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INNOVATION AND FIRM PERFORMANCE: EVIDENCE FROM FINNISH PUBLIC COMPANIES

Master's Thesis
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Abstract of master's thesis

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Abstract

In this paper, I examine the innovation activities and effect of commercialized innovations on firm performance, measured with productivity and market value, of Finnish public companies during 1988-2017. This study provides novel information on innovations which is a complex matter but very important for both private and public sector growth and competitiveness. There is no similar previous study with commercialized innovations. The topic is also current for Finland due to a recent report, Securing Finland's competitiveness and economic growth in the 2020s, by Erkki Ormala made for the Ministry of Economic Affairs and Employment of Finland and published in January 2019. His report finds that the conditions for innovating in Finland are weakening and that companies are moving their innovation activities abroad seeking better cooperation opportunities and financing for innovation. I show supporting evidence of an overall downward trend in the number of innovations, patents, R&D investments and public subsidies. Companies are also applying for international patents instead of Finnish patents. Another worrying finding is a decline in Finnish innovation productivity measured by the number of innovations in relation to R&D expenditures.

Building on this, I analyze unique innovation data collected by Technical Research Centre of Finland (VTT). The study and methods are largely based on the work by Bloom and Van Reenen (2002) with the biggest difference being my use of commercialized innovations instead of patents as a proxy for technology. The study finds innovations to have significant impact on performance and firms who innovate to be 10% more productive than those who do not. First main question finds that innovations themselves have a negative effect on productivity, but that higher level of innovation complexity would increase productivity. Second, I find a positive effect of innovations on market value and that higher innovation complexity has a negative effect on market value in the year of commercialization but turns positive in the following year of commercialization. These main results support the importance of innovation and innovation complexity on firm performance. To secure sustainable growth and competitiveness, companies would be recommended to focus on innovation productivity and the government should follow Ormala's (2019) suggestions on strengthening applied research, innovation funding and collaboration between operators.

Keywords innovation, complexity, performance, productivity, market value

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Tiivistelmä

Tässä maisterin tutkielmassa tutkin 1988-2017 aikavälillä suomalaisten pörssiyhtiöiden innovointia ja kaupallistettujen innovaatioiden vaikutusta yritysten suorituskyvyn osa-alueisiin tuottavuuteen ja markkina-arvoon. Tutkielma tarjoaa uuttaa tietoa niin yritysten kuin kansantalouden kasvun ja kilpailukyvyn kannalta tärkeistä innovaatioista. Vastaavaa tutkimusta kaupallistetuista innovaatioista ei ole aiemmin tehty. Aihe on myös ajankohtainen Suomessa, josta kertoo tutkimuksen kehyksenä toimiva Aalto-yliopiston professori Erkki Ormalan työ- ja elinkeinoministeriölle tehty ja tammikuussa 2019 julkaistu selvitys ”Suomen kilpailukyvyn ja talouskasvun turvaaminen 2020-luvulla”. Selvityksen mukaan Suomen innovaatioympäristö on heikkenemässä ja yritykset siirtävät innovaatiotoimintaansa ulkomaille parempien yhteistyömahdollisuuksien ja rahoituksen perässä. Vastaava kehitys ilmenee myös tutkimuksestani, joka osoittaa yritysten innovaatioiden, T&K-investointien, patenttien sekä valtion tukien laskeneen etenkin viimeisten kymmenen vuoden aikana. Lisäksi panttien osalta havaitaan muutos suomalaisista patenteista ulkomaisiin patentteihin. Huolestuttavana havaintona tutkielma löytää myös yritysten innovaatioiden tuottavuuden, eli innovaatioiden määrän suhteessa T&K-kuluihin, laskeneen.

Tämän viitekehyksen pohjalta analysoin Teknologian tutkimuskeskus VTT:n ainutlaatuista käsin kerättyä innovaatiodataa. Tutkimus pohjautuu pääasiassa Bloomin ja Van Reenenin (2002) ajatuksiin mutta eroaa erityisesti tarkastelemalla kaupallistettuja innovaatiota patenttien sijaan. Tutkielmassa löydän uusia ja merkittäviä tuloksia innovaatioiden vaikutuksista yritysten suorituskykyyn. Ensinnäkin, tulosten mukaan yritykset, jotka innovoivat, ovat 10% tuottavampia kuin yritykset, jotka eivät ole kaupallistaneet innovaatioita. Laajemman tarkastelun myötä tutkimustulokset kertovat, että innovaatiot itsessään vaikuttavat negatiivisesti tuottavuuteen, mutta korkeampi innovaation monimutkaisuus kasvattaa tuottavuutta. Toisaalta tutkimus taas löytää, että innovaatiot jo itsessään kasvattavat markkina-arvoa. Monimutkaisuus taas vaikuttaa aluksi kaupallistamisvuonna negatiivisesti markkina-arvoon mutta vaikutus muuttuu positiiviseksi kaupallistamisvuotta seuraavana vuotena. Tutkimus korostaa innovaatioiden ja niiden monimuotoisuuden tärkeyttä yritysten suorituskyvylle. Kestävän kasvun ja kilpailukyvyn takaamiseksi yritysten olisikin hyvä keskittyä innovaatioiden tuottavuuteen, kun taas hallituksen olisi hyvä seurata Ormalan (2019) suosituksia soveltavan tutkimuksen, innovoinnin rahoituksen sekä toimijoiden yhteistyön vahvistamiseksi.

Avainsanat innovaatio, monimutkaisuus, suorituskyky, tuottavuus, markkina-arvo

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1. Introduction

1.1. Research objectives

Globalized environment challenges business and innovation activities continuously. Companies cannot build their future only on cost cutting of their production resources anymore. Instead, they are asked to provide new high value adding products and services to the global market. Companies and countries need to keep up with the change to ensure future performance.

A recent report published in January 2019, Securing Finland's competitiveness and economic growth in the 2020s, conducted by professor Erikki Ormala from Aalto University states that the conditions for innovation has significantly weakened in Finland and that Finland is lagging behind other countries risking its economic growth. The report was commissioned by Minister of Economic Affairs Mika Lintilä with a request to examine the adequacy of resources for applied research and the role of VTT Technical Research Centre of Finland in promoting innovation activities that serve business and industry.

The report finds that companies, especially within the metal refinery and pharmaceutical industries, have been moving their research activities away from Finland. Over 17 percentage of research and development activities were conducted abroad, and it is estimated to increase to 28 percentage in 2019. The main reason is found to be the decline and cuts to available funding in Finland compared to more generous funding offered abroad. Also, cooperation between different actors has declined and companies have difficulties finding enough skilled employees in Finland. International companies are found to build new business activities abroad and not in Finland. As a solution to the weakening innovating environment, Ormala (2019) suggests better coordination, increasing of long-term financing available and predictability.

Considering that in today's economy, technological development is seen vital for economic performance, Ormala's (2019) report shows a worrying trend of a weakening environment and opportunities for innovating in Finland. Yet, even though the financing offered to innovation activities or the number of innovations might be larger in other countries, there are studies that show a broader decrease in the productivity of innovations. (Stumsky et al., 2010). Thereafter, there seems to be an ever-greater need for further research on innovations and especially on their relation to private and public performance.

There is still a question among researchers on how to best measure technology within empirical economics. Measuring technology as a residual from a production function has become one popular tradition with an important exemplification by Solow (1957). However, the production function estimation allows only an indirect analysis of productivity as its residual contains a measurement error. Another tradition has been to substitute technical change by observable proxies, most often being research and development (R&D) expenditures or patent and patent application counts (Bloom & Van Reenen, 2002; Blundell et al., 1998; Griliches, 1990; Hall et al., 2000). R&D expenditures are less undertaken and reported by Finnish companies resulting in a small and short-term sample too vague to be examined by itself. Third, and the main factor in this study, is innovation count. Innovation count is a rarer measure within researchers for one reason being the scarce availability of data on individual innovations in different countries. In the United Kingdom, for example, the innovation series end already in 1983 (Pavitt et al., 1987; Blundell et al. 1995).

Hence, there are three aspects of innovation studies, with relatively little earlier attention, to which this paper contributes. First, regarding the report form Ormala (2019), this study assesses the innovating activities by the Finnish companies which is very important to the future performance of the entire country. Second, I had the possibility to broaden the approach on innovation from R&D and patents to commercialized innovations thanks to hand collected innovation material gathered by Technical Research Centre of Finland VTT. Second, this study expands the usual view of purely high technological firms, for which the R&D expenditures are significant and available, to other, lower technology industries as well. The sample covers a group of Finnish public companies further increasing the novelty of this study and marking the first time that the underlying innovation data by VTT is used to the questions concerned. The unique data set also emphasizes the important work VTT is doing.

As the main question, I examine how innovation affects two company performance measures: productivity and market value. Interpreting production functions is easier as they are clearer to construct and comparable with existing studies. Market value, on the other hand, involves analysis for action with possible pay-offs only in far future as it is a more forward-looking measure.

I base this study and methods largely on the work by Bloom and Van Reenen (2002). Bloom and Van Reenen (2002) find that patents pose an immediate impact upon market values but the effect on productivity takes more time. I conduct my main hypothesis the same way and state that commercialized innovations will affect market value immediately and positively and later have a positive impact on productivity. Following their reasoning, I rationalize the delay of the innovating effect on productivity by the need to fully embody the new products and processes in training and new capital equipment, which takes time. Moreover, promotion of the new products might require further research and development and costly marketing activities. These correspond to vast sunk cost investments largely irreversible. Furthermore, I include real options theory to take into consideration the innovative action for new products and processes that are not yet conducted but would generate future value if the firm opts to proceed with it.

The predictions through the analysis in this paper imply that higher market uncertainty will lead to more cautious investment decisions and hamper innovation. However, as I study innovations that have already been commercialized, I suggest that being able to commercialize innovation during higher market uncertainty could imply better skills and resilience and thus uncertainty could turn the innovation effect positive.

I incorporate and adapt the theories of the relationship between patenting activity and performance into the relation with commercialized innovation counts to performance and test them empirically. In addition to the econometric analysis, I include visualized data to support the findings by Ormala (2019) of the decline in innovation.

1.2. Structure of the thesis

This paper is structured as follows. Section 2 discusses previous literature and research on the topic of innovation from different point of views. Section 3 describes the initial databases and the construction of the combined database and its key features used for analysis. It also includes some supportive figures based on data for the analysis. Section 4 outlines the examined empirical models used to estimate how innovating affects firm performance. In addition, the section describes a possible extension form the model accounting for real options. Section 5 presents the econometric results in detail and Section 6 concludes the paper with a summary and discussion on limitations and further research suggestions.

2. Literature review

2.1. Innovation in general

In today’s increasingly knowledge-based economy, organizational studies have been emphasizing the factors behind the ability to produce influential innovations. Innovation can be described as a fundamental organizational output as it has a direct effect on firm viability as well as an impact on social and economic change.

At macro level, innovation and especially technological innovation is crucial for country’s economic growth (Schumpeter, 1943; Solow, 1957; Hui et al., 2017). At micro level, innovation capacity indicates firm’s long-term competitive advantage (Porter, 1992; Hui et al., 2017). According to famous economic theory, long-term productivity growth is a consequence of mainly knowledge development (Schumpeter, 1949) and technical change (Solow, 1957). Furthermore, R&D is a key factor of technical change (Romer, 1990). Schumpeterian endogenous growth theory states that R&D expenditure affect positively productivity growth. (Moncada & Castello, 2016; Schumpeter, 1949).

Berghäll (2015) examines Finland's claimed structural shift to an innovation economy at the global technology frontier. His basis hypothesis states that when reaching the global technology frontier, countries need to base their growth models on innovation instead of investment. The paper finds that innovation raises efficiency in advanced economies but also that it is not significant in Finland. For Finland to increase efficiency and to catch-up the global technology frontier, more significant and important would be to improve education and new ICT technologies. In Finland, even in the leading high-tech industry, R&D impacts on productivity, measured by either efficiency, R&D intensity, technical change or the R&D elasticity, are rather weak, in contrast to labor elasticity, firm size and scale elasticity. (Berghäll, 2015).

However, even though it is widely accepted that technological development is largely important for economic performance, there has long been discussion and disagreement on how to best measure technology within empirical economics.

One traditional measure by Solow (1957) takes technology as a residual from a production function. This is widely used, though, the residual also contains the measurement error from the production function estimation measuring productivity only indirectly. Second tradition is to measure observable proxies for technical change such as research and development (R&D) expenditures as well as patent counts and citations. (Bloom & Reenen, 2002). According to Heimonen (2013), some studies approximate innovation with intellectual property rights such as patents, utility models, registered designs and trademarks as in others innovation is described as the intentional introduction and application within a group or organization of ideas, processes, products or procedures, new to the relevant unit of adaption, designed to benefit the individual, group, organization or wider society.

Research and development (R&D) indicators such as R&D intensity are also increasingly studied and used for international comparisons and targets for policies. However, for policymaking, it is important to observe whether the differences are intrinsic due to firm level underinvestment in R&D or structural due to sector differences (Moncada & Castello, 2016). The theoretical and methodological framework for corporate R&D intensity and the literature on the determinants of R&D investment in industry subgroups is very recent and rather limited resulting in mixed results on different industries and firm variables. (Becker & Hall, 2013; Moncada & Castello, 2016).

R&D and the number of patents received at the cross-sectional level, across firms and industries implies a strong relationship indicating that patents may be a good indicator of unobserved inventive output and that it is not just due to size differences. Even though the same relationship is much lower, evidence shows quite strongly that when a firm changes its R&D expenditures, parallel changes occur also in its patent numbers. The relationship is close to contemporary with some lag effects which are small and not well estimated (Hall et al 2000). This is consistent with the observation that patents tend to be taken out relatively early in the life of a research project. (Griliches, 1990). Blundell et al. (1998) provide evidence on patents being often applied for early on in the R&D process, so that further R&D expenditure may be needed to bring the products to market.

Patents contain also other information of which citation counts is the most popular measure. A patent that has many citations is more likely to generate value than rarely cited patents (Bloom & Reenen, 2002; Griliches, 1990). Hall, Jaffe and Tratjenberg (2000) study whether patent citations are useful in measuring the patent's importance. They estimate Tobin's Q by R&D to asset stocks, patents to R&D, and citations to patents ratios and find that they all have a significant impact on market value with one citation per patent increasing market value by 3%. With a deeper examination they find that the impact of knowledge stock ratios on market value varies largely across sectors.

Regarding the limitations of patent measures, one of the major issues is that not all innovations are patented. This can be because they do not meet the criteria for patents, or the inventor has made a strategic decision not to patent and instead rely on secrecy or other means to capture profits generated by the innovation. (Hall et al., 2000). There have been very few opportunities to research this issue of how representative patents are of the broad innovation scope because of the lack of systematic data. about inventions without patents. This is seen as an important subject for future research on which this paper tries to take a step forward.

Criticism also focuses on the empirical measures of R&D and patenting activities of innovation activity being inputs or intermediate outputs instead of the final outputs of products and processes (Griliches, 1990; Pavitt et al., 1987). Thus, the output of R&D investment activity is an intangible asset enhancing the firm's knowledge stock. In a case the output contribution is positive on future cash flows, the size of firm's market value should reflect its knowledge stock and thus indirectly its R&D investments. (Hall et al., 2000).

There are other possibilities for knowledge proxies but there is exists very little prior work on them. One prior study, variable of which is also used for this thesis analysis, by Blundell et. al. (1995) studies innovation counts as a proxy for knowledge. They model a count number of innovations commercialized by a firm in a year to examine the effect on market power and on tangible and knowledge capital stock. Their study finds that most companies involve in very little innovative activity while only a small group are very active. They derive that the observable differences across companies are not the only factors so empirical models for innovation activity would include unobservable permanent heterogeneity. Firm specific heterogeneity would be reflected in more of zero innovation counts in a cross-section data than if predicted by the standard Poisson and negative binomial models. As a solution Blundell et al. (1995) represent zero-inflated or positive count data models allowing a different process to define the number of positive counts and whether a count occurs or not. Nevertheless, a more robust choice for explicit examination of the dynamic feedback would be panel data. Analysis in this study is also based on panel data models, with fixed effects, to test on innovations.

2.2. Innovation and performance

There is various research on the impact of variables related to firm and offering characteristics, ownership structure, governance, venture capital participation, and investment bank prestige on post-issue performance in international markets but relatively little research on innovation performance (Jain & Kini, 2008).

Tested with British patenting data by Bloom and Van Reenen (2002) patents are shown to statistically significantly affect firm-level market value and productivity. Analyzing activity whose pay-off might be only for near future, market value is an appropriate measure being forward-looking. However, the study indicates that patents have an immediate impact on market value but take time to affect productivity. This can be due to the fact that the new products and processes covered by the patents take time to be implemented with new capital equipment and training and possible further expenses on R&D and advertising. However, patents provide exclusive rights to new technologies giving an option to wait execution of these sunk cost investments generating valuable real options. When market uncertainty is higher, the value of real options increases and, reduces the impact of new patents on productivity. (Bloom & Van Reenen, 2002).

Their statement forms the basis for my main hypothesis that also commercialized innovations have an immediate positive effect on market value and, with a delay, a positive effect on firm productivity. However, the uncertainty effect with commercialized innovations can be positive as commercializing innovations during more uncertain times could imply better implementation skills and resilience.

Castellacci and Zheng (2010) investigate the relationships between technological regimes and productivity performance of Norwegian firms and whether the relationship differs in different Schumpeterian innovation patterns. Their results indicate that total productivity growth is mainly achieved through technical progress, while technical efficiency has on average decreased. Technological regime characteristics are important for firm productivity growth, but not technical progress and efficiency as estimated model works differently in the two Schumpeterian regimes. Schumpeter Mark II industries is more dynamic environment for technical progress, while efficiency change has been more important in Schumpeter Mark I markets. In a Schumpeter Mark II regime, large incumbent innovators may lead productivity growth within the oligopolistic markets. On the other hand, in Schumpeter Mark I industries, productivity might be driven by intense competition by disruptive, more productive innovators (Foster et al., 1998; Castellacci & Zheng, 2010).

2.3. Innovation and stock market listing

As I carry my study on Finnish listed companies, I find it important to discuss some effects that going public and being listed on a stock exchange might have on firms' innovating activities.

A well-noted recent study by Bernstein (2015) indicates that going public has an effect on three dimensions of innovation activity: the creation of internally generated innovation, the productivity and mobility of individual inventors, and the acquisition of external innovation. The main hypotheses include a theory that selling equities publicly in frictionless financial markets should not affect subsequent innovation activity. However, under financial frictions, going public improves firms' access to capital, which can lead to an increased innovation activity. On the other hand, agency problems associated with the transition to public equity markets may undermine firm incentives to innovate.

Also, other research on the relationship between public versus private ownership structures and incentives to invest in innovative projects suggest that going public drives the exploiting of existing ideas while private firms have greater tendency to explore new ideas (Huasheng et al., 2013). Most probable reason behind this is that public firms are more transparent to outside investors encouraging them to reduce the risk-taking activities. Public companies have tighter disclosure requirements on e.g. interim earnings reports and annual reports as well as on analyst coverage. Moreover, public firms can adjust to possible bad news by an early exit strategy shielding insiders from failures and inclining their motivation to invest in innovative projects. On the other hand, prices of public securities react quickly, which incentivize insiders to go with conventional and quickly cashable projects even if it had a lower net present value than its alternative (Ferreiray et al., 2012).

Hui, Hanya and Zhang (2017) analyze the effect of the stock market on firm innovation with a unique Chinese firm-level data and find that both the quantity and quality of firm innovation activity as well as scope beyond core business increases after IPO. There is, however, a variation across financial constraints, corporate governance, and ownership structures. Furthermore, studies have shown that IPOs encourage firms to increase the number of inventors and helps in retaining existing inventors. IPO also has been shown to increase firm's Tobin's Q (total market value/total asset value of a firm) in the long run along with innovations. (Hui et al., 2017).

Stock market is an important resource of capital for firms and thus provides access to equity financing with lower cost than debt financing spurring firm's innovation activity (Hall & Lerner, 2010; Hui et al., 2017). According to Holmström (1989), the payoff of long-term, idiosyncratic nature of innovation is heavily skewed and risky making debt financing less efficient. This access to equity financing could make a listed firm to pursue more innovation activities. However, existing corporate finance literature refers to agency problems that weaken the operation efficiency after an IPO (Berle & Means, 1932; Jensen & Meckling, 1976). Wies and Moorman (2015), on the other hand, state that listing firms will increase their innovation levels and variety of each innovation but reduce their innovation riskiness and with fewer breakthrough innovations and fewer new-to-the-firm innovations.

2.4. Innovation, uncertainty and real options

There exists a large theoretical literature on the importance of real options in firms' optimal investment strategies including papers of McDonald and Siegel (1986) and Dixit (1989). They suggest that firms have an incentive to postpone irreversible investments while waiting for more information making the future value of investment more uncertain. Nembhard and Aktan (2009) discuss the uncertainty related to the commercialization phase with nanotechnology as their focus of study mentioning uncertainties such as timing of entry into different markets, the scale and scope and demand. Uncertainty is also innovation specific as nanotechnology, as an example, adds risk concerning human and environmental safety while toilet paper would pose a much lower risk.

Real options have been identified and divided into several basic types including 1) option to expand (expand operations if the initial investment turns out well), 2) option to switch (switch use between inputs), 3) option to delay investment (waiting can add value through resolution of uncertainty) and 4) option to abandon (abandon further investments after small initial trial investments if events do not go as planned). In addition, there are three more options being 5) learning option (sequential investments in R&D and commercialization process allow for learning) as well as 6) cooperative options and 7) competitive options (cooperation to share risk and add value or going alone and competing with innovation process). (Nembhard & Aktan, 2009).

Brach (2003) argues that new products and processes poses great real growth option value as, in addition to the current cash-flow generation, they can be used for new applications or introduced to new markets. Moreover, there is real growth option value in the innovations if the underlying environment or technologies on which it is used evolve, like the case with films for which the underlying platforms have evolved from TV to color films to 3D, via VCRs, DVDs and laptops creating potential for new cash flows along. On the other hand, within a highly uncertain market conditions, when investors would not otherwise value an innovation as a growth option, if can still be seen as a learning option acquired by the organization with new knowledge and experience to create future value (Brach, 2003). Firms could also adjust to market uncertainty by making small initial investments in couple of options for innovation projects and thus create real options to gain the right to act on them accordingly in the future, for example to expand, abandon, integrate, cooperate or enhance the innovation. A real option can be described as is an investment that buys a firm the right, but not the obligation, to make a consequent investment when they have more information. Even at the point of commercialization, it is still hard to predict whether an innovation will be successful or a failure, especially in highly uncertain environments. Real options conditions comprise of partial irreversibility, market uncertainty and the possibility for firms to delay their actions are clearly satisfied when there is a patent on the innovation giving the firm exclusive rights to it until the patents expire (Bloom et al., 2002). However, Rosenberg (2004) states that even if the basic research does lead to a new product concept, there remain several questions on, for example, how well will the new product perform and at what cost, and how rapid will the improvement of performance and decline of costs be, how does the innovation fit to the firm portfolio and capabilities and how soon will a new superior product be introduced.

Innovation is strategic decision as aimed permanent product and performance improvements support growth and competitiveness. Successful innovations well adapted by the market and customers are followed be a strong market share and profit (von Hippel, 1988). Innovations can have a positive effect also on intangible capital and profit and, thus, incentivizing innovating even in volatile economic and business conditions. Furthermore, researchers argue that vast expenditures are required for the innovation before knowing about the success of the resulting product or process. Additional uncertainties are brought by competitors, customers, suppliers, the legislation, and the company itself, influencing the innovation process and the success (Rosenberg, 2004). Porter (1990) emphasized the role of the underlying sophisticated markets and their influence on the innovation rate of industry and on their competitive advantages. Although innovators may know about these expenditures and uncertainties, they still seem to have the incentive to innovate. From their perspective, the chance to increase the market share and enhance profits via offering innovative products seems to outweigh the risks and expenses.

Even though it is more common to incorporate real options theories to patenting and R&D phases of the innovation process as they are clear investments posing high option value, due to the vast literature and evidence on options throughout the innovation lifecycle, I shall incorporate the real options approach to modelling investment in innovation. The emphasis is on real options retaining firm responses to changing market conditions, which, when uncertain, increase firm caution and reluctancy to invest in expensive projects. The option theory could be incorporated to the option after commercialization to expand the investments in the production or marketing or development or to commercialize in other markets, to use the acquired knowledge or to cooperate for better potential of the innovation, among others.

2.5. Innovation, investments and subsidies

For examining corporate R&D expenditures, Becker and Hall (2013) propose five intrinsic determinants: firm or industry specific economic and financial factors, product market competition, public policies, location and endowment, and the presence of foreign R&D. Following the matter, many empirical results indicate a positive correlation between R&D investment and sales growth (Herrera & Sánchez-González, 2012; Morbey & Reithner, 1990) as well as with productivity. The effect of cash flow on R&D investment are mixed with mostly significant positive effects or insignificant effects (Moncada & Castello, 2016)

Public policy support by tax credits and direct R&D subsidies have been found to have positive effects on firms' R&D investment. (Bloom et al., 2002; Hall et al., 2016; Moncada & Castello, 2016). Evidence on the "funding gap" for investment innovation is surveyed by Hall and Lerner (2009) focusing on financial market reasons for underinvestment and conclude that while there are high costs of R&D capital, partly mitigated by venture capital, for small and new innovative firms the evidence for high costs of R&D capital for large firms is mixed. Nonetheless, internal funds to innovation investments appear to be preferred by large established firms. (Hall & Lerner, 2009).

R&D subsidies are also shown to increase private R&D activity significantly in small firms driving the sale of products new for the firm. However, large firms that received a subsidy increased investment only in technological development and thereafter improved the sale of products new to the market. (Herrera & Sánchez-González, 2012).

One argument states that the output of innovation resources is the non-rival knowledge of how to make new goods and services. Along the openness of knowledge, the investing firm cannot seize the returns to the investment in knowledge. Thereafter firms are unwilling to invest which leads to under-provision of R&D investment in the economy. The issue can be solved using intellectual property protection, subsidies, or tax incentives after which it can still be difficult or costly to finance R&D investments with external sources (Hall B. & Lerner, 2009).

When it comes to the criteria for receiving a public subsidy for an innovation, for example, Tanayama (2007), introduces that Tekes' (current Business Finland) most important criteria for project evaluation for public funding are the technological challenge, novelty for markets and market risk. This suggests that a higher complexity level of innovation that this study also analyses, would increase the possibility for a public subsidy for the innovation. Assuming these characteristics would form the basis for better success of an innovation, this could suggest that innovations, which have received public subsidies, would increase the firm productivity.

However, despite the knowledge on how innovations subsidies and funding enhance both firm and the national level growth, there is a great issue with decreased public funding for innovation activities in Finland. The report by Ormala (2019) finds that the government financing for companies' innovation activities is currently only 0.08 percentage of GDP, which puts Finland on the 28th position, one of the lowest, when compared to other OECD countries. Some countries invest around 15 -20 percentage of GDP into supporting innovation. Business Finland's financing has been cut by 250 million euros during 2007 – 2017. Government has also cut its financing for VTT by 14% and VTT's cooperation financing through Business Finland by 42% during 2007 – 2017. These cuts have let to a decrease of private sector funding for VTT by around 50% since 2007. The lack of financing was described as the biggest reason to move innovating activities away from Finland.

2.6. Innovation and complexity

One of the dependent variables of this study is innovation complexity. It has the most observables among the innovation variables in Sfinno data. However, innovation complexity appears only in few studies.

By one description, complex innovation means that it includes more than one dimensions, which can lead to its harder understandability and implementation (Torugsa & Arundel 2016; Goffin & Mitchell, 2010). Adding to the difficulty to implement might consequently increase the risk of failure. Thus, greater number of investments could be required to reduce this risk. Goffin and Mitchell (2010) state that multi-dimensional (complex) innovations are likely to require different development factors than single-dimension innovations. Innovation complexity can depend on various dimensions. For example, an innovation can be complex indirectly as a transformative innovation that requires changes to existing organizational routines.

In this study, I include complexity as another explanatory measure complementing and giving more knowledge of the innovations. Here complexity is divided into four categories according to Sfinno data with following descriptions from the Sfinno Codebook: *1) High complexity:* Innovation is a system consisting of several functional parts, development is based on several disciplines. (Examples: paper machine, mobile phone network, cruise ship), *2) Medium artefactual complexity / high developmental complexity:*

Innovation is a unit, development is based on knowledge bases from several disciplines. (Examples: pharmaceuticals, software, generator), *3) Medium artefactual complexity / low developmental complexity:* Innovation is a unit, development is based on knowledge base from one discipline. (Examples: electronic wheel chair, drill), *4) Low complexity:* Innovation is a single coherent unit. (Examples: glue-laminated timber, mobile phone cover).

One study by Torugsa and Arundel (2016) examined the number of dimensions of significant innovations of Australian Government employees as a proxy for innovation complexity and found that an increase in complexity increases barriers for innovation implementation in workplace. In addition, complex innovations are found to be more likely in decentralized workplace with broader idea sources and encouraged creativity. However, according to their study, innovation complexity has a positive correlation with beneficial outcomes in the public sector encouraging interest in them. One example of positive outcomes is that with more simultaneous dimensions, the probability of at least one generating a valuable outcome increases among the uncertain payoffs. (Torugsa & Arundel, 2016; Damanpour et al., 2009).

Stumsky, Lobo and Tainter (2010) give an alternative perspective for innovations suggesting that innovations themselves are complex systems embedded within other complex systems. They define complexity within an anthropological framework of increasing differentiation and specialization in structure with increasing integration of parts. Productivity of innovations is not constant and problems with research can become intractable over time and thus innovation more complex and costly. More complex and costly innovations would then result in diminishing results. Increasing expenditures produce decreasing number of innovations per unit.

Stumsky, Lobo and Tainter (2010) acknowledge that some previous studies argue that innovation brings positive results through knowledge spillovers across sectors but state, based on their measures with patents per inventor, investments in technical research and development appear to diminish the outputs. The seemingly continuing progress and new breakthrough innovations and products being introduced do not reflect science being more productive but the increasing firm size and thus the ability to allocate more resources to research. First innovations provide the largest increments of improvement while improvements by later innovations get smaller and need more effort. Thereafter, complexity could be expected to increase firm productivity in the early stage of firm life and later decreases it. (Stumsky et al., 2010).

Table 1

The Distribution of Firms by Total Innovations, 1985 – 2017

	1 or more	5 or more	10 or more	20 or more	30 or more	60 or more
No. firms	57	8	8	8	5	1[1]

3. Data and Sample Construction

Data in this analysis combines three principal datasets including unique innovation data hand collected by VTT, Datastream annual company accounting data and Datastream daily share returns data on Finnish publicly listed firms. The following introduces data in more detail as well as the clearing and matching process.

3.1. Innovation data

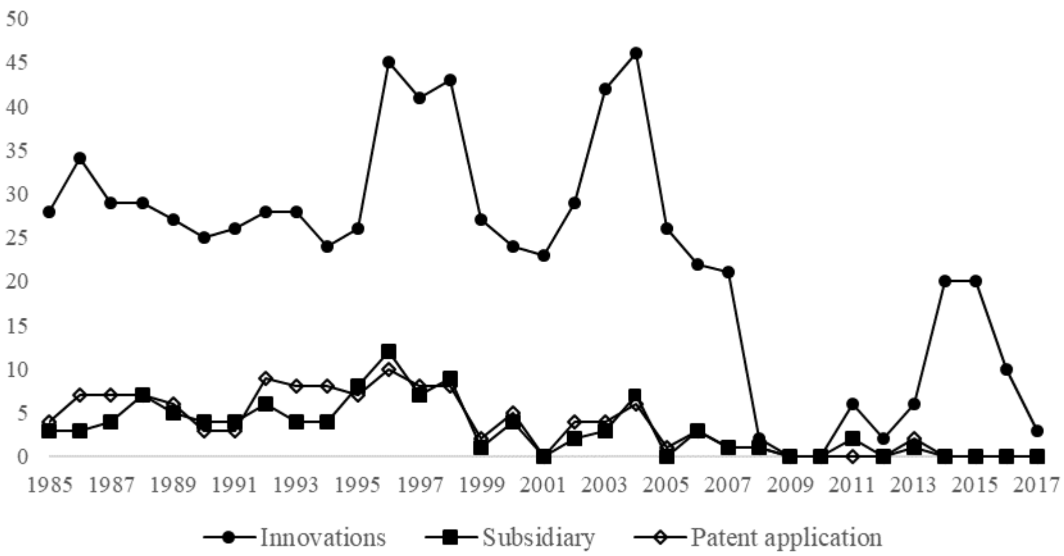
Main data in this study is my selection of a Sfinno dataset that comprises unique survey results from Finnish firms and organizations and innovation data from magazines hand collected by VTT Technical Research Centre of Finland Ltd. I received the dataset through a contact person in VTT and was able to select the variables for the final extract from their Sfinno Codebook which explains all variables. Sfinno data includes observations and information from Finnish companies defined innovative by VTT and their published innovations collected from different magazines as well as data from surveyed company representatives on the innovations. To match innovation data to the Datastream financial data for the needed Finnish listed firms, I connected the names by the parent company names and by Y-codes for Finnish corporate identification.

The intersection of the innovation and Datastream datasets gave out 87 who had commercialized at least one innovation between 1985 and 2017 and the innovations, which included a measure from their innovation's complexity. Total number of innovations for the group over the period was 760. Altogether Sfinno sample included 1212 innovations during 1985-2017 for 88 different Finnish firms listed on OMXH. Survey data for 2014-2016 is also missing as it is still in progress by VTT to be added to the Sfinno data. However, after checking the incoming companies, only few could have been matched to my sample adding

[1] Nokia Oyj with total 98 innovations

Figure 1

Innovations, subsidies and patent applications per year 1985 – 2017

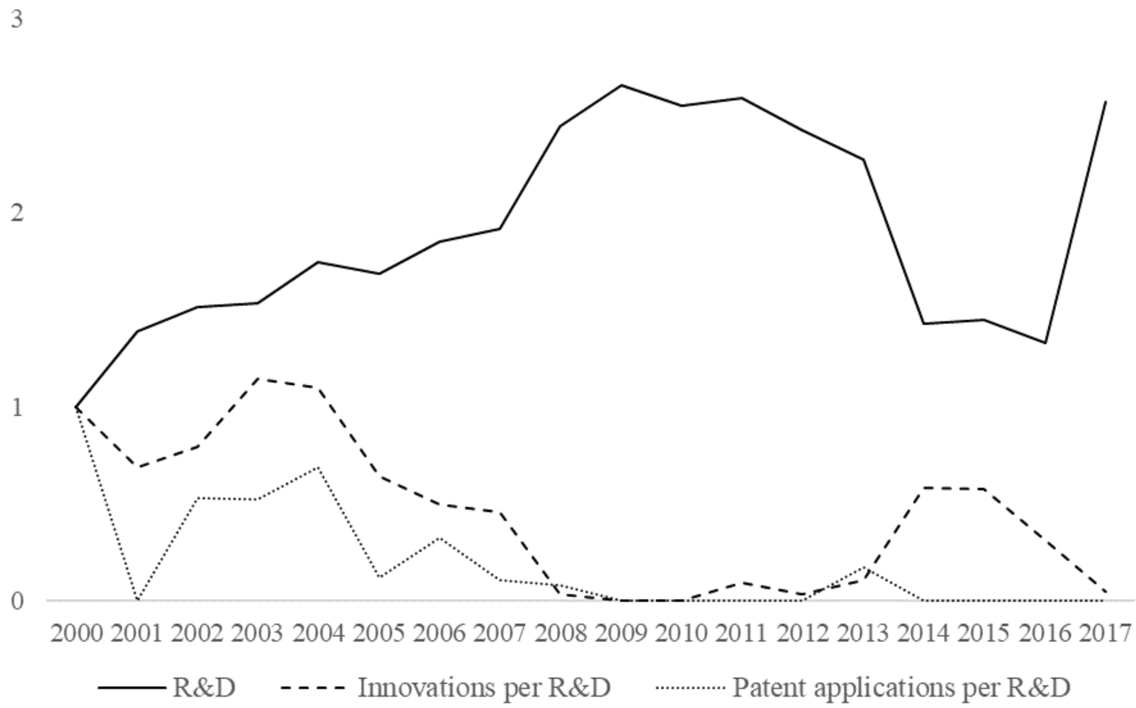


comparably unimportant number of innovations and for the sample. Table 1 shows the modest involvement of most of my group of Finnish public companies in innovative activities as only 10% (nine) of the innovative 87 companies (in the larger sample with missing financial information left) account for 50% of all 762 innovations. Blundell et. al. (1995) find the same concentration of innovating activities. Similar phenomenon is found even stronger when looking at the R&D expenditures as 9 out of the 70 innovative firms reporting R&D account for 87% of all R&D expenditures.

Innovations are graphed by their year of commercialization in Figure 1 including all 762 innovation observations for 87 innovative firms without matching to financial data. The graph also includes the yearly number of public subsidies received for innovation development comprising 14% of the sample innovations as well as number of patent applications that have been applied for 16% of these sample innovations during 1985-2017. Both subsidy and patent counts follow largely innovations' downward pattern during the 21st century and especially after the peak in 2004. The drop in 2008 onwards can be at least partially explained by the financial crisis and the uncertain market environment at the time. However, the figure shows a little increase in the number of innovations during 2013-2015 after which there is significant drop again in 2016 and 2017. What the figure doesn't show is the number of innovations under development so whether the downward trend continues or if it is going to change.

Figure 2

Innovation productivity in relation to R&D expenditures



Notes: The figure shows indexes for R&D expenditures in euros and for the number of innovations and patent applications per R&D expenditures in euros

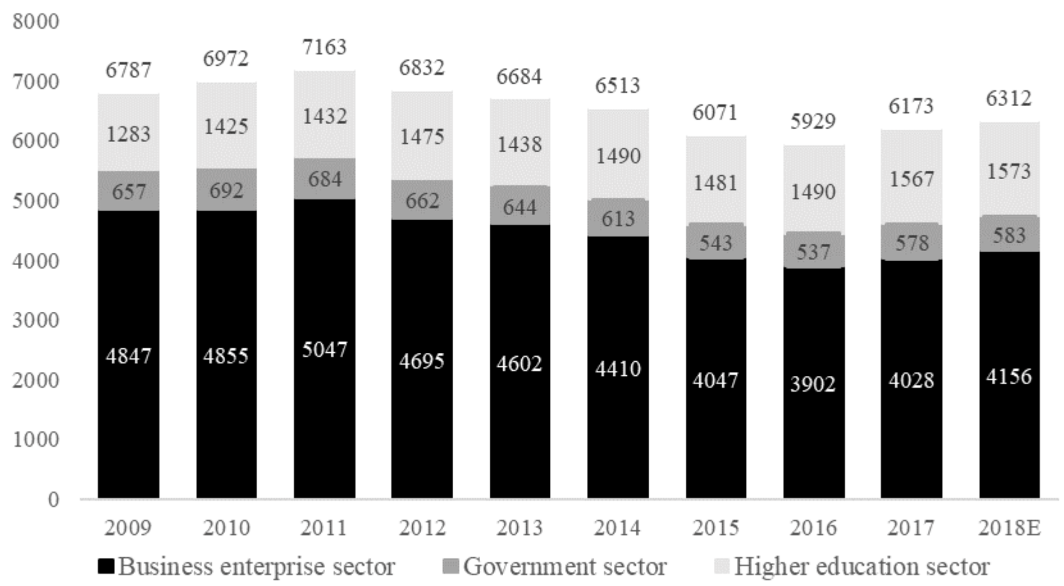
Also, it needs to be noted that the sample selection and the available data affect the counts. However, regarding the report by Ormala (2019), there needs to be a great improvement in the Finnish innovating environment and financing available to enhance innovation again.

Taking a deeper look on the innovations that have received a public subsidy for the development, Figure A2, shows that within higher complexity levels, majority of innovations have a subsidy while fewer of the lower complexity innovations have a subsidy. This supports the complexity criteria for granting a subsidy for innovations in Finland described by Tanayama (2007).

No innovations have been collected for year 2009 and the few 38 innovations commercialized in 2010 were missing information on their complexity and, thus, were excluded. Accounting these limitations, there have been two spikes of innovations during 1996 – 1998 and in 2003 – 2004. Otherwise the figure shows a slightly downward trend in the total commercialized innovations and patent applications of Finnish firms. This in line with findings by Ormala (2019) of the decline in Finnish innovations sue to weakening of the innovation environment and support in Finland.

Figure 3

R&D expenditure by performer sector in 2009 to 2017 and estimate for 2018 (mEUR)

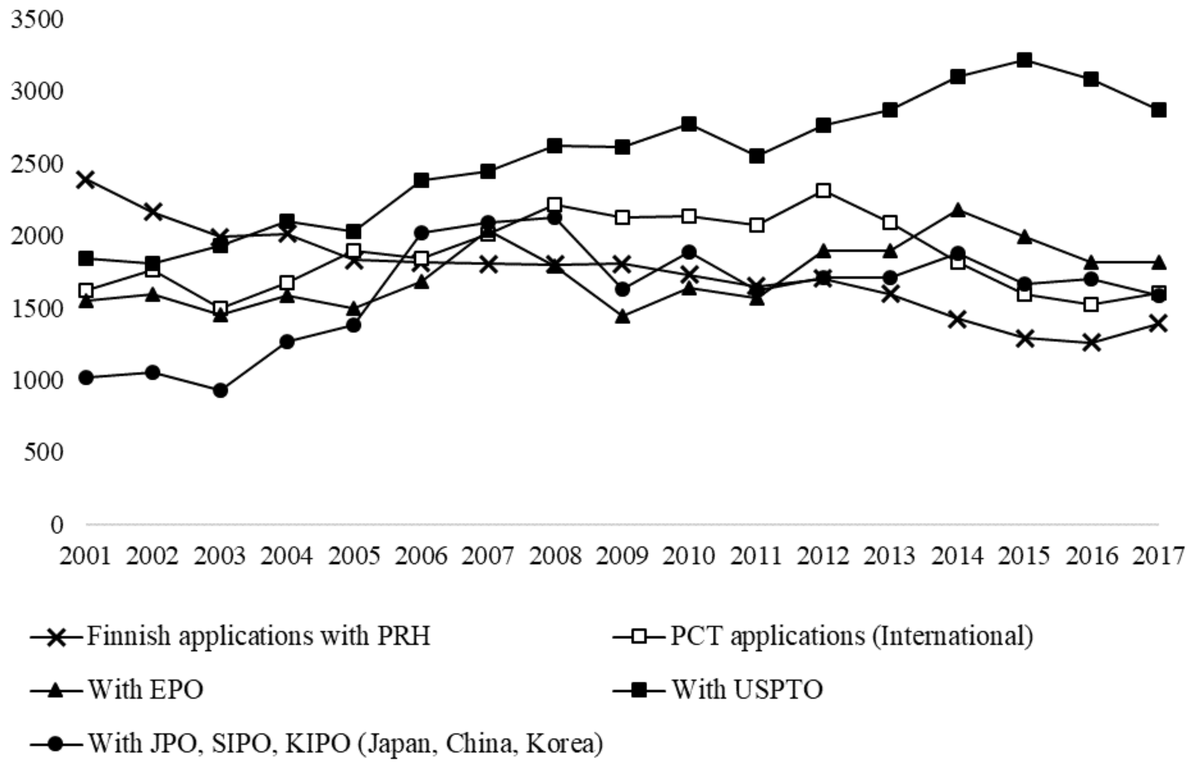


Even though there is not enough R&D data available to measure it as a comparable proxy for technological knowledge in the econometric analysis, they give interesting information. Figure 2 suggests an overall diminishment of innovation productivity, when measured by the number of innovations and patent applications per R&D expenditures, within my sample of Finnish public companies. The same decrease in innovation productivity is found be for example Stumsky, Lobo and Tainter (2010). The figure shows that during the period of 2000 to 2017, the index of simple R&D expenditures has mostly grown at least till 2011 while the indexes of the number of innovations and patents in relation to R&D have decreased after peaking in 2003 and 2004. There is a slump in the R&D during 2014 to 2016, which can be best explained by limited and partly missing R&D data. Also, there is no innovation data available for years 2009 and 2010.

To support Datastream R&D data for the studied sample of public companies, Figure 3 visualizes data collected by Statistics Finland on total R&D expenditures of Finnish enterprises, government and the higher education sector. There is a similar downward pattern in the overall R&D expenditures after the peak years in 2008 – 2012 with around 7 billion euros to around 6 billion euros annually. Still, there is a slight increase of R&D expenditures in 2017 and for the estimation in 2018. The enterprise sector is the biggest sector accounting for about 65% of the R&D in Finland.

Figure 4

Patent applications filed by Finnish applicants in Finland and other countries, 2001-2017



Notes: Figure indicates the change in patent applications in Finland and internationally by Finnish patent applicants over time during 2001-2017. The figure includes patent applications for Finland, Europe (EPO), the United States (USPTO), Japan, China and Korea together (JPO, SIPO, KIPO) as well as international applications (PCT). Data is collected from PRF online statistics. According to the Finnish Patent and Registration Office (PRH), Finland acceded to the European Patent Convention on 1 March 1996, which allows the EPO to grant patents which are then validated in Finland. Patents granted by the EPO are not automatically in force in Finland – the applicant must validate the patent in Finland after the grant by filing a translation of the patent and by paying a publication fee. The figure shows the number of patents that have been validated in Finland and are in force at PRH at the end of the year.

Moreover, in Figure 4 I use concise statistics from PRH public database on overall Finnish and international patenting activity in regards national and international patent measure for patent quality following the literature, it was not available for free for all patents and thus this research does not take it into consideration.

Figure 2 shows that patent applications filed by Finnish companies with the Finnish Patent and Registration Office (PRH) have been in nearly constant decline since 2001. The transformation towards international patent applications has been notable during the beginning of the 21st century till a recent downturn of patenting activity in 2014 for Asian (JPO, SIPO, KIPO) and European patents (EPO) and in 2015 for US patents (USPTO). There is also a drop in 2011 that can be explained by the eurozone debt crisis in 2010 – 2011.

Table 2

The top 12 innovating firms

Firm	No. innovations
Nokia	98
Valmet	55
Fortum	48
Ahlström	37
Wärtsila	36
Upm-kymmene	30
Metso	28
Outokumpu	27
Raisio	25
Stora Enso	23
Kemira	23
Orion	22

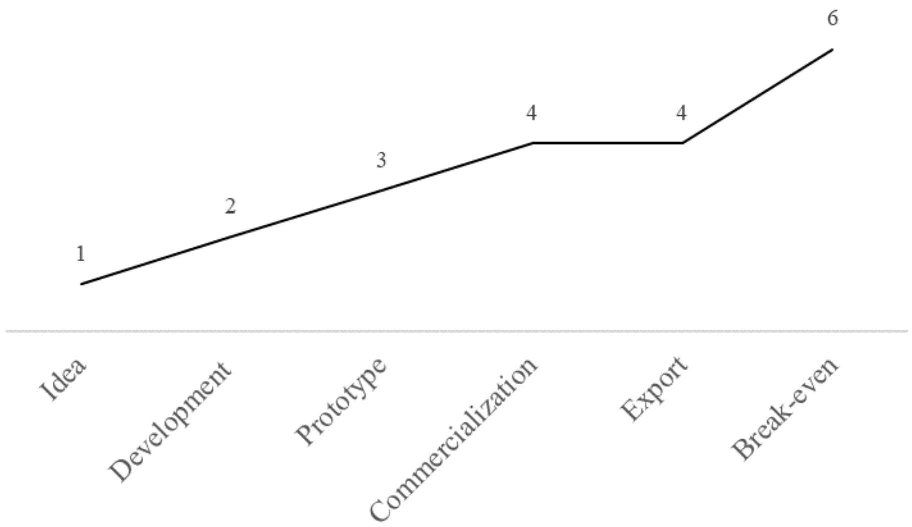
The latest datapoint for the domestic Finnish patent applications shows a 10% increase in 2017 compared to 2016. This is a positive but still a small change. It remains to be seen whether it continues.

Table 2 presents the innovation activity of the top 12 largest innovators. The firms in this selection reflect strong representation and innovative performance of paper and pulp, chemicals, machinery as well as electronics (Nokia) and information and communication (Sonera) sectors in Finland. Table A1 portraits two most recent examples of public company innovations from each complexity level (ascending order 1-4) which are totally new or pose a major improvement from firm perspective and which are new to the global market and have received a subsidiary.

There were 98 innovations with these criteria of which only 6 belonged to the high complexity group, 59/28 to the medium artefactual complexity with high/low developmental complexity group and only 4 innovations to the low complexity group depicting small representation of very high and low complex innovations. The last column in table 3 states wether a patent has been applied for the innovation or not. Altogether, there were 74 out patent applications and only 22 without while 2 did not report the information implicating that the majority of the novel innovations have been applied for a patent.

Figure 5

Median innovation life cycle (Years 1-6)



The NACE breakdown of selected firms is given in Table A2 which shows that the sample includes various sectors with, however, a concentration in the traditionally innovative chemicals/pharmaceuticals/engineering sectors as well as in the traditional Finnish wood and paper and machinery industries.

When analyzing the effects of the various interesting innovation characteristics of the Sfinno data, the sample is significantly reduced due to the limited availability of surveyed observations. The chosen innovations variables from the Sfinno data that I found important and used in regression analysis in this study described in the Sfinno codebook were 1) "complexity of innovation", measured on ascending scale from 1 to 4 as explained in section I.F, 2) "degree of novelty of the innovation from the firm perspective", divided into dummy variables for totally new perspective of the Finnish market/global market" as dummies for local and global novelty, 6) "Is there a patent application for the above-mentioned innovation? (Patent pending)" as a dummy for the innovations with patent application, 7) "Have you received a public subsidy for the development of the innovation?" as a dummy for those with subsidy and 8) & 9) "primary type of the innovation" as dummies for process and service innovations. Complexity of innovation (1) and the primary type (8 & 9) are the only one of these variables that are not collected by surveys and, thus, are significantly more comprehensive.

In calculating an innovation-based proxy for knowledge stocks I follow the existing literature of patent-based proxies (Bloom and Reenen, 2002) and use a more sensible stock measure rather than a flow measure as innovation benefits are likely to continue in the future.

Table 3

Years between life cycle levels

	Commer-cialization to break-even	Commer-cialization to export	Prototype to commerc-ialization	Developme nt to commerc-ialization	Idea to commerc-ialization	Idea to break-even	Commerci-alization to break-even
Median	2	0	1	2	3	4.5	2
Average	2.4	0.9	1.1	2.6	4.1	6.6	2.4
Max	11	7	7	15	23	30	11
Min	0	0	0	0	0	0	0

Complexity stocks are calculated with the same perpetual inventory method.

I calculate the innovation and complexity stock measures through the perpetual inventory method so that

$$(\text{Innovation Stock})_t = (1 - \delta) * (\text{Innovation Stock})_{t-1} + \text{Innovations}_t \qquad (2.1)$$

where the knowledge depreciation rate, δ, is set to 30% which is used by, for example, Griliches (1990). For the first-year calculation a prior steady state growth of innovations of 5% is assumed. Also 15% depreciation rate is used by others like Hall et al. (2000) and tested also by Bloom and Van Reenen (2002) who find little larger but otherwise similar results. The precise rate is believed to make very little difference.

Reassuring the knowledge stock variables', innovation stock and average complexity stock, ability to proxy a similar measure of the technological knowledge stock is their strong correlation of 0.84, whilst they should capture their own specific aspects of it.

In Figure 5 I depict the innovation life cycle as a median of 127 innovations for which there was information of the year for each phase. Basic lifecycle, for which VTT has collected data, consists of (1) the presentation of the basic idea of the innovation, (2) staring of the development, (3) introducing a prototype, (4) starting commercialization, (5) exporting, so when the commercialization of the innovation in foreign market began and finally (6) break-even -point of the innovation. Median lifespan shows a usual one year in between the idea, development, prototype and commercialization. Total median lifecycle is 4.5 years and the average life cycle is a little longer, 6.6 years, as well as the average time between phases compared to the medians as shown in Table 3. Exportation starts in the same year as innovation and the innovation breaks even financially after two years. However, Table 3 shows that there are innovation specific differences as the longest lifespan from idea to break-even within the sample is 30 years, from idea to commercialization is 23 years and, for example, from commercialization to break even is 11 years. The minimum time lag between each step is 0. For example, Orion Pharma's Stalevo-drug for Parkinson's disease was commercialized in 2004 but the idea of it was discovered already in 1993 and its development started later in 1999.

From Figure A1, it can be seen that the plotted innovation sample's time between the initial ideas and break-even of the innovation is rather linear with few innovations taking more time to break-even, especially in the 1970s and late 1990s.

3.2. Financial and Uncertainty Data

My analysis also includes company financials and uncertainty data for Finnish firms listed on Nasdaq Helsinki (OMXH) searched on Datastream database. Financial data includes net sales, market value and total capital as well as employee counts which are all company level yearly measures. In addition, I include Datastream information on daily stock returns and their variance as a proxy for uncertainty, reasoned in the following paragraph.

The initial group comprised 307 primarily quoted firms of which 155 were currently active and 152 were inactive. This set, for which I matched the Sfinno innovation data, was then cleaned for estimation. I started by excluding doubles and firms missing data on any of the values on sales, capital, employment or stock return variance and deleted firms with less than three consecutive observations. I also excluded negative and zero variables as well as outlier firms with jumps of greater than 150% in sales, employment and capital variables. Matching the Datastream data to the Sfinno innovation data was conducted first by matching the names of the listed parent companies to those and the subsidiaries in the Sfinno data using the first word of the name, which were then checked through, and second, by matching the Sfinno's firm specific Y-codes to the Datastream ISIN codes by using Orbis information for both as an intermediary.

NACE breakdown of the selected firms is given in Table A2 which shows that the sample includes various sectors with, however, a concentration in the traditionally innovative chemicals/pharmaceuticals/engineering sectors as well as in the traditional Finnish wood and paper and machinery industries.

Cleaning process left me with 163 firms with all necessary financials (2276 observations) of which 79 were matched to have commercialized at least one innovation during 1988 – 2017 and had an indicator for innovation complexity level.

Table 4

Descriptive Statistics for 79 Innovating Firms, 1988-2017

	median	mean	stan. Dev.	Min.	max
Capital (€m)	307.5	1464.4	3189.8	1.1	24632.0
Employment	3316	7352	12902	2	132427
Net sales (€m)	598.2	2094.5	4706.4	1.9	51058.0
Market Value (€m)	332.9	2268.2	11392.7	0.9	244974.6
Innovations	0	0.4	1.0	0	17.0
Average complexity	0	0.5	1.1	0	4.0
Innovation stock	0.5	1.3	2.4	2.3e-05	30.3
Average complexity stock	0.9	1.8	2.3	6.8e-05	10.0
Uncertainty	0.31	0.76	1.30	0.01	9.98
Observations per firm	16.0	15.3	7.8	0.0	30.0

Notes: 'Innovations' is the total number of innovations per firm year. Uncertainty is the standard deviation of daily share returns for available 72 firms while variance measure is used in empirical calculations. Sample covers years 1988-2017.

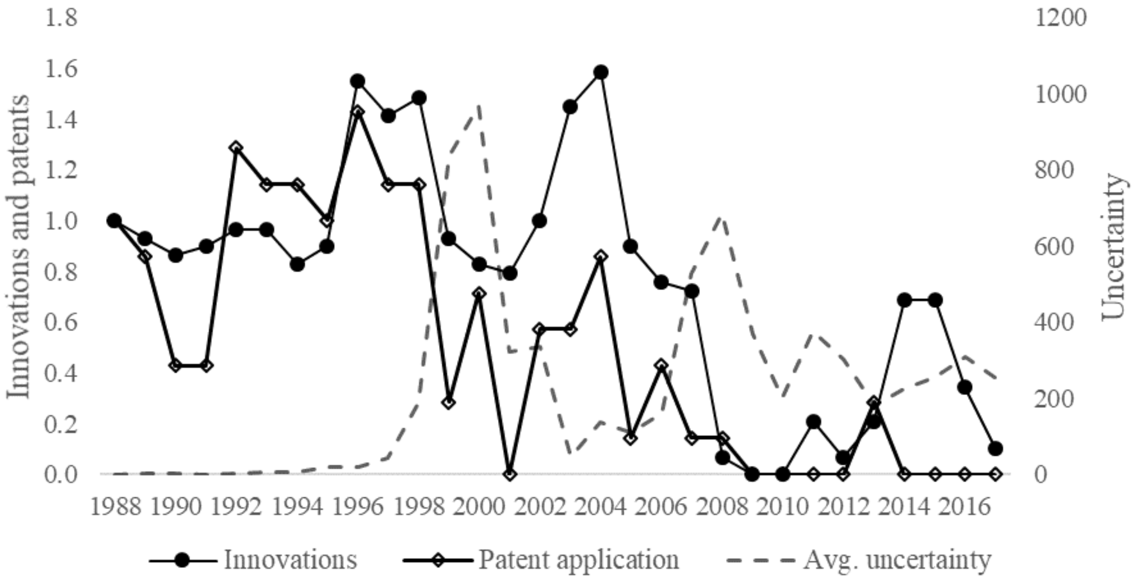
This sample of 79 innovative firms gives me 1213 observations and total 433 innovations. When applying more innovation variables, collected from surveys for subsidy, patent application, novelty for firm perspective, novelty form market perspective and the type of the innovation, reported data diminishes to only 87 observations for 30 firms and their 156 commercialized innovations.

Summary statistics for the group of 79 innovating firms during 1988-2017 is reported in Table 4. The last row shows a generally medium time series of data on each firm with a little over 15 years for each firm. Innovation numbers vary between firms as there are many commercializing only occasionally innovations demonstrated by zero innovation observations while some firms commercialize 17 in a single year (Nokia in 1997). Complexity represents the average complexity level from 1 to 4, of innovations commercialized in one year. Its level is lowered by the fact that there are many years with zero innovations and, thus, the stock measures are higher.

Uncertainty measuring needs to cover firms' uncertainty about future prices, exchange rates, technologies, wages rates, government policies and consumer tastes. Following Bloom and Van Reenen (2002) and, for example, Leahy and Whited (1998), as scalar proxy for firm level uncertainty capturing all these factors, I use variance of firm's daily stock returns, denoted σ_i^2. My sample with uncertainty measures includes 72 firms with 950 observations. In line with the real option theories' standard assumptions, this is a firm specific and time invariant proxy measure for uncertainty.

Figure 6

Innovations, patent applications and uncertainty per year 1988 – 2017 (1998 = 1)



It comprises capital gain on the stock, dividend payments, rights issues, and stock dilutions on a daily stock returns basis. Thereafter, it represents a forward-looking volatility of firm's environment which is implicitly weighted according to the impact of these variables on profits. It is also advantageous in measuring as there is accurately reported and high frequency data available and a low sampling variance.

Figure 6 shows an indexed uncertainty value which is the yearly volatility of OMXHPI index (OMX Helsinki Price Index) (Nasdaq, 2019). There is a positive correlation between the number of commercialized innovations and patent applications of 0.74 while uncertainty correlates negatively with innovation count at -0.35 and with patent count at -0.45. For example, clear spikes in uncertainty in 1999 – 2000 and again in 2008 at the beginning of the financial crisis, are accompanied with a drop of innovation counts.

4. Empirical Strategy

In this section, I provide predictions for the empirical tests that follow. I begin the empirical analysis by testing four predictions with OLS regression models for panel data which are all estimated with R. I include firm and year fixed effects and robust standard errors and examine whether the coefficient' is statistically significant at the 10%, 5%, or 1% level. The results are presented and discussed in section 5.

4.1. Models of Innovations and Company Performance

As a baseline specification for my analysis is a simple Cobb-Douglas production function in the form of

$$Q = AG^{\alpha} + N^{\beta} + K^{\gamma} \tag{4.1}$$

where Q is real sales, G is the knowledge stock, N is number of employees, K is total capital, so the book value of firm assets and A is an efficiency parameter.

Adding subscripts for firm *i* at time *t* and taking logs the equation becomes

$$logQ_{it} = logA_{it} + \alpha\ logG_{it} + \beta\ logN_{it} + \gamma\ logK_{it} \tag{4.2}$$

Efficiency, $A_{it} = exp(\eta_i + \tau_t + \upsilon_{it})$, is parametrized as a function of firm specific fixed effects (η_i), time effects (τ_t) and a random stochastic term (υ_{it}). In the empirical analysis I proxy the knowledge stock, G, with mainly innovation stocks (INNO) and complexity stocks (COMPLEX) as an additional measure.

$$logQ = \alpha\ logINNO_{it} + \alpha_1\ logCOMPLEX_{it} + \beta logN_{it} + \gamma\ logK_{it} + \eta_i + \tau_t + \upsilon_{it} \tag{4.3}$$

To examine whether other important innovation characteristics derived from the Sfinno data affect productivity, I create a more comprehensive equation

$$\begin{gathered} logQ = \alpha\ logINNO_{it} + \alpha_1\ logCOMPLEX_{it} + \beta\ logN_{it} + \gamma\ logK_{it} + \omega_1 SUBSIDY \\ +\omega_2 PATENT + \omega_3 NEWFIRM + \omega_4 IMPROVEMENT + \omega_5 NEWFI + \\ \omega_6 NEWINTERN + \omega_7 PROCESS + \omega_8 SERVICE + \eta_i + \tau_t + \upsilon_{it} \end{gathered} \tag{4.4}$$

with dummy variables including $\omega_1 SUBSIDY$, equal to one if the firm has received a subsidy for the development of the innovation, and zero otherwise, $\omega_2 PATENT$, a dummy on whether there has been a patent application for the innovation, $\omega_3 NEWFIRM$, a dummy variable for innovations that are novel from the firm perspective, $\omega_4 IMPROVEMENT$, equal to one for innovations with improvement from earlier innovations and $\omega_5 NEWFI$ for innovations new to Finnish market and $\omega_6 NEWINTERN$ for internationally new as well as $\omega_7 PROCESS$ and $\omega_8 SERVICE$ as a dummy variable for process and service innovations (others are product innovations). To correct the standard errors for heteroscedasticity, I estimate equations (4.3) and (4.6) by within groups, so by least squares dummy variables.

Regarding market value, the equations are not as common and well-established as production functions. The standard approach used in studies where innovation is measured by patents, as in Bloom et al. (2002) and Hall et al. (2000), has been first introduced by Griliches (1981) and takes the specification form

$$\log\left(\frac{V}{K}\right) = \delta\left(\frac{G}{K}\right)_{it} + \eta_i + \tau_t + \upsilon_{it} \tag{4.5}$$

where V represents the market value of the firm and the left-hand side of the equation (4.5) is basically average Tobin's Q. However, as I conduct this study by equation (4.6) with commercialized innovations as the knowledge measure G and with a relatively small sample of Finnih public companies with few innovations, I modify the right-hand side explanatory variable to be a simple innovation stock G, without dividing it with capital K.

$$\log\left(\frac{V}{K}\right) = \delta(G)_{it} + \eta_i + \tau_t + \upsilon_{it} \tag{4.6}$$

To see the results also from the basic model used in most studies, I conduct and report the results of the equation 4.5 as robustness checks. With value as the dividend and fixed capital as the divider, implication for high-tech firms with high levels of intangible knowledge capital will be their larger than expected market value in relation to their fixed capital.

4.2 Models for Uncertainty and Real Options

Real options theory with a real asset as the option is derived from theories that originate from finance to value financial options contracts (Black and Scholes, 1973).

The basic models described above for productivity and market value assume that the knowledge behind the innovations is used immediately and fully acted on by firms. The models were originally used by Bloom et. al (2002) with patents and cites as the proxy for knowledge stock, for which this assumption is even stronger as they prevail most often before the commercialization of the underlying new products or process innovations. As Bloom et al (2002) explain, the introduction of these innovations can require significant investments in additional plant and equipment, employee hiring and training as well as advertising and marketing. Even though, the point of commercialization has already some of these investments behind, there is still a lot of expenditures assumed for future. Most part of these initial expenditures are irreversible and not recoverable after undertaking. Thereafter, when market conditions turn uncertain, firms possess innovation real options.

Incorporating real options effects, the concept of knowledge stock needs to be extended into embodied knowledge and disembodied knowledge. Embodied knowledge embodies the product and process innovations which the firm has already invested in. Disembodied knowledge, on the other hand, embodies the ideas that the firm has planned for future commercialization or expansion or patent like in the underlying analysis by Bloom and Van Reenen (2002) but has not yet committed into actual implementation. The more uncertain the conditions, the more cautious will firm be as the value of the real options associated with producing or developing further the innovation.

I go through a stylized model illustrating the impact of innovation real options on market values, production and embodiment. Following Bloom and Van Reenen (2002), the model is rather simple to ensure a closed form analytical solution with potential to be extended in many ways if desired. The value of the firm is supposed to depend on its embodied innovations, P_k, $K = 1 \dots K$, and disembodied innovations P_j $j = 1 \dots M$, where $P_k$is the profit flow from innovation k if embodied. Disembodied innovations are those that the firm has the knowledge, idea and plan for or owns the intellectual property rights to, but their potential profit P generation would need a sunk cost development of I . Embodied innovations are already fully developed and commercialized with continuous flow of profits P. Therefore, the firm value (VAL) can be denoted

$$VAL(P_1, P_2, \dots, P_{K+M}) = \sum_{k=1}^{K} V^E(P_k) + \sum_{j=1}^{M} V^D(P_j) \tag{5}$$

where $V^E(.)$ and $V^D(.)$ are the values of embodied and disembodied innovations. A more general approach including other factors like capital, employees, interest rates and other factor prices by Bloom et al. (2001) would be more comprehensive and demonstrate similar delay effect of real options on firm actions but this paper's way keeps the innovation real options analysis controllable.

The arrival of new ideas for new innovations and enhancements are assumed continuous in a stochastic manner. To simplify, they are assumed to arrive at an exogenous[2] rate with a potential embodied profit flow rate of P initially coming from a cumulative distribution $H(P)$. Assuming the initial distribution of new innovations to have a large support, some new innovations are valuable enough to be directly embodied. Each innovation's potential embodied profit flow advances stochastically with changing market conditions and is assumed to follow a geometric Brownian motion process

$$dP = \mu P dt + (\sigma dZ_k + \sigma_F dZ_F) \tag{6}$$

where dZ_kdZi and dZ_F are independent innovation and firm level Weiner processes[3] representing separate innovation and firm level shocks. For example, for a automotive firm innovation level shocks would affect only the value of the particular car while firm level shocks would affect the value of all the cars in its portfolio. Assuming the independence of these two processes, we can write the overall uncertainty as $(\sigma^2 = \sigma_k^2 + \sigma_F^2)$. The value of innovations already embodied can be calculated as $V^D(P) = P/(\rho - \mu)$ where ρ is the firm's cost of capital and μ is the mean growth of innovation profits. If innovations are modelled more realistically with a fixed expiring date of T, the value would be $[P_k/(\rho - \mu)](1 - e^{\rho^T})$ but is ignored here as the expiry does not change the qualitative implication of results. To derive the value of disembodied innovations, so the innovation options, the differential equation on value function $V^D(P)$ is derived, which includes only an expected gain term as disembodied innovations have no profit flow:

$$\begin{aligned} V^D(P) &= e^{-\rho dt} E[V^D(P + dp)] \\ &= V^D(P) + \mu V_P^D(P)dt + \frac{\sigma^2}{2} V_{PP}^D(P)dt - \rho V^D(P) \quad \text{in} \lim dt \longrightarrow 0 \end{aligned} \tag{7}$$

Resulting from here is the form $V^D(P) = AP^{\beta}$, where A is a constant, and $\beta > 1$ is the characteristic equation's solution. Consequently, definition of firm value can also be

[2] The arrival rate of new innovations could be allowed to be determined endogenously by, for example, letting firms vary R&D spend. This would lead to more state and control variables into the dynamic programme preventing a preferred straightforward analytical solution (Bloom and Van Reenen, 2002).

[3] Weiner processes are stochastic white noise processes. This allows innovation and common firm level stochastic shocks. Their independence simplifies the mathematics notably but is not essential for the results (Bloom and Van Reenen, 2002).

$$VAL(P_1, P_2, \dots, P_{K+M}) = \sum\nolimits_{k=1}^{K} \frac{P_k}{\rho - \mu} + \sum\nolimits_{j=1}^{M} \mathrm{AP}_j^{\beta} \tag{8}$$

Sales are assumed to be representable as a multiple of profits due to markup pricing, so that some λ can be defined

$$SALES = \lambda \textstyle\sum_{k=1}^{K} P_k \tag{9}$$

While solving the firm's dynamic programme, Bloom and Van Reenen (2002) found that there is some value of embodied profit flow P^* at which paying the sunk embodiment cost I would become optimal for the firm and start generating the profit flow. Solving embodiment value P^* starts by deriving two optimality conditions. The first condition is the value matching requiring the option value to equal the discounted profit flows less the sunk cost of embodiment at P^*,

$$AP^{*\beta} = \frac{P^*}{\rho - \mu} - I. \tag{10}$$

The second condition is the smooth pasting condition taking another derivative and assuring optimal timing of embodiment,

$$\beta AP^{*\beta - 1} = \frac{1}{\rho - \mu}. \tag{11}$$

These two conditions can be combined to solve for the optimal embodiment profit flow P^*

$$P^* = \frac{\beta}{\beta - 1} I(\rho - \mu). \tag{12}$$

This equation depicts the effect of option value where investment in the innovation will not appear before the embodied profit flow has risen to $\beta/(\beta - 1)$ times $I/(\rho - \mu)$ while in the absence of real options, embodiment would appear when the profit flow corresponds to the flow cost of embodiment $P^* = I/(\rho - \mu)$. In more uncertain environments the embodiment threshold is higher due to the option value multiple $\beta/(\beta - 1)$ increasing in σ^2. The model enables predicting empirical relationships between sales, market values, patenting, and uncertainty.

As Bloom and Van Reenen (2002) reason with patent numbers, also innovation numbers $INNO$ (which equals $K + M$ in the above model), is to have a clear increasing effect on firm's valuation because even disembodied innovations carry option value. Moreover, the effect will be immediate since market values are forward looking measures and thus, by integrating with the initial innovation valuation, the innovating's effect on market values can be said to be positive,

$$\frac{\partial VAL}{\partial INNO} = \int_0^{P^*} V^D\,(P)dH(P) + \int_{P^*}^{\infty} V^E\,(P)dH(P) > 0. \tag{13}$$

Furthermore, increase in the number of innovations is also expected to increase firms' sales as some new innovation initiatives will have be sufficiently valuable in the beginning to be immediately embodied. Minding the embodiment threshold $P^*$and the initial values $H(x)$ distribution assumption, the impact value of new innovations on sales will be

$$\frac{\partial SALES}{\partial INNO} = 1 - H(P^*) > 0. \tag{14}$$

Market value's first order derivative, in consideration of uncertainty, will also be positive with the option value of disembodied patents increasing along higher uncertainty

$$\frac{\partial VAL}{\partial \sigma^2} = \sum_{i=1}^{N} \frac{\partial V(P_i)}{\partial \sigma^2} > 0. \tag{15}$$

The first order derivative of sales in relation to uncertainty is depending on the extent of the embodiment of the additional patents, which can be ambiguous. While higher uncertainty increases the embodiment threshold P^* which directly reduces the rate of patent embodiment, higher uncertainty will also make the potential embodied profit flows P more volatile increasing the chance that any innovation hits its embodiment threshold. These effects can take either direction like the model continues

$$\frac{\partial SALES}{\partial \sigma^2} \lesseqgtr 0. \tag{16}$$

Eventually another interesting factor is the cross derivative of new innovating activity and uncertainty.

For market value, the cross derivative is again positive with higher uncertainty increasing the value of new innovations. Being forward looking, the impact on market values will be immediate so that

$$\frac{\partial^2 VAL}{\partial INNO\sigma^2} > 0. \tag{17}$$

For sales, the cross derivative in relation to innovating and uncertainty will be negative because of the real options effect on embodiment threshold P^* reducing the fraction of new innovations immediately embodied under higher uncertainty. First derivative of the equation (14) with respect to uncertainty shows a negative result

$$\frac{\partial SALES}{\partial\sigma^2 \partial INNO} = -h(P^*)\frac{dP^*}{\partial\sigma^2} < 0 \tag{18}$$

where $h(P^*)$ is the probability distribution derived from $H(P)$.

The focus of this stylized model is only on innovations as productivity drivers, but my empirical equation comprises the independent role for the other production factors. Thereafter, the augmented Cobb-Douglas production function can be formed as:

$$logQ_{it} = \alpha\ logINNO_{it} + \alpha_1\ logCOMPLEX_{it} + \beta\ logN_{it} + \gamma\ logK_{it} + \psi\sigma i + \chi\,(\sigma_i * \mathrm{log}INNOit) + \eta_i + \tau_t + \upsilon_{it} \tag{19}$$

where the coefficients ψ and χ will capture uncertainty's direct and interaction effects. The sign of coefficient ψ is theoretically ambiguous while the interaction coefficient χ is expected to be negative. Bloom and Van Reenen (2002) remark the identifying the linear effect of uncertainty from η_i separately is not possible in the specifications where the latter are treated as fixed effects.

In the main empirical market value equation below with uncertainty interactions, coefficients θ and ζ on linear uncertainty and the interaction term are predicted to be positive real options theory

$$log\left(\frac{V}{K}\right)_{it} = \delta(\mathrm{G})_{it} + \theta\sigma_i + \zeta\,[\sigma_i * log(\mathrm{G})_{it}] + \widetilde{\eta_i} + \widetilde{\tau_t} + \widetilde{\upsilon_{it}}. \tag{20}$$

5. Findings

The first set of results explores the effect of innovation and complexity and other innovation characteristics on production. All specifications follow the models described in Section 4, controlling in most cases for firm and time fixed effects. I examine whether the coefficients are statistically significant at the 10%, 5%, or 1% levels. Robust standard errors are reported in parentheses.

Estimations on a standard production function on the sample firms are presented on Table 5. I conducted basic panel data OLS regression by oneway effect within model estimations on panel data as specified by Bloom and Van Reenen (2002). In column (1) I have conducted the production function for the complete population of 163 listed Finnish firms with required financial data from Datastream. According to expectations and similarly to the results by Bloom and Van Reenen (2002), capital and employment coefficients are both positive and significant at 1% levels in all regressions (1) to (6) and the sum of these two variables is close to unity which indicates constant returns in tangible factors.

Column (2) shows an estimation with my preferred within groups estimator including firm fixed effects to control for time invariant differences between firms. The coefficient for capital is slightly bigger (0.493) than in the first (1) regression (0.383). To the equation in column (3) I added a dummy variable equal to one if the firm is an innovative firm which includes firms within my sample that have commercialized at least one innovation during the sample period. Coefficients for capital and employment stay close to those in regression (2) but the innovative firm coefficient is also positive and significant at 1% level suggesting that firms who innovate would be 9.8% more productive than non-innovative firms.

Columns (4) to (6) compare these within groups results from the whole Datastream sample to the sub-sample of innovators. Contrary to the sample from the United Kingdom by Bloom and van Reenen (2002), the Finnish sample of public innovative companies shows lower point estimates on capital as well as on employment. This suggests that the Finnish public innovators are a bit less capital intensive than the lower tech firms listed on OMXH. Results from including innovations and complexity as proxies for knowledge in the production function are reported in the last three columns of Table 5. In column (4) I use innovation stocks, in column (5) complexity stocks and in column (6) them both. On both alternative measures in regressions (4) and (6) the innovation stock is significant at the 1% level. However, contrary to the hypothesis, innovation stock results suggest a negative effect on firm productivity by around -6% regressed by basic production function (4).

Table 5

Basic Production Functions

Log Sales	(1)	(2)	(3)	(4)	(5)	(6)
Firms	All	All	All		Innovators only	
Log Capital	0.383***	0.493**	0.492***	0.368***	0.377***	0.362***
	(0.016)	(0.008)	(0.008)	(0.021)	(0.021)	(0.021)
Log employment	0.532***	0.535***	0.529***	0.506***	0.502***	0.510***
	(0.016)	(0.008)	(0.008)	(0.019)	(0.019)	(0.019)
Log Innovation Stock				-0.062***		-0.141***
				(0.006)		(0.032)
Log Complexity Stock					-0.059***	0.080*
					(0.006)	(0.032)
Innovative firm			0.098***			
			(0.023)			
Firm fixed effects	No	Yes	No	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared	0.63484	0.93225	0.93278	0.64969	0.64549	0.65138
No. observations	2276	2276	2276	1213	1213	1213
No. firms	163	163	163	77	77	77

Notes: The dependent variable is `log sales'. Columns (1) to (3) present results using the complete population of Datastream firms, Columns (4) to (6) present the results for the sub-sample of firms with commercialized innovations. The estimations cover the period form 1985 until 2017. Models are estimated using OLS regressions by oneway effect within model in all columns. Column (1) controls only for year fixed effects while columns (2) - (6) control for firm and year fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

When complexity stock is measured as a standalone without innovation stock, column (5) results imply, at 1% level of significance, its slight 5.9% negative effect on productivity. However, when I include both innovation and complexity stock variables in column (6), innovation stock measure gets an even stronger negative coefficient of -0.141 significant at the 1% level while complexity has a positive coefficient of 0.080 significant at the 15 % level. Figure A3 shows plotted data of complexity and sales (productivity). These coefficients suggest that doubling the innovation stock would decrease the total factor productivity by 14% percentage but doubling the complexity stock, so the level of complexity of the innovations, could increase the productivity by 8%. This could, following the reasoning by Stumsky, Lobo and Tainter (2010), indicate that the Finnish public companies are relatively young and small with their investment in innovation as complexity is adding positively to productivity. On the other hand, this can also imply that Finnish

Table 6

Market Value with Innovation Measures

$log(V_{i,t}/K_{i,t-1})$	(1)	(2)	(3)
Innovation stock	0.021 (0.012)		0.058*** (0.017)
Complexity stock		-0.012 (0.014)	-0.058** (0.019)
Firm fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
No. observations	1127	1127	1127
No. firms	77	77	77

Notes: The dependent variable is `log(market value/lagged capital) '. Due to the need for a lagged capital observation the estimation period covers 1989 until 2017 Models are estimated using OLS regressions by oneway effect within model in all columns. All column control for firm and year fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

companies overall can produce innovations with such a level of complexity that they can manage well. Regarding the negative effect of innovations themselves on productivity, it is against the main hypothesis, but indicates the worrying trend of decreasing innovation productivity found by, for example, by Stumsky, Lobo and Tainter (2010), and within Finnish public companies in Figure 2.

Table 6 reports estimated effects of innovations on market value by the conventional specification of average Tobin's Q as defined first in equation (4.6). This equation is my main specification with a simple innovation stock measure as the left-hand side explanatory variable. As a robustness check, I conducted the equation with an explanatory variable innovation stock per capital stock, which is often used in literature (Bloom et al. 2002; Griliches 1981; Hall et al. 2000) and report the results in Table A3. However, these studies use patents as their proxy for innovations and I use commercialized innovations. Column (1) includes results with innovation stock measure, column (2) with complexity stock and column (3) with them both.

Measured as standalone variables, neither innovations or complexity is significant but when regressed together they are highly significant at 1% level with a coefficient of 0.058 for innovation stock and -0.058 for complexity stock. These results suggest that innovations have a positive effect on the market value, and that doubling the innovation stock would increase the value of firms per unit of capital by about 6%. This is in line with the hypothesis. Doubling the complexity stock, on the other hand, would have a negative 6% effect on market value according to the results. Complex innovations' immediate negative effect could be, for example, because investors do not understand the innovation well or do not believe in the firm's ability to make and secure the value of it in the future. The phenomenon could also follow the often similar drop in value on the day of a stock listing or the publishing of quarterly results as the market adjusts their earlier higher expectations and the stock value decreases.

However, when plotting sample data for complexity stock and market value, Figure A4 shows a mostly decreasing trend in market value along increasing complexity but 2% of the sample observations with the highest complexity stocks between 9-10 indicate an increase in market value. These companies include Nokia, Metso, Fortum and Wärtsilä. It is also important to note that the innovations by Finnish public companies are very different even though they would be classified as equally complex. Thus, their impact on market value can differ from overall results for some specific innovations. For example, in Figure A5, market value of Orion Pharma (previously Orion Oyj), a global pharmaceutical company, has grown rather steadily also after its major recent innovations, with complexity levels of three, in 2004 (Stalevo-drug for Parkinison's disease) and 2014 (drug for Alzheimer's disease).

When looking at the robustness check results in Table A3 with innovation stock per capital variable, none of the variable coefficients in columns (1) to (3) are found significant. The variable has less explaining power and reflects the small sample of Finnish public companies and the number of their innovations which is also very small in relation to their capital measures. As stated in previous studies like in Bloom and Van Reenen (2002), models for market value are future looking and less developed than those for productivity.

To account for some robustness tests for my main specifications, I conduct checks with lagged variables on the basic models which are reported in Table 7. Columns (1) and (4) include both the innovation stock and the lagged innovation stocks measures. In the estimation, I follow Bloom and Van Reenen (2002) who use the levels information from within groups estimator and then deal with any simultaneity problems by instrumenting with lagged explanatory variables. In columns (2) and (5) the right hand side variables lagged by one period to control for the possible endogeneity of current values of the explanatory variables. Only notable change is that the lagged complexity stock has a 5.5 % positive effect on market value while the immediate effect shown in Table 6 was negative (-0.058).

Table 7

Robustness Checks with Lagged Values

	(1)	(2)	(3)	(4)	(5)	(6)
	$Sales$	$Sales$	$Sales$	$log(V_{i,t}/K_{i,t-1})$	$log(V_{i,t}/K_{i,t-1})$	$log(V_{i,t}/K_{i,t-1})$
Log Capital	0.352*** (0.023)					
Lagged Log Capital		0.334*** (0.025)	0.350*** (0.023)			
Log Employment	0.520*** (0.021)					
Lagged Log Employment		0.463*** (0.023)	0.523*** (0.021)			
Log Innovation stock	-0.026* (0.012)					
Lagged Log Innovation stock	-0.035** (0.012)	-0.052*** (0.007)	-0.135*** (0.032)			
Innovation stock				-0.027 (0.024)		
Lagged Innovation stock				0.056* (0.024)	0.033** (0.012)	0.067*** (0.017)
Lagged Log Complexity stock			0.079* (0.322)			
Lagged Complexity stock						0.055** (0.019)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	1127	1127	1127	1127	1127	1127
No. firms	79	79	79	79	79	79

Notes: The dependent variable for column (1), (2) and (3) is 'log sales' and for columns (4), (5) and (6) is 'lo g(market value/lagged capital)'. The estimation period covers 1985 to 2017 for (4)-(6) and 1998-2017 for (1) - (3). Models are estimated using OLS regressions by oneway effect within model in all columns. All colum n control for firm and year fixed effects. Robust standard errors are reported in parentheses. *, **, and *** in dicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively

This is an interesting finding suggesting that a higher innovation complexity increases the market value in the following year of the commercialization of a new innovation. Thus, according to the results in Table 5, that market value decreases for more complex innovations at the time of commercialization but, as shown in Table 6, rises again in the next year.

Overall, the results indicate that the lagged variable is most informative in predicting productivity and that by time the negative effect of innovations after commercialization is emphasized. This is opposite to the results on patented innovations by Bloom and Van Reenen (2002), suggesting a stronger but again positive effect of the lagged patent stocks on productivity. On the other hand, in the market value equation the lagged values for innovation are also significant but positive. Column (4) results suggest that with a 10% level significance, lagged innovations would have a 5.6% increasing effect on market value while the current innovation stock coefficient is negative but not significant. Columns (3) and (6) test also the effect of lagged complexity on productivity and market value. The results are mainly similar with innovations having significant negative effect on productivity and positive effect on market value. In columns (2) and (5) I control for the possible endogeneity of current values of the explanatory variables with the right-hand side variables lagged by one period. They show no remarking change to the productivity or market value functions. When looking at Table A3 robustness checks for market value equations and lagged values on column (4), significant results for current and lagged innovation stocks are with similar signs but much larger. Column (5) coefficient is negative but not significant.

In Table 8, I report the results from examining the effects of uncertainty on the productivity response to innovating. Results of innovating uncertainty interaction terms in column (1) are not significant. Single uncertainty coefficient (σ_i) is almost 0 but theoretically ambiguous and insignificant. This firm specific uncertainty term is then dropped from the within groups specifications with firm dummies in column (2) as it is collinear with the firm dummies.

Column (2) shows a significant at the 5% level and slightly positive sign for the innovating uncertainty interaction term (0.004), which is in contradiction to the initial predictions as well as the results from Bloom and Van Reenen (2002) for patenting uncertainty interaction. However, the level of uncertainty in the Finnish market analyzed in this study is lower compared to the British market that Bloom and Van Reenen (2002) look at. For example, while in Table 4 the mean standard deviation of my sample Finnish public companies is 0.76 and median only 0.31 the mean standard deviation of the comparable British sample is higher at 1.47 and the median at 1.39. Moreover, as I measure the innovations that have already been commercialized, the results could indicate that innovating and especially the ability to bring ideas to the market in uncertain times is a success and will stabilize, the firm productivity.

Table 8

Real Options Effects of Uncertainty

	(1)	(2)	(3)	(4)
	Sales	*Sales*	$log(V_{i,t}/K_{i,t-1})$	$log(V_{i,t}/K_{i,t-1})$
Log Capital	0.505*** (0.015)	0.376*** (0.025)		
Log Employment	0.500*** (0.015)	0.501*** (0.023)		
Log Innovation stock	-0.038** (0.012)	-0.063*** (0.010)		
σ_i X Log Innovation stock	0.001 (0.002)	0.004** (0.001)		
Innovation stock			-0.042* (0.019)	-0.030* (0.015)
σ_i X Innovation stock			0.003 (0.002)	0.004*** (0.001)
σ_i	-0.000 (0.002)		0.006 (0.005)	
Firm fixed effects	No	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes
No. observations	856	856	856	856
No. firms	72	72	72	72

Notes: The dependent variable for column (1) and (2) is 'log sales' and for columns (3) and (4) is 'log(market value/lagged capital)'. The estimation period covers 1985 to 2017 for (1) and (2) and 1989-2017 for (3) and (4). Models are estimated using OLS regressions by oneway effect within model in all columns. Columns (1) and (3) control for only year fixed effects while (2) and (4) control for firm and year fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.

The levels and interaction effects of uncertainty on the market value in an OLS equation are estimated in column (3). Like the results on productivity, the innovating uncertainty interaction terms are not significant. However, in column (4) with firm fixed effects included and thus without the single uncertainty coefficient (σ_i), the coefficient for the innovating uncertainty variable is slightly positive (0.004) and highly significant at the 1% level suggesting its small 0.4% positive impact on market values. This in line with the predictions for a positive relationship on linear uncertainty and the interaction term when higher market uncertainty increases the real options' value. The innovation effect, on the other hand, is negative -0.030 and significant at the 10 % level. This is in contradiction to the positive effect of innovation on market value in the basic market value function without uncertainty measures. This suggests that innovations have a positive effect on market value when the markets are uncertain. Commercializing innovations can thus also give a positive sign of the firm performance and the commitment to invest and innovate and to take enough risk also in a more uncertain environment. However, the effect is very small at 0.4%.

When measuring with the innovations per capital explanatory variable, in Table A3 the results are rather similar to those in Table 8, although with bigger and less significant values. In column (6) I find no significant effect on market value. However, in column (7) with firm without the single uncertainty coefficient (σ_i), the innovating uncertainty coefficient is highly positive (2.240) and significant at the 10% level suggesting also its positive impact on market values. The innovation coefficient is negative but not significant.

In the final Table 9 I include analysis on several dummy variables for innovation characteristics retrieved from the Sfinno data: subsidy (if the innovation has been granted a public subsidy or not), patent application (if the firm has applied for a patent to the innovation), novelty for firm, novelty for Finnish market, novelty for international market as well as process and service innovation (rest are product innovations) which are depicted in rows 6-13 respectively. As data for these characteristic variables is mostly received by VTT surveys and as I am measuring them all at once the sample size is reduced to only 87 observations. Thereafter, there were no high expectations on receiving significant results and even with some results, the analysis is unreliable and imply a small sample bias.

Column (1) reports effects of innovation characteristics on firm productivity controlling only for year fixed effects. None of the characteristics coefficients is significant. The effects of capital and employment are similar as in the basic production function with highly significant (at 1% level) and positive coefficients. With insignificant coefficient, the negative effect of innovations themselves seems to diminish when adding more characteristic variables. When looking at the signs of the characteristic results, complexity and receiving a subsidy are positive while others are negative.

In column (2) I test market value model with innovation characteristics with the dependent variable as market value per current capital instead of lagged capital since it would reduce most of the sample observations from 87 to 20 observations. This is also a valid measure for the denoted Tobin's Q. Results show very few significant measures with only novelty for firm coefficient as negative -0.621 significant at only 10% level and improvement coefficient as -0.471 significant at the 5% level. Otherwise there are positive values for only complexity stock and the patent application which would be in accordance

Table 9

Innovation Characteristics

	(1)	(2)
	Sales	$log(V_{i,t}/K_{i,t})$
Log Capital	0.653*** (0.128)	
Log Employment	0.328* (0.159)	
Log Innovation stock	-0.057 (0.122)	
Log Innovation stock		-0.003 (0.052)
Complexity stock	0.024 (0.040)	0.034 (0.071)
Subsidy	0.017 (0.085)	-0.084 (0.160)
Patent application	-0.076 (0.081)	0.034 (0.153)
Novelty for firm	-0.140 (0.128)	-0.621** (0.232)
Improvement	-0.144 (0.092)	-0.471** (0.172)
Novelty for Finland	-0.274 (0.191)	-0.012 (0.357)
Novelty for international.	-0.283 (0.216)	-0.124 (0.405)
Process innovation	-0.011 (0.158)	-0.382 (0.300)
Service innovation	-0.011 (0.356)	0.684 (0.726)
Firm fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
No. observations	87	87
No. firms	30	30

Notes: The dependent variable for column (1) is 'log sales' and for columns (2) is 'log(market value/capital)' . The estimation period covers 1985 to 2013 for (1) and (2). Models are estimated using OLS regressions by oneway effect within model in all columns. Both control for firm and year fixed effects. Robust standard err ors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10 %, 5%, and 1% level, respectively with the predictions but are now insignificant. I also conducted the market value function with innovation stock per capital on the right hand side variable and the results were very similar to those of column (2) with same significant values.

6. Conclusions

6.1. Research summary and implications

Having in mind the weakened innovating environment in Finland and the escape of private sector's innovation activities, this paper has analyzed the effect of innovation on performance, measured with productivity and market value, of Finnish public companies. I also check the effect of market uncertainty on the innovating effect. The topic of innovations and its research is complex as it is a broad subject affected by various things including the innovating firm and, for example, its size, industry, strategy and resources as well by the surrounding environment with competition, stakeholders and government policies and subsidies. However, after a thorough analysis, I find that innovations have an economically and statistically significant effect on firm performance. These effects were estimated using unique data on commercialized innovations collected by VTT and by comparing Finnish public companies during 1988-2017. I also conduct analysis on various innovation characteristics but due to limited data available and thus a small sample size, I find few significant and barely reliable results.

The first main results examined with the empirical models was the effect of innovation on productivity measured in sales. First of all, findings indicate that firms who innovate are 10% more productive than non-innovating firms. Moreover, I find that innovations themselves have a negative effect on firm productivity while a higher level of complexity of the innovations has a positive effect on productivity. For example, doubling the innovation stock would decrease the total factor productivity by 14% percentage but doubling the complexity stock could increase productivity by 8% emphasizing the importance of complexity. This could also indicate that Finnish public companies are relatively young and small to be able to produce productive complex innovations or that they produce innovations with such a level of complexity that they can manage well. Regarding the negative effect of innovations themselves on productivity, it is against the main hypothesis, but indicates the worrying trend of decreasing innovation productivity that this study also finds with an increasing R&D expenditure in relation to stagnate number of innovations.

In addition to the negative effect of innovation on productivity and the concerning decline in innovation productivity, there is an overall downward trend found in all innovating measures including the number of commercialized innovations, patents and R&D investments as well as public subsidies for innovation. These findings are in line with those by Ormala (2019). Total R&D expenditures of the Finnish private sector have declined after the peak years in 2008 – 2012 form 7 billion euros to 6 billion euros annually. Moreover, patent applications filed by Finnish companies with the Finnish Patent and Registration Office (PRH) have been in nearly constant decline since 2001. Instead, there has been a notable transformation towards international patent applications.

The second set of results from the empirical analysis suggests that innovating has a positive effect on market value. Doubling the innovation stock would increase the value of firm per unit of capital by about 6%. However, complexity is found to have a negative 6 % effect on market value. Third part of the findings with lagged innovation and complexity stocks adds to the question. The results are otherwise similar but the lagged complexity stock is found to have a 5.5 % positive effect on market value while the immediate effect was negative. This interesting finding suggests that a higher innovation complexity increases market value in the following year of the commercialization. Complex innovations' immediate negative effect could be, for example, because investors do not understand the innovation well or do not believe in the firm's ability to make and secure the value of it in the future. This can also follow the phenomenon of a value drop on a stock listing or results publishing day as the market adjusts their earlier higher expectations. However, complexity effect turns positive the year after commercialization.

Finally, I find that higher market uncertainty has a small 0.4% positive impact of commercializing innovations on productivity as well as on market value. The effect is minor, but it could imply that firm's ability to bring new ideas to the market in uncertain times will have a stabilizing effect on its performance.

Altogether, I find that innovating is important to the productivity and market value. However, not any kind of innovation will increase productivity, but innovations with a higher level of complexity. Higher complexity will also have a positive effect on market value in the following year of commercialization. The negative effect of innovation on productivity and the decrease of the innovation productivity in relation to R&D investments is a worrying sign of the quality of the Finnish innovations. Moreover, the declining number of innovations and patents and the change from Finnish patents to international patents supports the findings by Erkki Ormala (2019) of weakened Finnish innovating environment.

Based on this study I conclude that companies should keep on innovating and focus on producing more complex and productive innovations to increase performance. The government on the other hand should follow Ormala's (2019) suggestions including developing applied research and strengthening collaboration between government, VTT, companies and universities for successful implementation of research and innovation activities. Moreover, Ormala (2019) suggests funding for innovating activities to be increased by a total of EUR 300 million during 2020–2022 as well as future skills and education conditions to be clearly identified and considered when defining degree targets of higher and vocational education and training. (Ormala, 2019).

6.2. Limitations of the study

In this section I discuss some of the issues of the estimations and analysis made in this study. First, one of the concerns is the limitations to innovation data. Even though the Sfinno dataset by VTT is very comprehensive, few years are missing information on innovations or complexity within the sample Finnish public companies. There are no innovations collected for year 2009 and the few 38 innovations commercialized in 2010 were missing information on their complexity. Survey data for 2014-2016 is also missing as it is still in progress to be added to Sfinno data by VTT. However, after receiving and checking these incoming companies, only few could have been matched to my sample adding comparably unimportant number of innovations.

Regarding previous literature on innovations, the proxy for knowledge has been either patents or research and development expenditures. This is also largely due to very limited availability on data on commercialized innovations like the one from VTT, which makes this study unique. However, for the analysis to be even more comprehensive and robust, it would have been good to examine empirically the Finnish patents and R&D expenditures as well. After looking for the information, data appeared to be too limited for econometric analysis. Moreover, access for patent data of patents applied globally would have cost a lot. Considering these limitations, I was still able to include available R&D data to show a decrease in it and in innovation productivity (Figure 2 & 3) as well as public patent data from Finnish Patent and Registration office (PRH) to show an internationalization trend in Finnish patent application (Figure 4).

Third issue concerns the analysis on the innovation characteristics except for complexity. As data for these characteristic variables is mostly received by VTT surveys and as I measured them all at once the sample size was reduced to only 87 observations. Thereafter, I find few significant results and even with some results, the analysis is unreliable and imply a small sample bias. Also, data is based on answers from randomly selected respondents posing a possible source of bias. Thereafter, even though the question on how different innovations characteristics affect the firm performance would have been very interesting, I do not discuss it further due to the very small sample.

Final concern is the selection issue using only public companies which leads to examination with no private firm control group. Even though it would have been interesting to compare their differences especially in innovating, analysis of private firms is complicated due to data availability. The characteristics of public and private companies are still discussed broadly in the section *2.3. Innovation and stock market listing* of the literature review including the following reasonings: It can be that cash-rich public firms might have fewer and less complex innovations due to probable higher litigation risk and thus mechanically generate the results in the paper. On the other hand, public companies have better access to financing and resources to innovate. However, existing corporate finance literature refers to agency problems that weaken the operation efficiency after an IPO. Listing firms could increase their innovation levels and variety of each innovation but reduce their innovation riskiness and with fewer breakthrough innovations and fewer new-to-the-firm innovations.

6.3. Suggestions for further research

The questions on innovation are important from both company and broader economic perspective for future growth and competitiveness. This study on innovative Finnish public companies finds interesting results while it also suggests a need for future research. Topics for further research include extending the sample of this thesis to both public and private companies and from different countries provided that similar innovation data is offered. It would be good for comparison to conduct research together with patent and patent citation data to see whether the effect on performance is different due to the earlier timing of patents than that of commercialized innovations. Another topic for further studies with this data is to examine technological spillovers touched by recent literature as well as the effects of different innovation strategies and company characteristics, like age or industry, on performance. Finally, more detailed analysis on the uncertainty effect as well as on government infrastructure and actions to support innovation would be interesting and could give more insight of the effect of the underlying market structure and the role of government in relation to innovation. There is a great potential for future research with VTT's Sfinno data to complement the findings of this study as well as to better understand the strengths and weaknesses and special patterns of Finnish innovation.

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Appendices

Figure A1

Year of idea and break-even of innovation

Figure A2

Innovations with and without subsidies by complexity levels

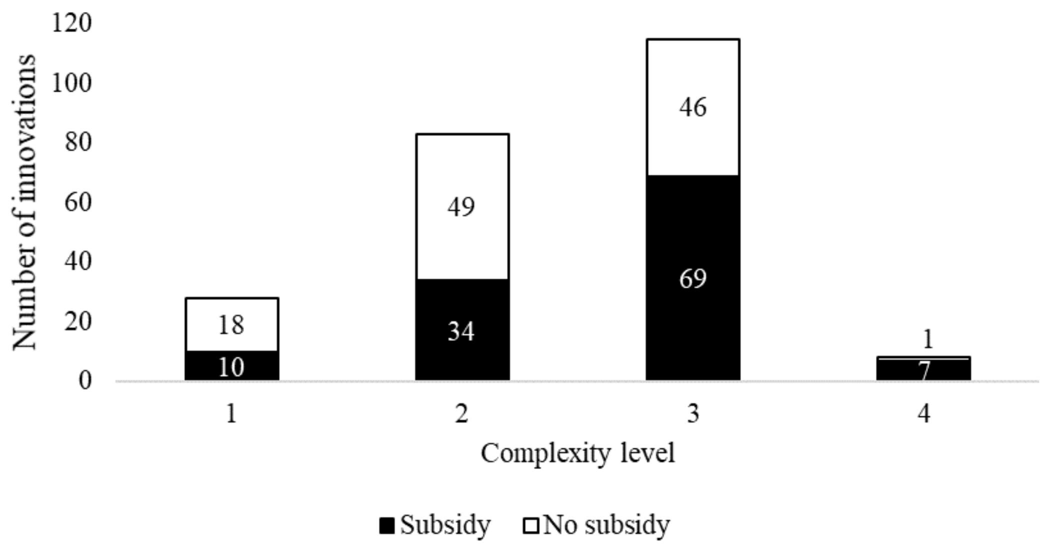

Figure A3

Plotted level of innovation complexity and sales (productivity) per sample innovation

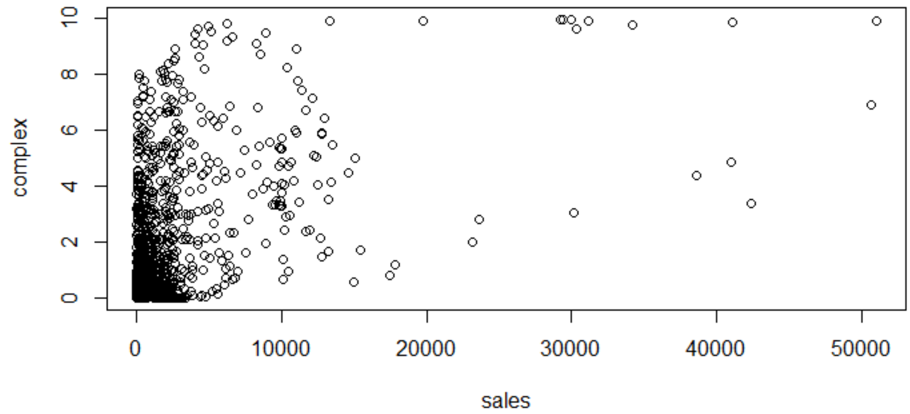

Figure A4

Plotted level of innovation complexity and market value per capital (Tobin's Q) per sample innovation

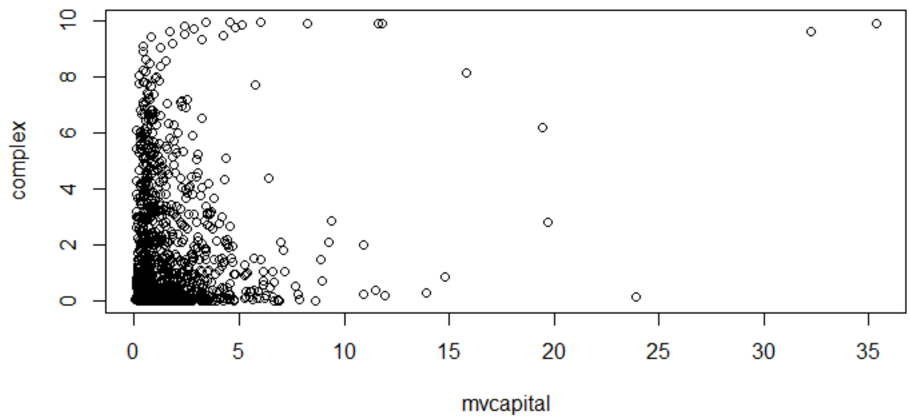

Figure A5

Orion's innovation and complexity stock and market value

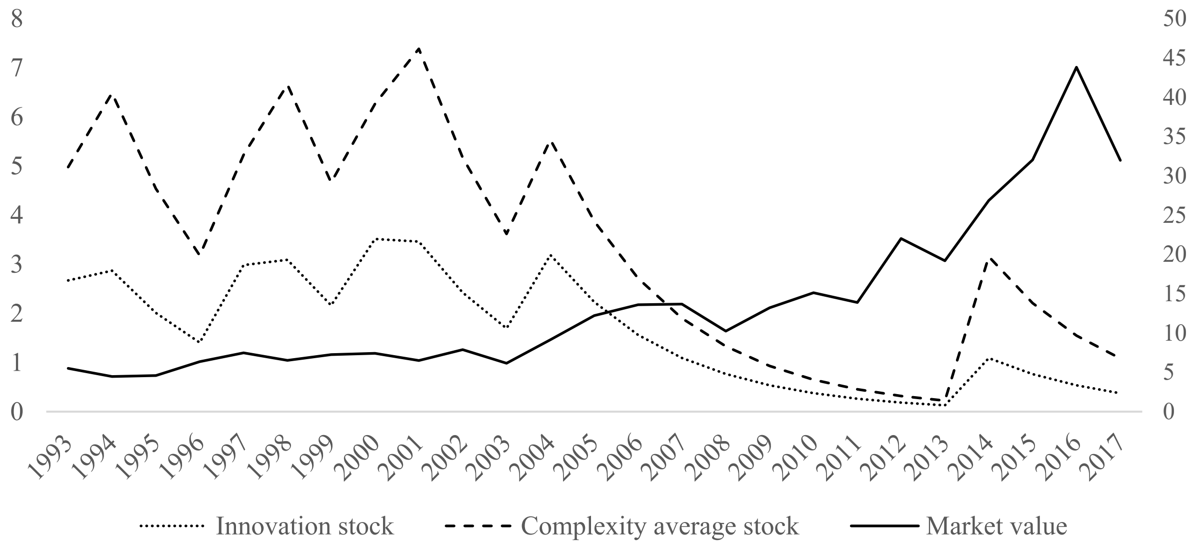

Table A1

Examples of innovations at different complexity levels (ascending order)

Company	Innovation topic	Commercialization year	Complexity level	Patent application yes/no
Fortum Oyj	Bio oil manufacturing concept based on pyrolysis	2013	4	yes
Stora Enso Building and Living	Urban MultiStorey - concept for CLT-based apartment construction	2011	4	no
Orion Oyj	Stalevo – Medicine for Parkinson's disease.	2004	3	Yes
Rocla Oyj	Abbot -Truck diagnostics solution for inbound logistics.	2004	3	No
HKScan Finland Oy	Rypsisporsas® - Local rapeseed pork meat with less saturated fats and more Omega 3 fatty acids.	2011	2	no
UPM-Kymmene Oyj	Intelligent packaging watch indicating the condition of the food. Reached 70-80% market share quickly.	2007	2	yes
Metsäserla Oyj (MetsäBoard Oyj)	Galerie Brite- gypsum press paper	1989	1	no
RAISIO Chemicals OY (currently part of BASF)	Recyclable and compostable barrier coating for paper & board for logistics savings	1995	1	Yes

Table A2

Industry Breakdown of Innovating Firms

Section	Divisions	Industry title (NACE Rev. 2)	No. of innovations	No. of firms
C		*Manufacturing of*		
	10 & 11	Food and beverages	29	6
	13	Textiles	5	2
	16 & 17	Wood and paper	41	6
	19	Coke and refined petroleum products	4	1
	20 & 21	Chemicals and pharmaceuticals	20	4
	22 & 23	Rubber and plastic and other non-metallic mineral products	19	6
	24 & 25	Basic metals fabricated metal products, except machinery and equipment	20	5
	26	Computer, electronic and optical product	35	8
	28	Machinery and equipment n.e.c.	52	9
	29	Manufacture of motor vehicles, trailers and semi-trailers	2	1
	32	Other manufacturing	1	2
D	35	Electricity, gas, steam and air conditioning supply	10	1
E	38	Water supply; sewerage, waste management and remediation activities	2	1
F	41	Construction	3	2
G	47	Wholesale and retail trade; repair of motor vehicles and motorcycles	2	4
H	51	Transportation and storage	2	1
J	62	Information and communication	15	14
K	64	Financial and insurance activities	1	1
M	74	Professional, scientific and technical activities	9	5

Table A3

Robustness Checks for Market Value

	Market Value with Innovation Measures			*Robustness Checks with Lagged Values*		*Real Options Effects of Uncertainty*	
$log(V_{i,t} / K_{i,t-1})$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Innovation stock/Capital	-2.509 (1.983)		-8.331 (5.234)	-5.232* (2.250)		-0.727 (1.600)	-2.355 (2.227)
Complexity stock/Capital		-0.666 (0.931)	2.953 (2.457)				
Lagged Innovation stock/Capital				5.270* (2.077)	-2.967 (1.830)		
σ_i X Innovation stock/Capital						2.065 (1.508)	2.240* (1.038)
σ_i						0.007 (0.004)	
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	No	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. observations	1213	1213	1213	1127	1127	856	856
No. firms	77	77	77	79	79	72	72

Notes: The dependent variable is `(market value/lagged capital) '. Due to the need for a lagged capital observation the estimation period covers 1989 until 2017 Models are estimated using OLS regressions by oneway effect within model in all columns. All column control for firm and year fixed effects. Robust standard errors are reported in parentheses. *, **, and *** indicate that the coefficient is statistically significant at the 10%, 5%, and 1% level, respectively.