
Shrinkage-Stats	**g-Prior**		
Av = 0.9956	RIC		

Source: author's own estimations.

The binomial-beta prior used during estimation is equivalent to assuming 50% prior inclusion probability for each determinant of interest. In turn, posterior inclusion probability allows to evaluate the individual impact a selected regressor has on the adjusted goodness-of-fit of the model (Sala-i-Martin et al. 2004). Thus, a parameter with PIP exceeding 50% prior can be viewed as a robust determinant of firms' financial performance. Column (1) indicates 10 such regressors. Furthermore, Raftery (1995) suggests the following scheme to extract additional information from PIP values: 50–75% bracket stands for weak evidence, 75–95% means positive evidence, 95–99% bracket shows strong evidence, while anything exceeding 99% represents very strong evidence in favour of the variable. Consequently, the application of this hierarchy indicates very strong evidence in favour of the R&D intensity, government subsidies, sales to assets ratio, leverage, market capitalisation, average wages, net fixed assets, pupil to teacher ratio, expenditure per pupil, and primary and secondary education enrolment determinants. PIPs of other considered variables were unable to provide even weak evidence.

Another important statistic can be obtained from consideration of the model as a whole in contrast to the individual-level inference. Barbieri and Berger (2004) advocate for the employment of the median probability model (MPM) for further predictions as opposed to the one possessing the largest PMP. The MPM consists of the determinants with PIP exceeding the 50% threshold. Specifically, in the model space obtained from the estimation, the MPM coincides with the model with the highest PMP (26.9332%).

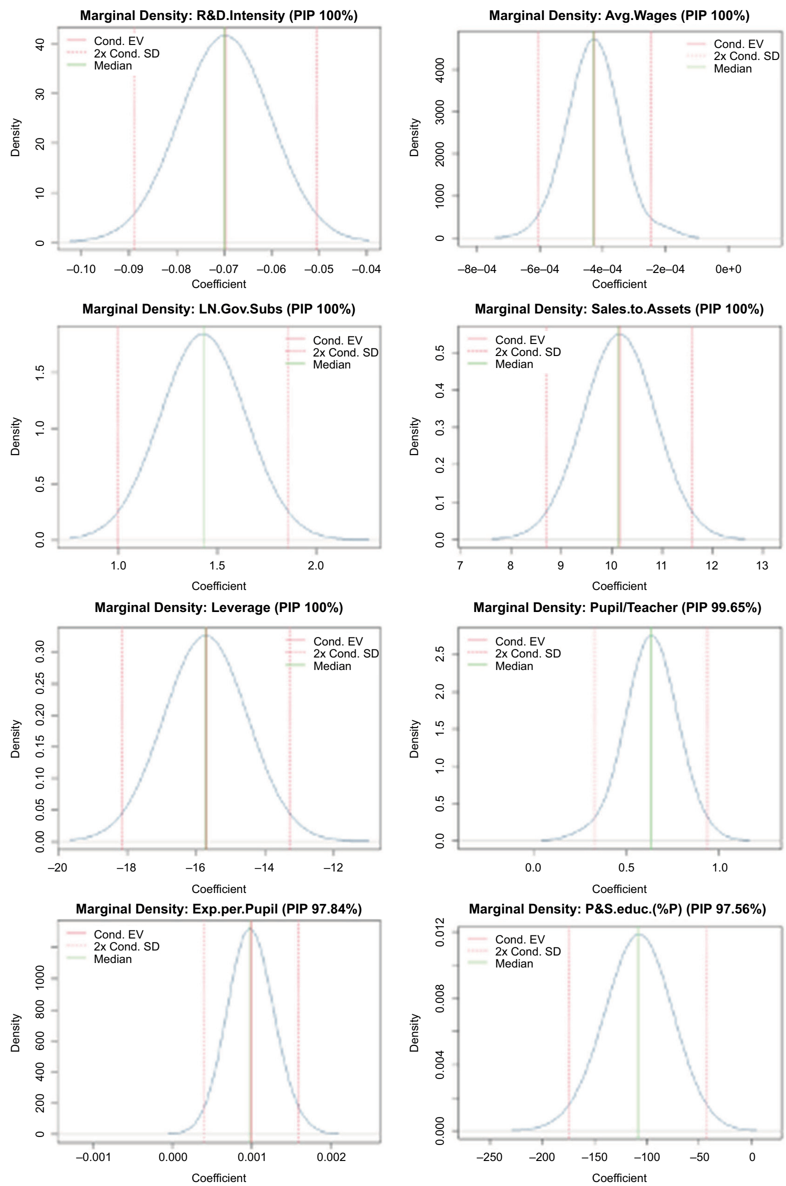
The remaining statistics in Table 2 are divided into conditional and unconditional ones. The interpretation of them is based on the prior belief that a determinant belongs to the true model. If one expects some regressors to be essential to the final model, then one assumes a 100% prior inclusion probability for them, and the statistic conditional on model inclusion should be used. Accordingly, if one has no prior expectations and information about the determinants, unconditional statistic should be utilised for the interpretation.

The conventional frequentist ratio of mean to standard deviation, which is the main method of hypotheses verification, has its analogue in the Bayesian case. Raftery (1995) continues with the framework: PSD/PM ratio higher than 1 is equivalent to the PIP of 50%, thus indicating the importance of the determinant. Sala-i-Martin et al. (2004) and Eicher et al. (2011a) advocate that the ratio of 2 approximates the usual 95% frequentist confidence region. Eicher et al. (2011a) also suggests value of 1.65 to be corresponding to 10% significance level, while Masanjala and Papageorgiou (2008) assume the value of 1.3 for the same level. Despite variation in interpretations, both conditional (Column (7)) and unconditional ratios (Column (4)) of 10 robust determinants of financial performance all exceed 2.

Marginal densities of the determinants, as well as their posterior sign certainty are depicted in Figures 16 and 17, in addition to Column (8). This statistic is convenient to visualise, as it computes the integral of the distribution of the parameter of interest from 0 to $+\infty$, which can be viewed as the probability of conditional PM to be situated on the right side of 0. Following the frequentist logic, if 97.5% of parameter's marginal density is located to the either side of 0, this parameter has a statistically significant sign at 5% level (Sala-i-Martin et al. 2004). In Figures 16 and 17, the red line represents the conditional PM, while the red dashed lines portray ±2 conditional SDs. Thereby, the space in-between the two dashed lines depicts 95% confidence

Figure 16

The Distribution of the Estimated Coefficient



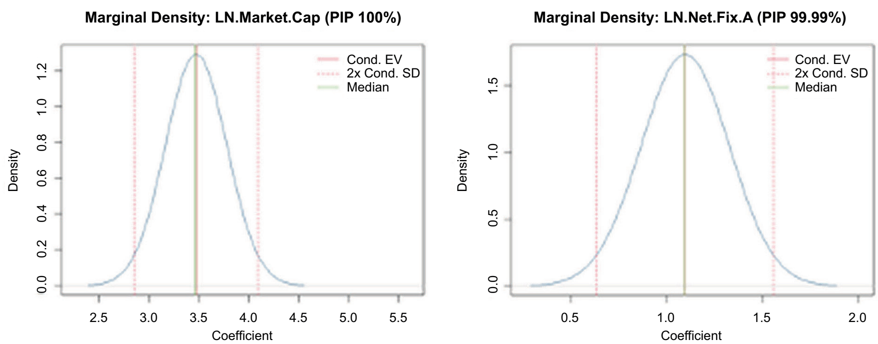
Source: author's own estimations.

interval. To conclude, R&D intensity, leverage, average wages, and primary and secondary education enrolment are strictly negative, while the remaining 6 determinants are positive.

In addition to the model composed of companies belonging to diverse industries (such as Energy, Financials, Materials, Industrials, Consumer Discretionary, Healthcare, IT, and Consumer Staples), industry-level models were estimated (Figures 18, 19, and 20). BRIC in combination with Random Model Prior was utilised, as in some industries number of observations was lower than K^2.

Figure 17

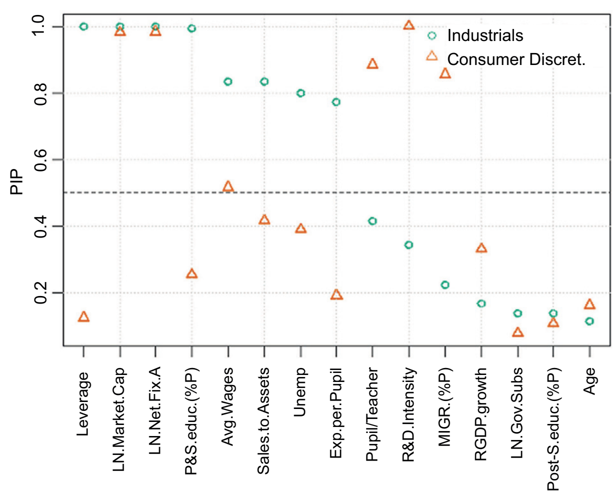
The Distribution of the Remaining Coefficients



Source: author's own estimations.

Figure 18

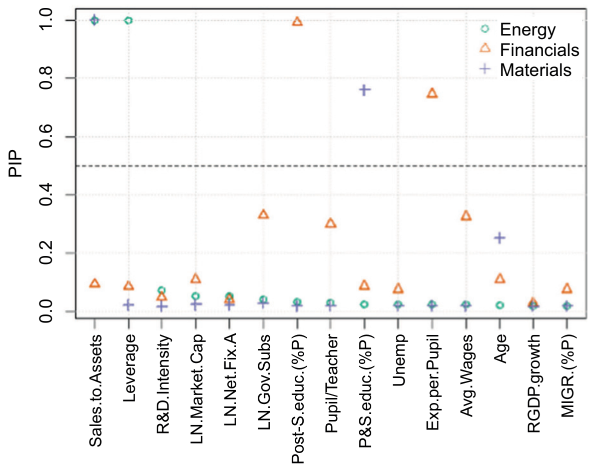
Comparison of Industrials and Consumer Discretionary Models



Source: author's own estimations.

Figure 19

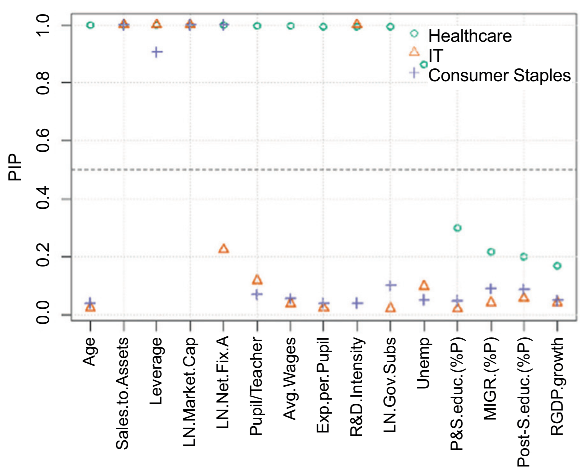
Comparison of Energy, Financials, and Materials Models



Source: author's own estimations.

Figure 20

Comparison of Healthcare, IT, and Consumer Staples Models



Source: author's own estimations.

Table 3

Industry-specific PIPs and Conditional PM/SD Ratios

	Consumer discretionary	Consumer Staples	Energy	Financials	Healthcare	Industrials	IT	Materials
R&D.Intensity	1.0000	0.0397	0.0719	0.0480	0.9927	0.3415	1.0000	0.0174
Age	0.1603	0.0396	0.0212	0.1086	1.0000	0.1127	0.0236	0.2525
RGDP.growth	0.3300	0.0493	0.0200	0.0285	0.1694	0.1679	0.0410	0.0165
Avg.Wages	0.5156	0.0561	0.0236	0.3254	0.9970	0.8339	0.0380	0.0185
P&S.educ.(%P)	0.2525	0.0482	0.0251	0.0862	0.2997	0.9945	0.0197	0.7592
Post-S.educ.(%P)	0.1059	0.0885	0.0318	0.9918	0.2009	0.1368	0.0562	0.0181
Exp.per.Pupil	0.1896	0.0397	0.0236	0.7450	0.9948	0.7721	0.0227	0.0194
Pupil/Teacher	0.8838	0.0702	0.0296	0.2990	0.9974	0.4146	0.1174	0.0200
Unemp	0.3887	0.0508	0.0245	0.0757	0.8647	0.7982	0.0984	0.0180
MIGR.(%P)	0.8549	0.0903	0.0188	0.0754	0.2188	0.2233	0.0410	0.0188
LN.Gov.Subs	0.0763	0.1005	0.0415	0.3298	0.9927	0.1372	0.0217	0.0288
Sales.to.Assets	0.4157	1.0000	0.9999	0.0935	1.0000	0.8328	1.0000	1.0000
Leverage	0.1230	0.9062	0.9999	0.0846	1.0000	1.0000	1.0000	0.0224
LN.Net.Fix.A	0.9820	1.0000	0.0517	0.0393	0.9999	1.0000	0.2243	0.0219
LN.Market.Cap	0.9819	1.0000	0.0520	0.1092	1.0000	1.0000	1.0000	0.0236

Note: Highlighted cells indicate Conditional PM/SD Ratios greater than 2.

Source: author's own estimations.

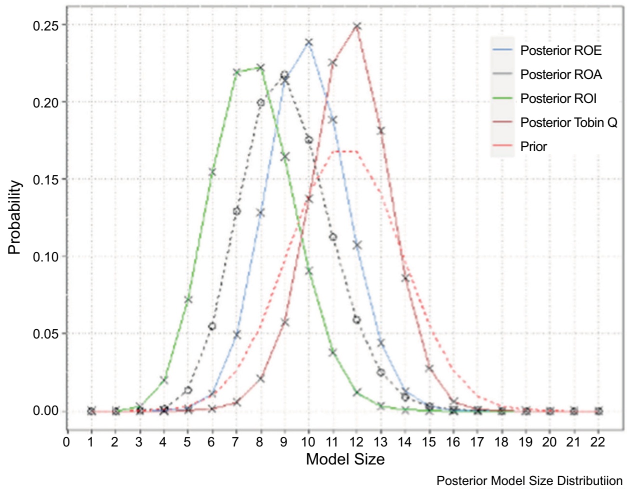
20 HLI companies were selected to conduct more in-depth analysis of financial performance during the COVID-19 pandemic. The set of data used for the estimation comprises more qualitative variables to assess firm-specific managerial practices; however, the time since the beginning of the pandemic is limited, so number of observations is rather scarce. Figures 21 and 22 summarise the statistics obtained from the estimation of models with different FP proxies. Interestingly, models with ROE as dependent variable favour separate set of regressors. PMPs for all regressands do not differ significantly. Nevertheless, out of 4 proxies, pseudo-R^2 is significantly higher for

Tobin's Q: 77.3257%, compared with 62.6807% for ROA, 50.459% for ROE, and 47.6079% for ROI. Thus, Tobin's Q is selected as a dependent variable.

UIP g-prior was selected due to the fact that despite EBL-prior model included two more variables, namely Covid-19 per 100k and R&D intensity, pseudo-R^2 score in it was lower by 2.779%.

Figure 21

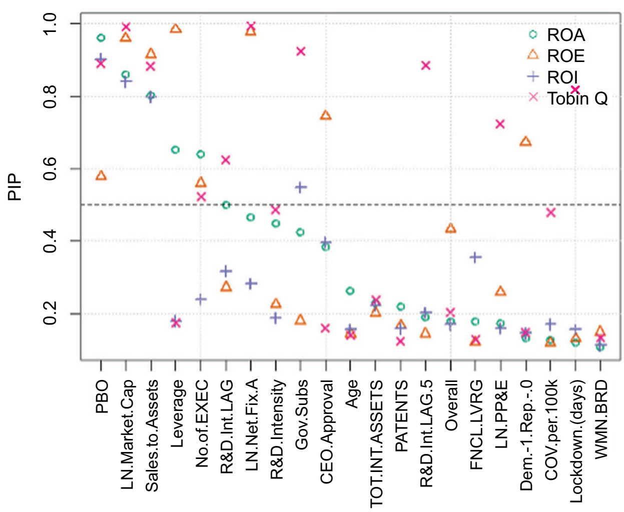
Comparison of HLI Models with Different FP Proxies



Source: author's own estimations.

Figure 22

PIPs of HLI Models with Different FP Proxies



Source: author's own estimations.

The obtained statistics are exhibited in Table 4. Number of executives, R&D intensity 1-year lag, and property, plant, and equipment display only weak evidence. Government subsidies, positive business outlook, sales to assets ratio, and R&D intensity 5-years lag indicate positive evidence, while market capitalisation as well as net fixed assets show very strong evidence in favour of being the true determinants of FP.

Table 4

The Results of BMA Estimation under UIP and Fixed Model Prior for HLI

	Posterior Inclusion Probability	Posterior Uncond. Mean	Posterior Uncond. SD	Uncond. |Mean/SD| Ratio	Posterior Cond. Mean	Posterior Cond. SD	Cond. |Mean/SD| Ratio	Cond. Positive Sign
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
LN.Net.Fix.A	0.9949	–0.6970	0.1958	3.5593	–0.7005	0.1898	3.6901	0.0000
LN.Market.Cap	0.9926	0.4802	0.1194	4.0218	0.4838	0.1124	4.3039	1.0000
Gov.Subs	0.9210	0.0000	0.0000	2.2448	0.0000	0.0000	3.1036	1.0000
PBO	0.8936	3.1176	1.4042	2.2202	3.4888	0.9546	3.6547	1.0000
Sales.to.Assets	0.8873	0.8645	0.4361	1.9826	0.9744	0.3275	2.9751	1.0000
R&D.Int.LAG.5	0.8836	–0.2005	0.1054	1.9031	–0.2269	0.0811	2.7993	0.0011
Lockdown.(days)	0.8182	0.0058	0.0036	1.6132	0.0071	0.0026	2.7467	1.0000
PP&E	0.7308	0.0000	0.0000	1.1610	0.0000	0.0000	1.9139	0.9993
R&D.Int.LAG	0.6243	0.1896	0.1738	1.0905	0.3037	0.1173	2.5887	0.9904
No.of.EXEC	0.5204	0.0342	0.0398	0.8610	0.0658	0.0310	2.1203	1.0000
R&D.Intensity	0.4836	0.1075	0.1327	0.8101	0.2222	0.1043	2.1302	1.0000
COV.per.100k	0.4734	0.0000	0.0000	0.7797	0.0000	0.0000	1.9909	1.0000
TOT.INT.ASSETS	0.2381	0.0000	0.0000	0.2114	0.0000	0.0000	0.4680	0.3088
Overall	0.2005	0.1215	0.3639	0.3340	0.6062	0.6056	1.0009	0.8904
Leverage	0.1724	0.1136	0.3987	0.2849	0.6589	0.7502	0.8783	0.9295
CEO.Approval	0.1598	0.1386	0.5969	0.2322	0.8674	1.2638	0.6863	0.9000
Dem.-1.Rep.-.0	0.1494	0.0306	0.1288	0.2378	0.2050	0.2744	0.7471	0.9187
Age	0.1360	–0.0001	0.0015	0.0495	–0.0006	0.0041	0.1354	0.4727
WMN.BRD	0.1337	0.0013	0.0057	0.2212	0.0095	0.0129	0.7322	0.9893
FNCL.LVRG	0.1311	0.0005	0.0025	0.1849	0.0035	0.0060	0.5808	0.9062
PATENTS	0.1278	0.0000	0.0000	0.0985	0.0000	0.0000	0.2853	0.6276

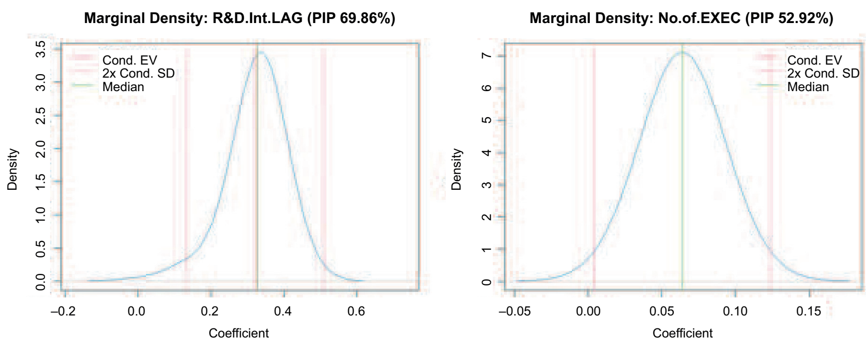
Mean no. regressors	**Draws**	**Burnins**	**Modelspace 2^K**
10.6726	1.00E + 06	1.00E + 05	2097152
% Topmodels	**Model Prior**	**Corr PMP**	**No. Obs.**
54	fixed / 10.5	0.9989	80
Shrinkage-Stats	**g-Prior**		
Av = 0.9877	UIP		

Source: author's own estimations.

The highest PMP model (2.5569%) does not differ substantially from the MPM (PMP = 2.3769%): it does not include number of executives variable. Unconditional PM/SD ratios are quite low compared to the conditional ones, with LN.Net.Fix.A, LN.Market.CAP, Gov.Subs, and PBO considered statistically significant at the 5% level. Sales.to.Assets and R&D.Int.LAG.5 are slightly short of hitting the 95% confidence interval, while Lockdown.days is significant at 10% level, according to Masanjala and Papageorgiou. (2008)'s definition. Coefficients' probability distributions are depicted in Figures 23 and 24.

Figure 23

The Distribution of the R&D Intensity Lag and No. of Executives Coefficient



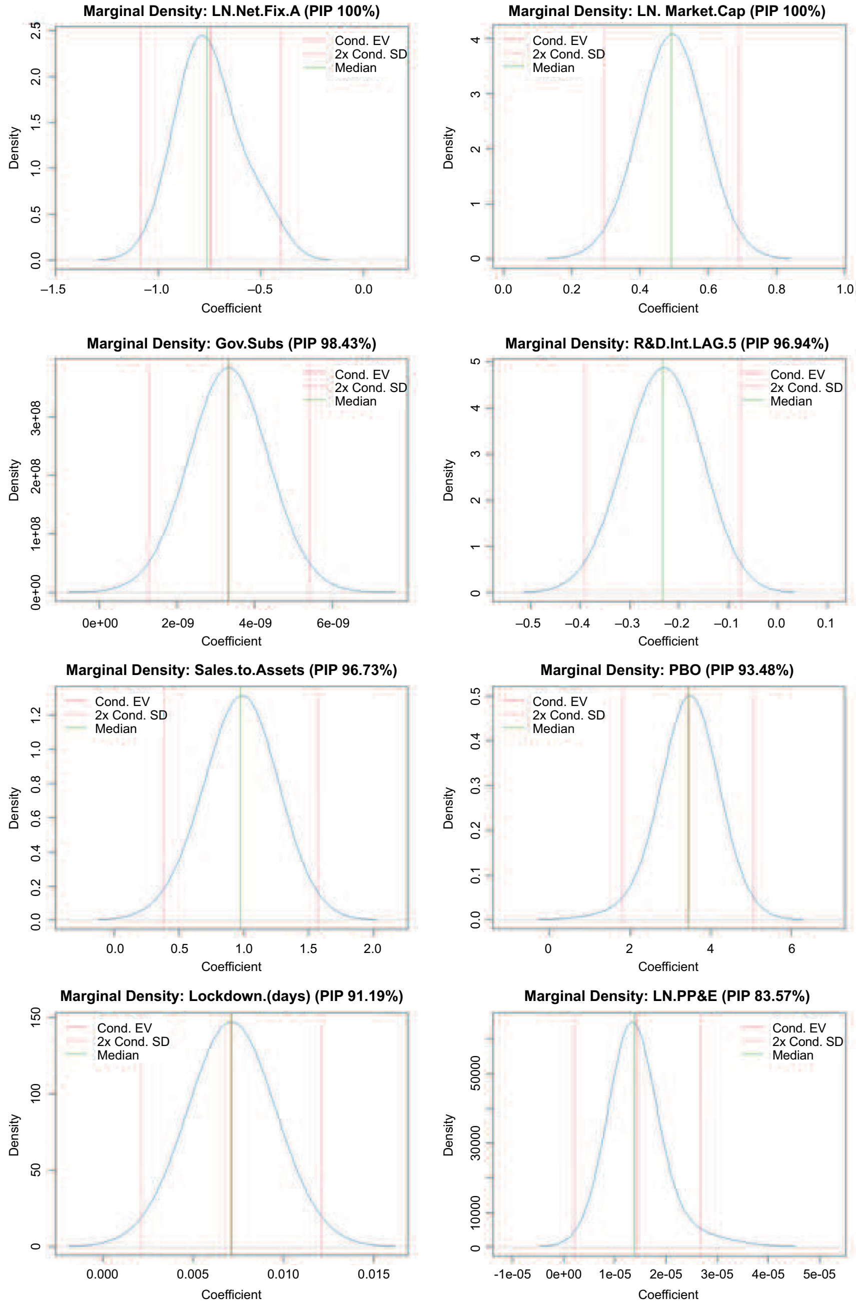
Source: author's own estimations

Discussion of the results

Meta-analysis conducted by Capon et al. (1990) indicates that in 2/3 cases the coefficient of R&D intensity was positive. However, in all the models obtained under the current study, where R&D intensity was statistically significant, it has a negative sign. For instance, in the aggregated model (Table 2) one percentage point increase in a firm's R&D intensity results in 0.0698 drop in ROA. Depending on chosen industries, countries, and financial performance proxies (see Capon et al., 1990; Nandy, 2020; Ayaydin and Karaaslan, 2014; Liu et al., 2021), as well as accounting treatment of R&D (Usman et al. 2017) econometric modeling generated various results and relationships between innovation and financial performance. Empirical outcomes obtained in the present research suggest that among companies competing for the name of high-leverage innovators, R&D efficiency rather than spent amounts matter.

Figure 24

The Distributions of the Remaining Coefficients



Source: author's own estimations.

Also, industry-level models provided evidence in favour of the great importance of the variable in particular industries, namely consumer discretionary, healthcare, and IT spheres. Moreover, R&D investments, depending on the planned duration of the projects, may be unable to pay off in a single year period, so one- and five-years lags were introduced in the HLI model to account for short- and long-term projects accordingly. Companies face trade-off between explorative and exploitative behaviour, when deciding whether to undertake R&D projects; however, "high-R&D firms" are more likely to initiate long-term R&D investments (Vithessonthi and Racela, 2016). The HLI model indicates one-year lag to be positive, which goes in line with Usman et al. (2017)'s findings, while five-years lag to be negative. The sign of the leverage variable follows the majority of empirical studies (N.Capon et al. 1990).

5. Conclusions

The main goal of this research was to determine factors driving the success of the US innovation companies, especially during the COVID-19 pandemic. The paper uncovered some of the empirical studies, where numerous researchers estimated variables which impact financial performance of the innovation-based companies, including the periods of crisis. With the use of the Bayesian Model Averaging, the impact of innovation related investments, firm characteristics and management performance on the corporate financial returns was assessed. The leading US innovation companies during the period from 2012 to 2021 were taken as a sample for the purpose of the present analysis. Various quantitative (financial performance) and qualitative (management performance) factors were included in the regressions. Control variables, such as macroeconomic variables (population, unemployment, education), were also taken into consideration. Empirical results illustrate the reliability and non-reliability of the selected parameters. In accordance with the results, the BMA estimations proved that there is a significant impact of firm's characteristics (both quantitative and qualitative) and firm's management performance on the corporate financial returns of the US innovation-based companies (industries) before and during the COVID-19 pandemic.

Overall, the essence of the chosen econometric method allowed for claiming that robust determinants of financial performance among 281 US companies in the R&D field from 2012 to 2018 were obtained. First, ROA was found to be the most suitable proxy of a firm's financial performance for testing the set of variables proposed by theoretical and empirical literature.

The most significant determinants of FP are not limited to a specific level: the final model consists of the firm-, industry-, and state-level variables, while commonly used balance-sheet parameters were among the least significant. In addition, econometric modeling conducted on the industry level emphasised the diversified nature of drivers of financial performance.

The model designed to research the behaviour of 20 HLI companies during the COVID pandemic showed the importance of managerial practices and approved the correlation between employees' perception of workplace atmosphere and financial performance. Compared to the whole pre-pandemic sample, the age of an HLI company played an opposite role: younger companies were performing better. This phenomenon can be explained by the fact that the IT sector, which is relatively new, was the most flexible during the pandemic and imposed lockdowns. In all the models discussed, FP appeared to be negatively influenced by R&D intensity. This is mainly due to the long-term financial and strategic effect, which R&D projects have. Thus, it is suggested for future studies to examine the relationship and significance of R&D intensity's lags over a wider time span.

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Impact of Innovation and Management Performance on Corporate Financial Returns Exemplified by the US Research and Development Sector Firms Before and During the COVID-19 Pandemic

Abstract

This paper aims to evaluate to what extent investments in R&D, firm innovation-related spending, firm characteristics, and management performance impacted the financial results of the US companies before and during the global COVID-19 pandemic. The main research question is whether the COVID-19 pandemic has a significant positive impact on the financial results of the US innovation-based companies. The main hypothesis of the research is that innovation-related investments, firm characteristics, and management performance have a significant positive impact on the financial results of the US innovation sector firms. Finally, it is expected that the greatest significance in the US innovation industry-level models is acquired by the healthcare and IT sectors.

Keywords: COVID-19, pandemic, innovation, investment, financial performance, US industry models, IT

Wpływ innowacyjności i wyników zarządzania na zyski finansowe przedsiębiorstw na przykładach amerykańskich firm z sektora badań i rozwoju przed pandemią COVID-19 i w jej trakcie

Streszczenie

Opracowanie ma na celu ocenę, w jakim stopniu inwestycje w badania i rozwój, wydatki firm związane z innowacjami, charakterystyka firm i wyniki zarządzania wpłynęły na wyniki finansowe amerykańskich firm przed i podczas globalnej pandemii COVID-19. Główne pytanie badawcze dotyczy kwestii, czy pandemia COVID-19 ma znaczący pozytywny wpływ na wyniki finansowe amerykańskich firm opartych na innowacjach. Główną hipotezą badania jest natomiast to, że inwestycje związane z innowacjami, charakterystyka firmy i warunki zarządzania mają znaczący pozytywny wpływ na wyniki finansowe amerykańskich firm z sektora innowacji. Jak wynika z przedstawionych badań, największe znaczenie w amerykańskich modelach branżowych innowacji mają sektory opieki zdrowotnej i IT.

Słowa kluczowe: COVID-19, pandemia, innowacje, inwestycje, wyniki finansowe, amerykańskie modele branżowe, IT

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