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Master Thesis Strategy Economics:

Competition and other determinants of firm-level innovative in- and output in US-manufacturing.

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Abstract:
This research investigates both in- and output innovation in US manufacturing. In doing so, the following research question is assessed: *"What is the relationship between firms' innovative in- and output and firm level characteristics in US manufacturing and how do those differ between high- and low-tech firms?"* The analysis uses panel data and count data models with fixed effects. The results suggest a U-shaped relationship between lagged competition and a firm's innovative input and an inverted U for innovative output. This divergence is attributed to the likelihood of individual firms' innovative output being dependent on other firm's R&D expenditure, which causes the U to become an inverted U. Furthermore, convincing evidence is found that this relationship is moderated by a firm's distance to its industry's technological frontier, where the importance of competition is reduced if a firm is far from the frontier. Additionally, firm size generally seems to have a positive influence on innovation, but a more complex relationship appears to be present there, since the relationship's specific shape differs between model specifications, which suggests a missing factor. Furthermore, firm profitability increases innovation, which is suspected to be due to the funds it provides, whilst firm growth apparently reduces innovation due to firms being complacent when they are growing. Finally, since the analyses of high- and low-tech firms suggested different (magnitudes of) relationships, there seem to be differing influences on innovation for the determinants that are investigated. However, since those results were not consistently significant, this is a tentative observation.

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1. Introduction

In today's increasingly technologically advanced society, innovation is important, as it is one of the primary drivers of economic growth (Morck & Yeung, 2001). The focus of this thesis is on firms' technological innovation, which is generally achieved with research and development (after this: R&D).[1] Technological innovation is "the implementation of technologically new or improved products or processes" and R&D is "creative work undertaken on a systematic basis in order to increase the stock of knowledge … and the use of this stock of knowledge to devise new applications" (Matsuo et al., 2002, p. 18 & p. 30, respectively). Importantly, studies have consistently found the societal returns on R&D to be higher than the private returns (Jones & Summers, 2020), which means that the benefit of R&D to society is larger than its benefit to the company in question. Therefore, firm investments in R&D are likely to be less than the societal optimum. Consequently, many governments aim to increase firms' R&D investment and thus, hopefully, innovation. To that end, a completer understanding of innovation and its determinants is needed. Moreover, research has found that those relationships differ between high- and low-tech industries. As such, this thesis' research question is:

"What is the relationship between firms' innovative in- and output and firm level characteristics in US manufacturing and how do those differ between high- and low-tech firms?"

Innovation has many determinants, but none are as contentious as competition. The first to develop a theory on the relationship between competition and innovation was Adam Smith (1776), who believed competitive pressure would lead to increased innovation, since firms in a competitive market need to innovate to survive. Schumpeter (1942), on the other hand, hypothesised that innovation increases with market concentration, because firms in concentrated markets have the resources needed to innovate. Adam Smith's side of the argument was reinvigorated by Arrow (1962), who theorised innovation to increase with competition. A more recent theoretical and empirical study by Aghion et al. (2005) reignited the debate by combining both theories, where laggard firms are discouraged from innovating

[1] The reason for this focus is related to the measures of innovation: innovation output is measured using the (citation weighted) patent count and patents are (usually) not the result of non-technological innovation.

by competition whilst neck-and-neck firms are encouraged to innovate by competition. When combined with competition's relationship with an industry's equilibrium structure, this creates an inverted U-shape for the relationship between innovation and competition.

This new relationship was subsequently tested by other researchers with varying results, as some studies confirm the relationship whilst others find a different relationship. The only real consensus on the relationship between competition and innovation is that there is no real consensus. As Schmutzler (2010, p. 2) summarises the issue; 'Even though economist have been trying to understand the effects of the intensity of competition on R&D investments for decades, the issue remains unsettled.' Moreover, Correa and Ornaghi (2014, p. 279) state that 'The available empirical evidence on the relationship between competition and innovation is minimal and has produced some contradictory results.' Therefore, this paper aims to shed light onto the ambiguous and complex relationship between competition and innovation, specifically by finding evidence for or against the inverted-U.

To do so, this research will fill-in a caveat in current research into the topic; Research that has investigated the relationship using innovative output as the dependent variable (Aghion et al., 2005 & Beneito et al., 2017) has used the Price-Cost-Margin (PCM). However, the PCM is not the most consistent measure of competition, since it can both in- and decrease in response to increased competition, as will be set out in this paper. Research that has used a better measure of competition, the Boone indicator, (Peroni & Ferreira, 2012; Berube et al., 2012; and Polder & Velthuizen, 2012) had innovative input as the dependent variable. The Boone (2008) indicator captures the degree to which firms' profit is sensitive to their variable costs, which responds to changes in competition correctly, as set out by Boone (2008). Consequently, it is a more robust measure of competition, which improves the validity of results. Since there is no research using a more robust measure of competition that investigates innovative output, which better reflects actual innovation than input measures, that will be this research's primary contribution.

Additionally, a firm's distance to its industry's technological frontier is believed to moderate the relationship between competition and innovation (Aghion et al., 2005). Since firms that are further from their industry's technological frontier can be expected to have a less pronounced relationship between competition and innovation, as they are discouraged from innovating due to their technology falling behind, which reduces the relevance of competition in their innovation decision making. Nevertheless, many researchers (Beneito et al., 2017; Polder & Velthuizen, 2012; and Correa & Ornaghi, 2014) do not include this moderation, instead only using a squared term of competition to allow for a non-linear relationship. Moreover, when it is included in the model, the squared term of competition is often not included (Peroni & Ferreira, 2012; Berube et al., 2012), which could lead to the relationship being misunderstood. Therefore, since a firm's distance to the industry's frontier is vital in understanding the complex relationship between competition and innovation, this research extensively considers moderation by it, including moderation of a squared term of competition. Moreover, all studies that do include moderation by the DTF and a squared term of competition (Aghion et al., 2005 and Hashimi, 2013) investigate the relationship with innovative output, e.g. patent scores. As such, there are no studies that include both when investigating the relationship with innovative input, e.g. R&D expenditure. Consequently, that is another addition to the literature on the relationship between competition and innovation by this research, since it is believed that not including the DTF misses an important part of the relationship, as firms' distance to their industry's technological frontier is an important aspect that affects the relationship between competition and innovation.

Lastly for competition, research often finds differing relationship with innovation for high- and low-tech industries, since firms' reaction to competition is shaped by industry characteristics. For example, Aghion et al. (2005) and Hashimi (2013) find that the inverted U shaped relationship between competition and innovative output is steeper in industries that are more neck-and-neck, which means that firms are technologically close to the industry's frontier, as the innovative in- an output of firms that are not neck-and-neck, e.g. laggard firms, is less dependent on competition, since they are discouraged from innovating by their distance to their industry's technological frontier. Therefore, this paper investigates the relationship of competition with innovation separately for high- and low-tech industries, as suggested by Berube et al. (2012), amongst others.

Firm size has been thought to influence innovation since Schumpeter (1950), as larger firms have the resources to innovate and the market power to monetise innovation, but research has failed to give consistent results on this relationship; some find that firm size increases innovation more or less proportionally (Symeonidis, 1996; Coad and Rao, 2010), others find that innovation increases at a less than proportional rate (Sherer, 1965; Shefer and Frenkel, 2005), and others still find a declining rate (Bhattacharya and Bloch, 2004). Evidently, more research is required, specifically into the difference between high- and low-tech industries, as researchers (For example: Audretcsh, 1995 and Bhattacharya & Bloch, 2004) have found their relationship between firm size and innovation to differ. Concretely, the former found that small firms have higher rates of innovation in high-tech industries, whilst the latter found that the declining positive relationship between firms' size and innovation is lower in low- than in high-tech industries. Therefore, this research investigates the relationship between firm size and innovation separately for high- and low-tech industries as well, as literature has shown diverging results.

For firm profitability, the belief is that it provides firms with the resources to innovate, so the relationship is theorised to be positive. However, some research (Audretsch, 1995) finds that this is only applicable in high-tech industries due to low-tech industries being in the later stages of their lifecycle, which leads them to be complacent when they make a profit. Other research (Bhattacharya and Bloch, 2004), on the other hand, find this relationship only for low-tech industries, which they attribute to managers in low-tech industries seeing innovation as expendable, which leads them spend on innovation only when the firm is making a profit. Consequently, this research aims to test the relationship between firm profitability and innovation separately for high- and low-tech industries, as research has shown differing relationships for those. Moreover, since this research uses panel data, which the research mentioned above did not, its results can be expected to be more robust.

Lastly, firm growth is believed to have a positive relationship with innovation by some (for example: Coad and Rao, 2010), as it provides resources and confidence in firm survivability, whilst others (Etro, 2005) believe that firm growth has a negative relationship with innovation, as it causes complacency. Moreover, Audretsch (1995) and Bhattacharya and Bloch (2004) find conflicting results when investigating high- and low-tech industries separately. Evidently, this relationship could benefit from additional research as well, especially using panel data, since the research mentioned did not. Therefore, this paper tests the relationship separately for high- and low-tech industries, as it can be expected to explain some of the differing results.

To perform the analyses mentioned above, this research uses panel data on US manufacturing firms for the period 1978-2010. The dataset used by Bhaskarabhatla et al. (2021), who obtained their data from Compustat and the US Patent and Trademark Office, is adapted to create the final dataset that is used. The reasoning for the focus on manufacturing firms lies in their use of R&D to innovate, which is much less relevant for services firms. As such, the relationships can be expected to differ for services firms, which could cause insignificant results when they are included. Since the dependent variables, firms' R&D expenditure for innovative input and a citation weighted patent measure for innovative output, are count data and suffer from overdispersion, they will be investigated using a negative binomial regression model with fixed effects, as those can account for systemic differences. However, since some doubts exist with regards to the fixed effects in negative binomial regression (Allison & Waterman, 2002; Guimaraes, 2008; Greene, 2007; and Allison, 2012), the data is alternatively analysed using a Poisson fixed effects model, which should return robust estimates as long as specific probabilities are not estimated, as suggested by Woolridge (2020). Moreover, the Poisson model allows for robust standard errors, clustered at the firm level. Additionally, the logarithm of the dependent variables is often taken by researchers (for example by Peroni and Ferreira, 2012; Berube et al., 2012; and Polder and Velthuizen, 2012) to allow for the use of a regular regression model with fixed effects. Interestingly, this is done by all researchers that investigate innovative input, so their dependent variable is the logarithm of R&D expenditure. However, this leads to poor estimates (O'Hara and Kotze, 2010) and could be one of the causes of the diverging results found by researchers. Consequently, this research only uses the negative binomial and Poisson models, which is another addition of this study to the body of research on these topics.

Understanding the determinants of innovation is needed for various reasons. First, as mentioned above, innovation is one of the primary drivers of (real) economic growth and the societal optimum is likely to be above current levels of innovation. Therefore, promoting innovation is likely to have positive effects for society, at least on aggregate. Consequently, research that helps understand what drives innovation can be valuable to society. Second, government agencies perform competition control and, to that end, have to approve large mergers and acquisitions (M&A). To do so, an understanding of competition's relationship with innovation is imperative, especially with the goal of innovation promotion in mind. Third, climate change is no longer a crisis that can be ignored and, since innovation is needed to discover and implement more sustainable ways of living, we must increase our understanding of the determinants of innovation, to optimise our firms and industries that are working on environmental innovation.

The rest of this paper is structure as follows; Chapter two reviews the literature on both innovation and competition, with a focus on their supposedly inverted-U shaped relationship, as well as the other determinants of innovation, to set out the theoretical framework needed. Chapter three describes the data used, its origin, the modifications required to form the final dataset, and the measures that are used. Chapter four gives the methods that will be employed as well as the reasoning for their use. Chapter five analyses the result of the models that were run and interprets the relationships found. Finally, chapter six gives a short summary and discussion of the findings and the conclusion of this research, as well its implications for firms and policy makers, limitations, and possible suggestions for future research.

2. Literature review

2.1 Innovation

2.1.1 Types of innovation

Innovation happens when a new invention or idea is commercialised in its use. This means that an invention has to be produced and marketed before it can be deemed an innovation (Garcia & Calantone, 2002). Innovation can be divided into several types, of which the most important for this research will be discussed here. First of all, a distinction can be made between technological and non-technological innovation (sometimes called managerial innovation as well). Technological innovation is defined by the OECD as:

"An iterative process initiated by the perception of a new market and/or new service opportunity for a technology-based invention which leads to the development, production and marketing tasks striving for the commercial success of the invention" (Garcia & Calantone, 2002, p. 112).

The main difference is thus, unsurprisingly, the technological aspect. For clarity, an example of technological innovation is the following: vacuum cleaners used to lose their suction power when the bag filled up. Dyson solved this problem by applying the technique to remove dust from the air that is used in industrial sawmills to vacuum cleaners. This new approach is a technological innovation since there was a market opportunity where a technology-based invention was implemented to create a new product. Additionally, technological innovation usually leads to a patent application.[2] Non-technological innovation, on the other hand, is not the result of R&D and does not culminate in a patent application. Therefore, the focus of this research is on technological innovation, since the data used concerns R&D expenditure and patents. Moreover, because of the major advances technological innovation can provide, it has the most potential to significantly improve people's lives, which makes it more relevant to study. For example, things like new medical equipment and more sustainable energy production all require technological innovation.

Another well-known typology of innovation concerns process and product innovation. Process innovation consists of new or more efficient ways of manufacturing, whilst product

[2] It must be noted that not every technological innovation is followed up by a patent. For example, as patents require a substantial degree of disclosure of the innovation, some firms choose not to patent their innovation and opt for secrecy to protect it from imitation. Furthermore, this patenting-propensity has considerable variation between industries (Cohen & Levin, 1989).

innovation involves a new product, as the name suggests. However, research by Damanpour (2010) made a quantitative analysis of research findings and found there to be no significant differences between the relationship between competition and innovation for those two types of innovation. Therefore, this research will not differ between product and process innovation as that is the primary relationship it seeks to investigate.

2.1.2 Innovative in- and output

Innovation is typically measured using the innovative in- or output (Cohen & Levin, 1989). The innovative input consists of what resources the firm in question puts into the research process. Therefore, this information is often widely available, which makes measures easy to construct. The innovative output, on the other hand, comprises of what the firm gets out of the research process. Consequently, a company's innovative output is harder to measure and often less easily available for research. Moreover, many measures used for output innovation are often self-assessed by managers, which reduces their reliability, as they might overstate the innovative results, for example in an attempt to inflate their performance. Indeed, meta-research by Hülsheger et al. (2009) has found that effects are overestimated if self-assessed measures of innovation are used. Patents are a more robust measure of output innovation, since they are an official record that requires an extensive application which is reviewed before it is approved.

Both the innovative in- and output are important, but what they indicate differs. Innovative input effectively measures the effort a company makes to innovate, whilst the output is concerned with the result of the innovative process, which better reflects actual innovation. Therefore, the innovative input is a determinant of the innovative output, as confirmed by many studies.[3] However, it must be noted that their correlation is not 1 to 1, as innovation is a very uncertain process. For example, a firm could be massively investing in R&D, but all those projects could fail and thus not reward the firm with a patent. Another example would be a firm that minimally invests in R&D, but hits the 'jackpot' straight away, resulting in a very lucrative patent. Therefore, this research will consider both in- and output innovation and aim to assess their relationship as well. The specific measures that are used for this research

[3] For example: Acs & Audretsch, 1988b and Comanor & Scherer, 1969.

will be discussed in the Data chapter below. Finally, since innovative output is largely determined by innovative input, this research uses the term innovation for both types in this theoretical framework. Nevertheless, where the distinction is relevant, the terms innovative in- and/or output will be used.

2.2 Competition

Competition is one of the main forces that drives our capitalist system. In a nutshell, competition forces companies to have lower prices, offer more quality, and/or introduce a new product to outperform their competitors. Therefore, in a situation without competition (e.g. a monopoly or when firms form cartels), consumers are generally worse off. Consequently, understanding competition and how it affects firms and their (innovative) strategies is essential. As a result, one would expect competition to be one of the most researched and thus most clearly delineated subjects in economics. Nevertheless, although it is researched quite frequently, scientific consensus on its effects and measures is paradoxically still absent. Part of the issue concerns the different concepts of competition; the term is often used for both market concentration and competitive pressure. Whilst market concentration is an important concept, it only incorporates the number of firms and their (relative) size. Accordingly, it misses the intensity of competition and thus, the competitive pressure firms are subjected to, whilst that is exactly what is most important to a firm. As an example, two industries (A & B) can have many firms with comparable market shares (e.g. a comparable market concentration), but the competitive situation can be very different: firms could coexist fairly peacefully in industry A and compete heavily in industry B. Many measures of ‘competition’ would not capture the difference between the two, as they only capture the market concentration and not the true competitive situation of firms in the given industry. To clarify this problem, this subchapter gives a variety of measures of competition and their caveats.

2.2.1 Herfindahl-Hirschman Index

Competition reflects the extent to which firms compete in a given market. Therefore, the most basic of competition measures give the number of firms active in a certain market.

However, since firms active in a certain market can be of differing sizes, this can give a distorted picture of the competitive situation. Therefore, other measures were created to measure competition more accurately. The most prominent is the Herfindahl-Hirschman Index (HHI) (Rhoades, 1993). This measure gives the market concentration by adding the square of each firm's market share (e.g. 31 %):

$$HHI = S_i^2 + S_{ii}^2 + S_{iii}^2 + \cdots S_n^2$$

It gives values ranging from 10.000 to 0, in which higher values reflect a more competitive market.[4] This measure is used by many national competition authorities to assess the competitive environment pre- and post-merger, like the US Federal Trade Commission. Moreover, Tingvall and Poldahl (2006) use it in their study on the relationship between competition and innovation, which will be discussed in 2.3.3. However, a major issue with the use of the HHI is that it requires a precise demarcation of the product and geographic markets the firms in question operate in (Beneito et al., 2017). This is especially complicated today, with increasingly global markets and the prevalence of multinational companies, and thus subject to considerable measurement error. Moreover, in his paper on competition's theoretical parametrisation and empirical measures, Boone (2008) show that an industry's HHI can either decrease or increase due to more intense competition. Consequently, the HHI is a flawed measure of competition which can lead to biased results, since it only captures market concentration and not the actual competitive situation.

2.2.2 Four-firm concentration ratio

Another measure of competition that is frequently used, for instance by Mansfield (1981), Acs & Audretsch (1988b), and Audretsch & Acs (1991), is the four-firm concentration ratio. This ratio gives the combined market share of the four largest firms in an industry. Although certainly useful in some instances, this measure has a caveat as well, which is best highlighted using a concrete example: Suppose there is an industry A, with 10 firms each with a market

[4] To illustrate this, in the extreme situation of a monopoly, there is a single firm with a market share of 100%: HHI = 100^2 = 10.000

share of 10% and an industry B, with 4 firms with a market share of 10% and many firms with very small market shares. Both industries would have a four-firm concentration ratio of 40, but using that ratio to indicate the competitive situation of every firm in that market would give a skewed idea of competition. Moreover, the four firm concentration ratio suffers from the problems set out with the HHI as well; it captures market concentration, not the actual competitive situation, and is dependent on industry demarcation.

2.2.3 Price-cost margin

An alternative measure of competition that is popular, is the price-cost margin (PCM). For example, it is used to study the relationship between competition and innovation by Polder and Velthuizen (2012), Peroni and Ferreira (2012), Tingvall and Poldahl (2006), Hashimi (2013), and Berube et al. (2012), as well as Aghion et al. (2005). The reasoning behind this measure is fairly simple: Since, in principle, all firms try to minimise their cost, the ratio between the price they ask and the cost they make reflects their competitive position. For industry-level studies, this is aggregated to give the industry's (weighted) average PCM. Although it can be a useful indicator of competition, there are some problems associated with this measure, as set out by Boone (2008): Like the HHI, the industry-PCM can both decrease and increase when competition becomes more intense. For example, suppose that every firm's PCM decreases due to competition. The weighted average industry PCM can then still rise, subject to two conditions: The most efficient firms have higher PCMs and the rise in competition increases their market shares (relative to less-efficient firms). Therefore, using the weighted average PCM of an industry is a flawed measure, especially for firm-level studies.

2.2.4 Relative profits

Due to the problems of the measures of competition mentioned above, economic research has turned to the identification of more robust measures of competition. The aforementioned paper by Boone (2008) examines a variety of competition measures and proposes a new one: relative profits (RP). This measure is based on what Boone calls the 'profit reallocation effect', which entails that an increase in the intensity of competition increases the profit of the most efficient firms relative to the less efficient firms, since profits are reallocated to the most efficient firms. Consequently, this is less dependent on precise industry demarcation. Additionally, this measure is used to study the relationship between competition and innovation by Berube et al. (2012), Peroni and Ferreira (2012), and Polder and Velthuizen (2012). Finally, this measure and its operationalisation will be further expanded on in the next chapter (3.3.2 Competition).

2.2.5 Firm perception of competition

Competition is notoriously hard to measure, as set out before. Nonetheless, an important theoretical distinction needs to be made. The focus of this study is at the firm-level, which allows for the measuring competition at the firm level, thereby providing a finer look into the complex relationship between competition and innovation. Therefore, conventional measures of competition that quantify competition at the industry-level are not as useful. To illustrate this, think of the example used for the four-firm concentration ratio: if that measure is used, every firm would get the same competition 'score', which works for firms in industry A, but would give a skewed picture of the competitive situation for the smaller firms in industry B. Moreover, firms rarely have a complete understanding of their competitive situation, as the full market and all their competitors' prices, sales, and innovative in- and output are usually not (completely) known. Nevertheless, their (innovative) strategy will likely be at least partly based on their limited understanding of their competition. Therefore, it can be said that it is effectively the firm's perception of their competitive environment that drives competition-related firm behaviour.

In his paper, Tang (2006) investigates the effects of firms' perception of competition and finds that a firm's perception of its competitive environment is indeed important for innovation and a better measure of competition at the firm level. He finds both negative and positive relationships between competition and innovation. Another study that considers firm perception of competition is Carlin et al. (2004), which uses survey-based data from transition economies. They confirm the importance of firm perception of competition in their findings and find that rivalry is important for innovation, meaning that at least a few firms need to compete for firms to innovate. This result is in line with Arrow's argument, since competitive pressure is needed to incentivise firms to innovate. Moreover, they conclude that there is some evidence for the inverted U-shape of the relationship between competition and innovation, which is discussed in the next subchapter.

2.2.6 Competition summary

Evidently, many different measures are used to quantify competition. However, using measures like the HHI, the PCM, and the four-firm concentration rate can give a distorted image of competition, as shown by Boone (2008) and set out above. Moreover, most of them depend on a precise industry demarcation, which is often unavailable or untrustworthy, especially in today's interconnected world where markets are often global. Boone's indicator is preferred because it acts most consistent with theory in capturing competition (Boone, 2008). Additionally, it does not depend on a precise industry demarcation to give a valid indication of competition's intensity, since it measures the extent to which firms' profit is affected by their variable costs.

2.3 Innovation and competition

2.3.1 Classic theories on the relationship between competition and innovation

Adam Smith, widely regarded the grandfather of capitalism, believed competition to increase innovation. In his seminal work, The Wealth of Nations (Smith, 1776), he theorised that competitive pressure would lead firms to innovate in an attempt to reduce costs. Consequently, the absence of competitive pressure, on the other hand, would not incentivise firms to innovate. More concretely, Smith understood innovation to be increased by competition, a positive relationship.

On the other hand, Schumpeter (1942) believed the relationship between innovation and competition to be negative. In his theory on innovation, he hypothesised that innovation increases with market concentration. He based this on the premise that large market power provides a firm the resources to innovate. Furthermore, the innovation would (potentially) increase the firm's profits, thereby incentivising firms to take the 'risk' that comes with the unsure outcomes of the innovative process. In contrast, a firm that faces heavy competition does not have the resources to fund R&D, nor the market power to capitalise on a successful innovation, and thus innovates less, according to his theory. Consequently, Schumpeter describes a relationship opposite to Smith's.

Adam Smith's side of the argument was strengthened by Arrow (1962), whose theory is based upon the difference in profits pre- and post-innovation, for example: A monopolist can set his own price, which will be optimised for profits, so the enterprise is almost always very profitable. This reduces the incentive to innovate, because the monopolist does not need innovation to make a profit and there are no competitors innovating. Furthermore, if the monopolist does innovate, it might cannibalise his profits as the demand for the innovation might replace the demand for his other, older, products. Contrastingly, a company in a competitive market needs to innovate to make a profit, thus providing considerable incentive to innovate.

2.3.2 Aghion et al.'s inverted U-shape

Aghion et al. (2005) develop a theory that effectively combines both the Schumpeterian and Smith's theory. They create a theoretical model based on the difference between pre- and post-innovation rents, where neck-and-neck firms are encouraged to innovate by competition, whilst laggard firms are discouraged from innovating by competition.[5] The former is essentially Smith's and Arrow's argument, as the neck-and-neck firms need to innovate to escape competition, whilst the latter can (partly) be derived from Schumpeter's, as those laggard firms lack the resources to innovate. Concretely, the effect of competition on innovation is thus moderated by a firm being far from or close to the industry's technology frontier. When combined with competition's relationship with the equilibrium of the industry, these effects create an inverted U-shape for the relationship between competition and innovation. Their analysis uses data on UK-firms that are listed on London's stock exchange and confirms their theorised inverted U-shape.

In a follow up paper, Aghion et al. (2018) set up laboratory experiments to confirm their findings. In the experiments, pairs of subjects are created that each represent a firm and

[5] Neck-and-neck firms are firms that are technologically close to each other, whilst laggard firms are falling behind in technology. This 'technological distance' is captured by the Distance to Frontier variable, which will be expanded on in subchapter 3.3.3.

together an industry. The two firms in the industry have a relative technological level, so the industry can be neck-and-neck (when they have the same level) or have a laggard and a leader (when one has a higher level than the other). At the start of each period one of the firms chooses whether and how much to invest in R&D, which affects its chance of successfully innovating. If a subject successfully innovates, he/she moves to a higher technological level. After each period, rents are divided based on the subjects' relative technological level. If their levels differ, the subject with the highest level receives all the rewards. If the levels are the same, the rents they receive are equal, but depend on the competition treatment: They can be under no, intermediate, or full competition, where they share the entire rent, half the rent, or no rent, respectively. Their experiments confirm both the effects that combined lead to the inverted-U shape. Such an experiment has the advantage of exogenous control over their key variables, since they cannot rule out endogeneity problems in their empirical paper (Aghion et al., 2005). However, it must be noted that laboratory studies have their own downsides, as the results they produce are not always directly applicable in reality. Nevertheless, the combination of both empirical and laboratory evidence is valuable, as they complement each other's limitations.

2.3.3 Other research on the inverted-U relationship

After Aghion et al. (2005), other researchers have aimed to confirm the inverted-U that was found. Since this paper is on the firm level, especially research that is on the firm level is summarised here. Tingvall and Poldahl (2006) test Aghion et al. (2005)'s inverted U at the firm-level, using R&D-expenditure as innovation input. Their analysis uses data on Swedish manufacturing firms for the period 1990-2000. They use two different measures of competition and, intriguingly, find different results. The models that use the HHI confirm the inverted-U and are robust to different specifications and estimators. Moreover, their results with the HHI indicate that breaking up monopolies fosters innovation, but every subsequent increase in competition will probably reduce R&D input. The PCM, however, does not confirm the inverted U, instead finding support for Schumpeter's belief that competition reduces innovation.

Two Dutch researchers, Polder and Veldhuizen (2012) test the inverted U relationship as well, both at the industry- and at the firm-level. Their analysis uses data on Dutch firms for the period 1999-2006 and covers not only manufacturing but services and other non-manufacturing industries as well. Furthermore, their dependent variable is (a variant of) R&D-expenditure. For their industry-level models, they use Boone's indicator and the industry-level PCM. Their results confirm the inverted U with the former but are insignificant with the latter. In their firm-level models, they use Boone's indicator and both the firm- and industry-level PCM. They find support for the inverted U with the industry PCM and Boone's indicator, but a positive effect of competition on innovation when using the firm-level PCM.

In their study on competition and innovation in Luxembourg, Peroni and Ferreira (2012) use data on services and manufacturing industries in 2006. Their dependent variable is R&D-expenditure. They conclude that the relationship between innovation and competition is non-linear. However, they find no convincing support for the existence of an inverted-U shape. Instead, they find support for a U-shaped relationship between innovation and competition, since both the firm-level PCM and the Boone indicator show a negative effect of competition on innovation when combined with a positive effect of their DTF. They partly attribute their results to the nature of Luxembourg's markets: small and with low levels of competition.

Another study into this subject was conducted by Berube et al. (2012), who investigated the relationship using Canadian panel data for the period 2000-2005. Their research uses Boone's indicator and both the firm- and industry-level PCM. Moreover, their dependent variable is firms' R&D expenditure. Their results are fairly consistent across those specifications of competition, as they all give positive and significant effects of competition. Moreover, their DTF-effect is consistently negative and significant. Furthermore, the interaction term between competition and the DTF is significant in the models that use the firm-level PCM and Boone's indicator. However, the interaction term between competition and the DTF is insignificant in the models that include the industry-level PCM. They conclude that their results support both the Schumpeterian theory and the results found by Aghion et al. (2005).

Hashimi (2013) attempts to find the inverted-U using data on publicly traded US manufacturing firms for 1976 to 2001. In his research, he uses the industry-level Lerner index, which is a variant of the PCM. Furthermore, he measures innovation using a citation weighted patent score. Curiously, he finds a slightly negative relationship between innovation and competition, which they test with several alternative measures and assumptions, but the result remains negative. Consequently, he modifies Aghion et al. (2005)'s model by increasing the maximally allowed technology gap. This modified model then explains some of the conflicting results, since it betters fits the nature of his data; Crucially, Hashimi concludes that a primary cause of these differing effects between the UK and the US lies in the fact that UK manufacturing industries are more neck-and-neck than their US cousins, since when the technology gap is large, firms are discouraged from innovating by high levels of competition, e.g. a negative effect. Finally, he suggests future research looks into separate models of various industries to explain the difference in effects.

Other research investigating the inverted-U relationship between competition and innovation was conducted by Beneito et al. (2017). They tested data on Spanish manufacturing firms, with their panel starting in 1990 and ending in 2006. Furthermore, their dependent variable is patent based. Using the industry-level PCM/Lerner index and an industry-level measure of product substitutability, they find a positive relationship between competition and innovation. They subsequently adapt their model and find both an inverted-U and a positive relationship between competition and innovation. However, it must be noted that their research was at the industry level, which this research is not.

More researchers that found a positive relationship are Correa and Ornaghi (2014), who analysed industry-level data on US manufacturing and non-manufacturing for 1970-2001. To that end, they use both patents and average productivity growth as measures of innovation. Furthermore, they use a variety of methods to measure market concentration, namely both the weighted and unweighted average profitability of firms in an industry (which are variants of the PCM/Lerner index), which improves the robustness of their research. However, they conclude with the observation that their measures of competition and other standard measures are not optimal, and suggest the use of Boone's (2008) indicator. Finally, in their more reflective and non-empirical paper, De Bondt & Vandekerckhove (2012) discuss a variety of theoretical models on innovation and competition, as well as a range of empirical contributions to the debate. They find that, whilst there is no clear consensus, most evidence tentatively points towards an inverted-U relationship.

To sum up, the inverted-U shape, found by Aghion et al. (2005), was tested by several researchers, with varying results. Some confirm the relationship, whilst others find a negative or positive relationship. Additionally, some researchers find a U-shaped relationship between competition and innovation instead. Evidently, the relationship between competition and innovation requires further research, which is the aim of this paper. There are several possible reasons for this divergence; the use of imperfect measures of competition, differing country characteristics, varying industry types, different empirical models, and inconsistent measures of innovation, to name a few. Nevertheless, there is growing consensus that the relationship is non-linear and parabolic. As such, this research uses two variants of its hypotheses for competition: on with an inverted U and one with a U-shaped relationship. A reason for the conflicting results of other studies could lie in the fact that many of them do not include moderation with the DTF, instead only including a squared term of competition to find the hypothesised inverted U. Consequently, this research will aim to assess whether the relationship is indeed moderated by the DTF. Furthermore, apart from filling in the lacuna in the literature I set out in the introduction, this paper will additionally investigate if there is a difference between high- and low-tech industries, as suggested by Hashimi (2013). Research by Aghion et al. (2005) and Hashimi (2013) into the relationship between competition and innovation has found that the inverted-U is steeper in industries that are more neck-and-neck, and the low-tech industries are more neck-and-neck in this research's data.[6] Therefore, it can be expected that the relationship between competition and innovation is more pronounced for those low-tech firms. Furthermore, this hypothesis is based on the relatively large knowledge increase required to innovate in low-tech industries, compared to high-tech industries (Audretsch and Acs, 1991), which causes the relationship between competition and innovation to be more pronounced in low-tech. Therefore, this research has the following hypotheses:

H1A: *The relationship between competition and innovation follows an inverted-U shape.*

H1B: *The relationship between competition and innovation follows a U shape.*

[6] The DTF (see 3.3.3) averages 0.61 and 0.50 in high- and low-tech industries, respectively.

H2A*: The inverted-U shaped relationship between competition and innovation is moderated by a firm's distance to the industry's technological frontier.*

H2B*: The U-shaped relationship between competition and innovation is moderated by a firm's distance to the industry's technological frontier.*

H3A: *The inverted-U shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries.*

H3B: *The U-shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries.*

2.4 Other determinants of innovation

2.4.1 Firm size

Firm size is an established determinant of innovation. Schumpeter (1950) believed firm size to have a positive relationship with innovation, as larger firms have more resources that allow them to innovate. Furthermore, several researchers (Cohen & Levin, 1989; Acs & Audretsch, 1988a; and Galbraith, 1952) theorise that the supposed large firm advantage is due to the following factors: innovation is very costly, which small firms cannot afford as well as large firms; large firms have the economies of scale and market power required to monetise their innovation; and large firms can invest in several R&D projects, which reduces risk. However, Rothwell (1989), Acs & Audretsch, 1988a, and Cooper (1964), have argued that smaller firms can actually out-innovate larger firms, which they attribute to their behavioural advantages, like flexibility, less bureaucracy, and more straight-forward management structures. Nevertheless, Rothwell (1989) stresses that neither small nor large firms have an unambiguous advantage in innovating. Still, some empirical studies have confirmed this small-firm innovative advantage. For example, Scherer (1965) finds that, although innovative output increases with firm size, it does so at a less than proportional rate, which indicates a small-firm advantage in innovation. However, other studies, like Murro (2013) and Alsharkas (2014), have found that size has a positive relationship with innovation. Furthermore, Becker & Dietz (2004) investigate German manufacturing firms and conclude that their innovative input rises less than proportionally with size, so they find a decreasingly positive relationship.

Additionally, they find a positive relationship when they have new products introduced, as a proxy for innovative output, as the dependent variable. Moreover, Symeonidis (1996) and Coad & Rao (2010) conclude that R&D expenditure increases with firm size more or less proportionally. In their systematic review of literature, Becheikh, Landry, and Amara (2006) find that findings diverge, with most finding a positive relationship. Additionally, they conclude that the relationship is complex and depends on industry factors, amongst other things. Clearly, there is conflicting evidence on this relationship as well, which is likely to be attributable to the difference between industries, which is discussed below.

The most consistent conclusion of studies into the relationship between firm size and innovation is that it differs between industries (Becheikh, Landry, and Amara, 2006; Scherer, 1965; Acs & Audretsch, 1988a; and Acs & Audretsch, 1988b). Specifically, this is largely attributable to the different characteristics of high and low-tech industries (Audretsch & Acs, 1991). For instance, Audretsch (1995) finds that small firms have higher innovation rates in high-tech industries, whilst there is no discernible relationship with innovation in low-tech industries. Moreover, Shefer & Frenkel (2005) find that firm size is negatively related to the percentage of sales that is invested in R&D for high-tech firms. Consequently, they describe a decreasingly positive effect of firm size on innovation. Furthermore, a common finding in research on the relationship between firm size and innovation is that it is non-linear (Bound et al., 1982; Scherer, 1965). For example, Bhattacharya and Bloch (2004) find that firm size increases innovative activity at a declining rate. Furthermore, in their study, they find that the rate of decline of the positive relationship is lower in in low- than in high-tech industries. Additionally, Audretsch and Acs (1991) find increasing innovative returns to size for their low-tech subsample. They attribute this to the relatively large knowledge increase required to innovate in low-tech industries, compared to high-tech industries. Finally, in his analysis of Canadian manufacturing firms, Thornhill (2005) finds a significant positive relationship between firm size and innovation for low-tech firms only.

Evidently, the relationship between firm size and innovation is not as clear as it might theoretically seem at first glance. Nevertheless, there is evidence that the relationship is non-linear and depends on the industry's technological environment. Furthermore, research has found that the relationship differs between high- and low-tech industries; size's relationship with innovation seems to be increasingly positive in low-tech industries, whilst it might be decreasingly positive in high-tech industries. This split in relationships can be attributed to the following: As Audretsch and Acs (1991) argue, the increase in knowledge required to innovate is relatively small in high-tech industries. Therefore, in high-tech industries, the larger size of a firm and thus available funds for innovation does not provide a real benefit in innovating, as the increase in knowledge required is relatively small. In low-tech industries, on the other hand, the increase in knowledge required to innovate is relatively large, which causes size to give an advantage in innovating, as it provides the resources to achieve the relatively large increase in knowledge required.

Another reasoning lies in the type of innovation generally pursued: Low-tech firms are often more focused on process innovation than high-tech companies, who focus more or product innovation (see for example Fontenele et al., 2016). Since process innovation provides benefits relative to the scale of production (it reduces variable cost, so its gains are determined by the decrease in variable cost multiplied by the number of units produced), it can be expected that large firms innovate more, as they have more to gain. Therefore, it is theorised that firm size has a positive relationship with innovation in low-tech industries. In high-tech industries, on the other hand, the relationship can be expected to differ somewhat. Since product innovation is not as dependent on scale and risks cannibalising sales of other products, large firms have less of an advantage if they innovate. Whilst the relationship between firm size and innovation is likely still positive in high tech industries due to the increased funds size provides, innovating whilst large has some downsides as well. Consequently, it can be expected that firm size has a less pronounced positive relationship with innovation in high-tech industries.

Therefore, this research has the following hypotheses:

H4: Firm size has a positive relationship with innovation.

H5: The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms

2.4.2 Firm profitability

In theory, similar to Schumpeter's expectation of firm size increasing innovation by providing the resources to innovate, firms that turn a profit have more resources to facilitate R&D and thus innovation. Consequently, one would expect a positive effect of firm profitability on innovation. However, not all research finds this relationship. Bhattacharya and Bloch (2004) do not find a significant effect of (lagged) firm profitability on innovative activity for their full sample. When split into high- and low-tech industries, their results indicate that only low-tech firms' innovative activity is increased by their profitability. Contrastingly, other research, for example by Audretsch (1995), has found that a company's profitability increases innovative activity only in high-tech industries, whilst it has an insignificant or negative effect in low-tech industries. He and Branch (1974) attribute this to low-tech industries typically being in the later stages of their life cycle, which leads them to be complacent when profits are high and to innovate out of necessity when profits are low. High-tech industries, on the other hand, are usually in the earlier stages of their lifecycle, where innovation is more frequent. Therefore, firms in those high-tech industries need to constantly innovate to keep up with their competitors. To do so, funds are needed, which is provided by profitability.

Whilst there is certainly no consensus, most literature does seem to point toward firm profitability having a positive relationship with innovation, if it has an effect. This makes sense intuitively, since innovation is costly and without profit, firms are unlikely to have such funds. Furthermore, since research has hypothesised that firms in low-tech industries only innovate out of necessity when profits are low, one might expect a negative relationship between growth and innovation in low-tech industries. However, since the availability of funds that enable innovation, which is facilitated by profit, seems to be a more potent effect, this research expects that effect to dominate. Consequently, the effect of firm profitability on innovation is probably still positive in low-tech industries. Nevertheless, it might be smaller than in high-tech industries due to the complacency effect in low-tech industries, mentioned above. Therefore, this research uses the following hypotheses:

H6: Firm profitability has a positive relationship with innovation.

H7: The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries.

2.4.3 Firm growth

Firm growth provides resources and confidence in the firm's survivability. Therefore, firm growth can be expected to increase innovation in a similar fashion as firm size and profitability as:

"The faster a firm's sales are increasing, the more confidence it will have about its ability to secure the benefits from uncertain R&D projects, and the more patience it can afford to show in waiting for these benefits" (Mueller, I967, p. 73).

Indeed, research by Coad and Rao (2010) amongst others, has found that innovation increases with firm growth in sales more or less proportionally. However, Etro (2005) has found that firm growth reduces firms' R&D expenditure. He attributes his contrasting result to the two-way causality of growth and innovation that most studies suffer from;[7] since innovation is very likely to increase growth, studies that do not separate this effect from the effect of growth on innovation result in a positive effect of growth on innovation. Since he separates the effects, Etro (2005) finds that, when a firm is experiencing growth due to other sources than innovation, it is discouraged from spending on R&D.

There has been research that did not find a significant relationship between firm growth and innovation as well. An example is Bhattacharya and Bloch (2004), who find that lagged firm growth does not significantly increase innovative output. Interestingly, this effect remains unsignificant when split between high- and low-tech industries, whilst Audretsch (1995) finds that firm growth significantly increases innovative output only for low-tech industries. Other than that, Audretsch (1995) hypothesises that, in high-tech industries, low firm growth might actually increase a firm's innovative effort, which amounts to a negative relationship. His reasoning for this lies in the high-growth nature of those industries; if firm growth is (relatively) slow, that is indicative of a need for new products and thus innovation. However, low-tech industries, on the other hand, generally have comparatively lower growth rates, as they are usually in the later stages of their lifecycles, as mentioned in the previous subsection. Therefore, a low-tech firm that is experiencing growth is likely to reduce its R&D expenditure, since it does not see the need to innovate when sales are growing. Contrastingly, a low-tech

[7] To reduce this cause of bias, this research uses lagged values of growth, which will be expanded on in the Methods chapter.

firm that has reducing sales, e.g. a negative growth rate, would be more likely to invest in R&D since it needs to innovate to survive. However, it must be noted that this concerns the innovative effort, e.g. the innovative input. As mentioned above, other research has found firms' innovative output to be positively influenced by firm growth, at least in low-tech industries. This could be attributable to a consequence of firm growth; when a firm grows, the need to achieve fast results is less, which gives inventors more time to continue their research instead of being forced to start a new project in search of fast results. Since this effect has been found in low-tech industries only, it could be that it is smaller in high-tech industries and has therefore not been statistically significant. However, this positive relationship could be the result of innovative output having a positive effect on growth. All in all, due to the low-growth nature of low-tech industries, it can be expected that firm growth's relationship with innovation, whether positive or negative, is more pronounced and thus larger in low-tech industries. Based on the literature and intuition mentioned above, this research uses the following hypotheses:

H8: Firm growth has a negative relationship with innovative input.

H9: Firm growth has a positive relationship with innovative output.

H10: The negative relationship between firm growth and innovative input is more pronounced in low-tech industries than in high tech industries.

H11: The positive relationship between firm growth and innovative output is more pronounced in low-tech industries than in high-tech industries.

3. Data

3.1 Original dataset

The dataset used by this research was originally constructed by Bhaskarabhatla et al. (2021) for their research. Their dataset contains publicly listed US-manufacturing companies, both high- and low-tech. As their research was concerned with finding out whether inventors or firms are the drivers of innovation, their dataset consists of information on companies, inventors, and patents. Their patent data was obtained from the United States Patent and Trademark Office and their firm characteristics were acquired from Compustat. Furthermore, each observation is inventor-based, which means that each inventor has its own observation for each year and that observation contains (financial) information on the company that employed them in the given year as well as their patents. Consequently, the dataset needs to be reshaped to investigate the relationship between competition and innovation at the firm level. To do so, the dataset needs to be firm based, meaning that every firm should have an observation in every year (1978-2010), if available. However, since some firms might cease to exist or enter later and some data is missing, the resulting dataset will be an unbalanced panel, meaning that some firms do not have an observation in certain years.

3.2 Reshaping the dataset

For most variables, reshaping the dataset is not complicated. For example, a firm Y's income in year X is the same for every inventor that works for that firm. Consequently, using a random inventor's values for firm characteristics as the firm is no issue, as many variables are consistent across inventors at a firm. Nevertheless, to maximise consistency and to reduce potential problems with errors in the data, both the median value and the mean are obtained, and the two resulting datasets will be used alternatively used to run future models.[8] One variable where problems might have occurred is with the citation weighted patents, due to aggregation of patents that are attributed to two authors at the same firm. However, the constructors of the original dataset, Bhaskarabhatla et al. (2021), already created a variable for the number of citation weighted patents for each firm.

[8] Doing so did not produce different results, so it is not reported.

3.3 Measures created and used

After reshaping the dataset, some measures need to be adapted and some created. This section describes the operationalisation of some of those measures. First, firm growth is the percentage difference in sales with the year before. Second, the Ebitda is a firm's earnings before interest, taxes, depreciation, and amortisation and is used to measure firm profitability.[9] Third, a firm's sales is the amount of sales a firm has reported. Both the Ebitda and sales are deflated to constant price levels to negate the impact of inflation on the results. Additionally, they are both included in logarithmic form to reduce the effect of outliers and obtain a more even distribution. Next, the more complicated variables are discussed in their own subchapter.

3.3.1 Innovation

For innovation, this research used both the innovative in- and output. The measures used are fairly straight-forward and require no additional calculations and/or variables. The innovative input is measured with a firm's total R&D expenditure. Furthermore, like with the Ebitda and sales, it is deflated to constant price levels. The innovative output, on the other hand, is captured using the above-mentioned citation weighted patents score already created by Bhaskarabhatla et al. (2021). With a citation-weighted patent score, patents are assigned a score using their number of citations, which thus weights them for their number of citations. Doing this allows the research to take the quality of patents into account.[10]

3.3.2 Competition

As extensively considered in the previous chapter, competition is hard to measure. For reasons stated before, this paper uses Boone's indicator. Following Berube et al. (2012), all observations that have a negative Ebitda are deleted. Moreover, this should not affect Boone's indicator, since it takes negative profit firms into account by nature (Berube et al.,

[9] The Ebitda is especially useful in this regard, since it excludes factors that might vary between firms that would be included if the net profit were used, like taxes or depreciation.

[10] This is important as not all patents are created equal, e.g. some are far more valuable and influential than others (Comanor & Scherer, 1969; Cohen & Levin, 1989).

2012). Boone's indicator was not present and thus requires some construction. As mentioned before, the Boone indicator is based on the profit reallocation effect. For each industry-year combination, a regression is run with profits as the dependent variable and costs as the main independent variable. The coefficient of costs (β_1 in the formula below) then reflects the degree of competition in the given industry. Following Peroni & Ferreira (20120, amongst others, employment is included as a control for firm size. The resulting equation is the following:

$$Ln(\pi_i) = \beta_0 + \beta_1 \ln(C_i) + \beta_2 \ln(L_i) + \varepsilon_i$$

Where π_i gives the profit of firm I,[11] C_i gives the average variable cost of firm i, and L_i gives the employment of firm i. However, the data used does not include a direct measure of variable costs. Nevertheless, it can be approximated with the following strategy: Since fixed costs, especially in manufacturing, largely consist of machines and buildings that are factored in using depreciation, the Ebitda does not include them and other non-variable costs. Therefore, the average variable costs can be proxied the following way:

$$C_i = \frac{(S_i - E_i)}{S_i}$$

Where C_i again gives the average variable cost of firm i, S_i gives the sales of firm I, and E_i gives the Ebitda of firm i. Moreover, since the firms are in the same industry, it is likely that the degree to which this differs from the actual unobserved variable costs is consistent across firms within the industry, which reduces the potential bias on the results. Finally, since Boone's indicator is a negative number (the effect of costs on profit), its absolute value is taken, following Peroni & Ferreira (2012) and Berube et al. (2012), amongst others. Consequently, Boone's indicator is a positive number, where higher values reflect a higher intensity of competition. Furthermore, industry-year combinations where the estimated Boone's indicator was not significant were dropped, since those apparently failed to capture the level of competition accurately.

[11] The Ebitda is used measure profit, since it is less affected by differences in, for example, depreciation between firms.

3.3.3 Distance to frontier (DTF)

The DTF variable is used to indicate a firm's degree of technological advancement, as firms' reaction to competition is moderated by it, for the reasons previously set out in 2.2.2. An industry's frontier is the firm with the highest Total Factor Productivity (TFP) as that firm apparently makes the most of its inputs, which reflects high efficiency and thus the degree of technological advancement. TFP is commonly calculated using a firm's sales and the input of capital, labour, and materials (Van Beveren, 2012). However, the data lacks specific variables for costs and there is no way to calculate those specific types of costs using the data that is available. Therefore, this research uses another proxy to capture a firm's TFP and thus DTF.

The TFP indicates how efficiently a firm uses its inputs to create its output. Since manufacturing industries are particularly asset-intensive and the cost of capital and labour is likely to be very similar for firms in the same country and industry, this research will proxy the TFP using firms' return on assets (ROA), which is present in the dataset. With this proxy for TFP, the DTF variable is created in the following way: In each industry, the firm with the highest ROA is the frontier-firm. The other firms' distance to the frontier is then given by the following equation (where TFP indicates the ROA, the capital F indicates the frontier firm, j the industry, t the year, and i the firm):

$$DTF_{it} = (TFP_{Fjt} - TFP_{it})/TFP_{Fjt}$$

The resulting DTF variable is continuous and ranges from zero to one, with values closer to zero reflecting a position closer to the industry's technological frontier. To enable an alternative, easier analysis, the DTF variable is subsequently transformed into a dummy, which is done following Hashimi (2013): First, the mean value of the distance to frontier is determined for every industry. Next, the DTF-dummy takes a value of one if a firm's DTF is larger than its industry's mean DTF and a value of zero if its DTF is smaller than the industry's mean DTF. Consequently, the dummy takes a value of one for laggard firms and a value of zero for neck-and-neck firms.

3.4 Final dataset

The resulting dataset is a panel of US-manufacturing firms for the period 1978 – 2010. The panel variable is each firm's individual identifier and the time variable is the year of the observation. The panel contains information on firms' (financial) characteristics, as well as their innovative in- and output. Additionally, the dataset includes each firm's North American Industry Classification System (NAICS) indicator. Consequently, the firms can be divided into industry categories to allow this research to investigate the relationship between competition and innovation in certain industries independently. Furthermore, the NAICS indicators are used to define industries for the construction of the variables mentioned above. Moreover, the indicators are used to divide the firms into high- and low-tech industries.[12] In doing so, the three-digit classification is used, following Thornhill (2016).[13] This categorisation allows this research to account for differences in the effects of determinants of innovation, as found by, for example, Bhattacharya & Bloch (2004) and Audretsch (1995). The variables' descriptive statistics are given in Table 1, below.

Table 1: Descriptive Statistics

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	N	Mean	Std. Dev.	Min	Max	Variance
Boone's indicator	13,141	13.61	3.614	4.159	35.38	13.06
Sales	13,141	5,327	14,822	2.249	275,953	2.197e+08
Ebitda	13,141	836.8	2,416	0.0151	46,188	5.835e+06
Growth %	11,578	0.0643	0.202	-0.863	3.477	0.0408
High-Tech dummy	13,141	0.820	0.384	0	1	0.148
RND expenditure	13,141	291.8	897.6	0	14,441	805,739
CWPS	13,141	413,713	3.912e+06	0	1.186e+08	1.531e+13
DTF	13,141	0.569	0.215	0	1.000	0.0461
DTFD	13,141	0.546	0.498	0	1	0.248

[12] For clarity, high-tech industries are industries like chemical, machinery, and computer manufacturing, whilst low-tech industries produce, for example, food, textile, and furniture.

[13] For completeness, a full list of the NAICS sectors used, their number of observations, and their classification as either high- or low-tech is given in Annex 1.

4. Methods

This chapter sets out the econometric methods that are used to analyse innovation and its determinants. To that end, the general method for the innovative in- and output models is first set out. After that, the specific strategy for analysing the different variables and their hypotheses is set out.

4.1 Innovative input models

The models that investigate a firm's innovative input use firms' R&D expenditure as the dependent variable. Since R&D expenditure is never negative, is an integer, and contains a considerable amount of zero observations, it is count data. Therefore, an appropriate model needs to be used. A common method to analyse count data is the Poisson model.[14] An assumption of the Poisson model is that the data follows a Poisson distribution, which means that the mean and the variance are the same. However, this assumption is not fulfilled since the variance is much larger than the mean,[15] which is called overdispersion. Therefore, a negative binomial regression model is more suitable, as it allows for the variance to be larger than the mean, following Hashimi (2013). Furthermore, to account for systemic differences between firms, a fixed effects model is used following Berube et al. (2012), Polder & Velthuizen (2012), Beneito et al. (2017), and Aghion et al. (2005).[16] Moreover, industry and year dummies are added to the models to include fixed effects for those factors as well. However, there are some doubts as to the validity of fixed effects negative binomial regression models, as it generally does not truly control for all time invariant characteristics (Allison & Waterman, 2002; Guimaraes, 2008; Greene, 2007; and Allison, 2012).[17] Therefore, a fixed effects Poisson model is used as well, since it is robust to overdispersion as long as probabilities of specific event counts are not estimated (Wooldridge, 2020). Moreover, unlike the fixed effects negative binomial regression model, it allows for the use of robust standard

[14] This method is used by Aghion et al. (2005) and Beneito et al. (2017), for example.
[15] See the summary statistics in Annex 2; Additionally, the presence of overdispersion was confirmed by the built-in tests of the negative binomial models.
[16] The choice for fixed effects models is based on a Hausman specification test as well.
[17] This is evidenced by the significant and non-zero coefficients for unchanging firm characteristics like the high-tech dummy in the results section, which are zero and insignificant in the Poisson models, as they should be.

errors.[18] Since both models have caveats to some degree, the most convincing results will be those where both models are consistent. However, when they differ, the Poisson model's estimates are likely more accurate and will thus be preferred. A commonly used alternative (for example by Peroni and Ferreira, 2012; Berube et al., 2012; and Polder and Velthuizen, 2012) is to take the logarithm of the dependent variable and use a regular regression model. However, this can lead to biased results, since transforming the data that way leads to poor estimates (O'Hara and Kotze, 2010). As such, this research uses both a fixed effects negative binomial model and a fixed effects Poisson model with robust standard errors. Finally, this strategy of using both the negative binomial and Poisson model is used by Correa and Ornaghi (2014) as well.

The models used for the innovative input take the following shapes:

$$R\&D\ Expenditure = \beta_1 * Competition + \beta_2 * Size + \beta_3 * Profitability + \beta_4 * Growth + \beta_5 * DTF + \varepsilon_i$$

This model will subsequently be expanded with squared and/or interaction terms, depending on the variable/hypothesis being investigated, which will be separately expanded on after the general explanation of the innovative output models below. Moreover, the expanded version of the model in question is then used on a high- and a low-tech sample to check their differences.

Since endogeneity is a concern, lagged values of the explanatory variables are used to minimise the potential adverse impact of endogeneity on the estimation results, as done by Berube et al. (2012) and suggested by Peroni & Ferreira (2012). Moreover, to reduce the effect of outliers, firms' size and profitability are used in logarithmic form, as mentioned before. Finally, year fixed effects are included in all models, with the use of time dummies, to remove shocks. Furthermore, industry fixed effects are included to control for differences between industries. However, they are only included in the negative binomial regression models, since they create collinearity issues in the Poisson fixed effects models.

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[18] Another difference with the negative binomial models is that the Poisson models do not include industry dummies.

4.2 Innovative output models

The dependent variable for these models, the CWPS, is count data as well.[19] Therefore, as mentioned above, models that are designed to analyse count data need to be used. However, like with R&D expenditure, the variance of the CWPS is much larger than its mean,[20] which means that there is overdispersion.[21] Therefore, in theory, the Poisson model might not give accurate estimates in this case either. Consequently, these models, like the models above, are investigated using a negative binomial approach, following Hashimi (2013). Moreover, like with the input models, the negative binomial output models include firm fixed effects, following Berube et al. (2012), Polder & Velthuizen (2012), Beneito et al. (2017), and Aghion et al. (2005).[22] Additionally, the year and industry dummies are added to the models here as well to include those factors' fixed effects. Nevertheless, the doubts on the validity of fixed effects negative binomial models, mentioned above, are naturally applicable here as well. Therefore, as with the innovative input models, a fixed effects Poisson model with robust standard errors is used as well.[23] Furthermore, since the innovative input is an important determinant of the innovative output, the logarithm of R&D expenditure is included in all innovative output models. The resulting models take the following shape:

$$CWPS = \beta_1 * R\&D\ Expenditure + \beta_2 * Competition + \beta_3 * Size + \beta_4 * Profitability + \beta_5 * Growth + \beta_6 * DTF + \varepsilon_i$$

Like with the input models set out above, this model will subsequently be expanded with squared and/or interaction terms as well, depending on the variable/hypothesis being investigated. Moreover, the expanded version of the model in question is then used on a high- and a low-tech sample to check their differences.

Since endogeneity is a concern here as well, lagged values of the explanatory variables are used to minimise the potential adverse impact of endogeneity on the estimation results, as done by Berube et al. (2012) and suggested by Peroni & Ferreira (2012). Finally, like with the

[19] Like firm R&D expenditure, it is non-negative, integer, and has a considerable amount of zero observations.
[20] Again, see the summary statistics in Annex 2.
[21] Additionally, the presence of overdispersion was confirmed by the built-in tests of the negative binomial models.
[22] Like with the innovative input models, this choice was confirmed with a Hausman specification test as well.
[23] Like the innovative input Poisson models, these do not include the industry dummies either.

innovative input models, the firms' Ebitda and sales are used in logarithmic form to reduce the effect of outliers.

4.3 High- Vs. Low-Tech

To investigate the potential difference between high- and low-tech industries as suggested by Hashimi (2013), two different strategies are used to increase robustness. First, the models set out above will be alternatively ran with high- and low-tech samples. Second, the models set out above are modified to include interaction effects to explore the influence of being high- or low-tech on the relationships between innovation and its determinants. In doing so, only the variable that is being investigated will be interacted with a dummy for being high- or low-tech.

4.4 Competition models

A variety of strategies has been used to obtain the inverted U hypothesised by Aghion et al. (2005). In general, there are two: First, the inclusion of a squared term of competition to allow for a non-linear relationship, which is done by Aghion et al. (2005), Peroni and Ferreira (2012), Polder and Velthuizen (2012), Correa and Ornaghi (2014), and Beneito et al. (2017), By including this term, the relationship can take the shape of an inverted U if the coefficient of the unsquared term is positive and the coefficient of the squared term is negative. Second, the inclusion of an interaction effect of DTF with the competition measure, used by Aghion et al. (2005), Berube et al. (2012), and Peroni and Ferreira (2012). By adding this interaction term, the marginal effect of competition on the innovative in- or output become dependent on firm's DTF, which introduces the non-linearity that can create the hypothesised inverted U. Moreover, Aghion et al. (2005) use a third strategy as well, where they combine the two mentioned above. Concretely, they interact both the squared and the unsquared term with a firm's DTF. As mentioned in the introduction, almost all researchers include either the squared term of competition or the DTF moderation, but not both. Consequently, they miss an important aspect of the relationship, which reduces the validity of their results. As such, this research does moderate both squared and unsquared competition with the DTF, which should provide a more accurate image of the relationship between competition and innovation. Finally, Hashimi (2013) uses a similar strategy but with a dummy to reflect the DTF and thus a firm's categorisation as a neck-and-neck or laggard firm. This strategy is used as well to facilitate easier interpretation, especially considering the interaction with the high-tech dummy that is included in this research as well.

4.5 Size Models

To allow size's relationship with innovation to be non-linear, a squared term of firm size is included in the models that investigate the relationship between size and innovation.

4.6 Full Models

Lastly, a model that includes all squared and/or interaction terms, to the extent possible, is estimated for both innovative in- and output. In doing so, the first models will use the full sample and include both squared size and competition terms, as well as interaction of the DTF dummy with the latter. Subsequently, a model that includes squared terms of competition and size is run on samples split between high- and low-tech firms. After that, the same model is estimated on the full sample, but then with the inclusion of high-tech dummy interaction for all main variables, e.g. competition, size, profitability, and growth.

5. Results

5.1 Competition

5.1.1 Input Models: Unmoderated

The results of competition for the innovative input models can be found in Table 2, on the next page. First, only the negative binomial basic models have a significant competition term, which is negative. Therefore, that suggests a negative relationship between lagged competition and innovative input. However, both the negative binomial and the Poisson models that include competition squared have significant terms for both the squared and the unsquared term. As such, this suggests that the relationship is non-linear. Moreover, the signs for the unsquared terms are all negative, whilst all four squared terms show a positive sign. Combined, this leads to a U-shaped relationship, as the maximum value of Boone' indicator is on the positive slope. Therefore, this result provides no support for H1A *(The relationship between competition and innovation follows an inverted-U shape)* but supports H1B (*The relationship between competition and innovation follows a U shape*) instead. This divergence with most literature could be the result of the use of the logarithm of R&D expenditure as the dependent variable and a regular regression by all studies into the relationship between competition and innovative input, which can cause inaccurate estimates, as set out before. Nevertheless, these results indicate that the quadratic models best capture the relationship between lagged competition and a firm's innovative input.

With regards to the other variables, they are all significant and their signs are as expected; lagged sales and lagged profitability have a positive influence on a firm's innovative input whilst lagged firm growth has a negative relationship with a firm's innovative input. Finally, only the continuous DTF terms in the negative binomial models are significant. Since they are positive, this indicates that firms that are further from their industry's technological frontier are encouraged to spend on innovation. This could be indicative of firms attempting to catch up with their competitors when they are laggards, whilst firms that are neck-and-neck do not have this additional incentive to spend on R&D. However, the DTF terms are not moderating the relationship between lagged competition and innovation here, so there could be omitted variable bias in those terms' results.

Table 2: Competition Input Models: Basic and Squared

VARIABLES	(1) NB: Basic	(2) P: Basic	(3) NB: Basic	(4) P: Basic	(5) NB: Sq	(6) P: Sq	(7) NB: Sq	(8) P: Sq
Boone	-0.00989***	-0.00406	-0.0107***	-0.00414	-0.0360***	-0.0654***	-0.0369***	-0.0636***
	(0.00129)	(0.00551)	(0.00129)	(0.00550)	(0.00630)	(0.0211)	(0.00633)	(0.0216)
$Boone^2$					0.000822***	0.00194***	0.000825***	0.00188***
					(0.000194)	(0.000691)	(0.000195)	(0.000706)
Ln(Sales)	0.314***	0.757***	0.365***	0.777***	0.318***	0.751***	0.370***	0.777***
	(0.0164)	(0.0735)	(0.0151)	(0.0645)	(0.0163)	(0.0710)	(0.0150)	(0.0625)
Ln(Ebitda)	0.167***	0.144***	0.110***	0.125***	0.167***	0.151***	0.110***	0.125***
	(0.0146)	(0.0527)	(0.0131)	(0.0471)	(0.0145)	(0.0522)	(0.0131)	(0.0469)
Growth %	-0.0564***	-0.120**	-0.0647***	-0.125**	-0.0587***	-0.125**	-0.0671***	-0.132***
	(0.0203)	(0.0504)	(0.0205)	(0.0506)	(0.0203)	(0.0501)	(0.0205)	(0.0501)
DTF	0.194***	0.0634			0.194***	0.0898		
	(0.0293)	(0.0965)			(0.0294)	(0.0933)		
DTFD			-0.00220	-0.00677			-0.00316	-0.00497
			(0.00944)	(0.0259)			(0.00943)	(0.0256)
Observations	10,194	10,194	10,194	10,194	10,194	10,194	10,194	10,194
Number of Firms	911	911	911	911	911	911	911	911
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

5.1.2 Input Models: Moderated

The results of the moderated models can be found in Table 3, on the next page. The first model specification follows literature in moderating the unsquared competition model with the DTF.[24] However, since the results above indicated a quadratic relationship, both the competition terms in that model are interacted with the DTF as well. Moreover, this was also done by Aghion et al. (2005). Additionally, the quadratic models are interacted with the DTF dummy (DTFD) as well, as done by Hashimi (2013), since dummy-moderation is easier to interpret. First, the two basic models, moderated with the DTF, have a significant competition term and a significant moderation term. Moreover, both unmoderated terms are negative whilst both moderated terms are positive. Since the DTF ranges from 0 to 1, with values closer to 1 indicating a larger distance to the industry's frontier, the interpretation is the following: Firms that are at the frontier (DTF = 0) are captured by the unmoderated term only, which indicates that lagged competition has a negative relationship with a firm's innovative input. This relationship is then compensated by a firm's distance to its industry's technological

[24] This is done by Peroni and Ferreira (2012) as well as Berube et al (2012).

frontier, since those terms are positive. Moreover, when a firm is the furthest from its industry's technological frontier (DTF = 1), it might even be encouraged to increase its innovative input by lagged competition, since the positive moderated terms are slightly larger than the unmoderated negative terms. However, the confidence intervals of the terms overlap, so that is a tentative conclusion. What can be said with some degree of certainty is that being further from the industry's technological frontier reduces the negative effect of lagged competition on a firm's innovative input. However, since these models do not include the squared term that seems to best capture the relationship, that observation is preliminary.

Table 3: Competition Input Models: Moderated

VARIABLES	(1) NB: Basic Mod	(2) P: Basic Mod	(3) NB: Sq & Mod	(4) P: Sq & Mod	(5) NB: Sq & D-Mod	(6) P: Sq & D-Mod
Boone	-0.0217***	-0.0213**	-0.124***	-0.158***	-0.0848***	-0.0977***
	(0.00280)	(0.00946)	(0.00801)	(0.0506)	(0.00628)	(0.0265)
$Boone^2$			0.00316***	0.00423***	0.00218***	0.00267***
			(0.000274)	(0.00151)	(0.000204)	(0.000836)
DTF	-0.146*	-0.311	-1.664***	-1.260**		
	(0.0758)	(0.214)	(0.131)	(0.641)		
DTF * Boone	0.0240***	0.0315**	0.224***	0.169**		
	(0.00497)	(0.0146)	(0.0178)	(0.0830)		
DTF * $Boone^2$			-0.00587***	-0.00424*		
			(0.000609)	(0.00242)		
DTFD					-0.937***	-0.548**
					(0.0753)	(0.216)
DTFD * Boone					0.114***	0.0657**
					(0.0102)	(0.0296)
DTFD * $Boone^2$					-0.00304***	-0.00162*
					(0.000331)	(0.000893)
Ln(Sales)	0.317***	0.741***	0.215***	0.716***	0.214***	0.757***
	(0.0163)	(0.0751)	(0.0163)	(0.0707)	(0.0139)	(0.0615)
Ln(Ebitda)	0.165***	0.156***	0.189***	0.175***	0.152***	0.133***
	(0.0146)	(0.0552)	(0.0156)	(0.0555)	(0.0141)	(0.0471)
Growth %	-0.0565***	-0.115**	-0.0251	-0.112**	-0.0405*	-0.126**
	(0.0203)	(0.0501)	(0.0214)	(0.0494)	(0.0218)	(0.0492)
Observations	10,194	10,194	10,194	10,194	10,194	10,194
Number of Firms	911	911	911	911	911	911
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

Second, the models that include the squared term of lagged competition and moderation of the DTF give significant estimates for all terms. Moreover, the signs are consistent for the Poisson and negative binomial models. Both unmoderated terms, who capture the relationship for the firm at the frontier, show that the relationship between lagged competition and innovative input follows a U shape,[25] which is in line with the results of Table 1. Furthermore, the DTF terms by themselves are negative, which suggests that being further from the industry's technological frontier reduces a firm's innovative input. As such, firms are discouraged from spending on R&D by being a laggard. Additionally, like in the basic moderated models, the moderated terms show opposing signs to the unmoderated terms. Therefore, the results suggest that being further from the industry's technological frontier reduces the effects of lagged competition on a firm's innovative input. Furthermore, the results even indicate that the relationship might be reversed for firms that are the furthest from the industry's technological frontier, since the moderated terms are larger than the unmoderated terms, which would create an inverted U.[26] However, in the case of the Poisson models, the confidence intervals do overlap, so that inference is again tentative. Regardless, these results support H2B (*The U-shaped relationship between competition and innovation is moderated by a firm's distance to the industry's technological frontier*).

Third, the quadratic models that are moderated by the DTF dummy have all terms significant as well. As such, that supports H2B as well. Furthermore, the signs are consistent with the those of the quadratic models that include the non-binary DTF moderation. The unmoderated terms now show the relationship for a firm that is closer to the industry's technological frontier than the industry's mean DTF (since then DTFD = 0), e.g. a neck-and-neck firm. Together, the terms form a U-shaped relationship between lagged competition and a firm's innovative input. Nonetheless, as in the quadratic models moderated by the non-binary DTF, the moderated terms again show opposite signs to their corresponding unmoderated terms. Due to the moderating term being binary, the interpretation is now slightly simpler; Firms that are laggards, e.g. those that are further from the technological frontier than the industry average (DTFD = 1), seem to have a relationship between lagged competition and innovative

[25] As with the quadratic models of Table 1, the maximum value of Boone's indicator lies on the positive slope.

[26] For the negative binomial model: -0.124 + 0.224 = 0.100 and 0.00316 – 0.00587 = -0.00271, which would create the following model: $y = 0.100\,x - 0.00271\,x^2$, where the maximum value of competition is on the negative slope, which thus forms an inverted U.

input that follows an inverted U in the negative binomial model, since the moderated terms are larger than the unmoderated terms. However, in the Poisson model, the moderated terms are smaller than the unmoderated ones, which suggests that the relationship between lagged competition and a firm's innovative input is less pronounced for laggard firms.

With regards to the other main variables, they are all significant and their signs are as expected in all models; lagged sales and lagged profitability have a positive influence on a firm's innovative input whilst lagged firm growth has a negative relationship with a firm's innovative input. Finally, the un-interacted DTF terms, whether continuous or dummy, all feature negative signs. At first glance, this might seem to contradict the DTF-results of Table 2. However, the models of Table 3 feature moderation by DTF terms, which is not included in Table 2. Consequently, the DTF terms in Table 2's models miss the moderation, which could be causing omitted variable bias for the DTF terms' results, which could in turn be causing the differing signs.

To sum up, the relationship between lagged competition and a firm's innovative input seems to follow a quadratic shape, as suggested by literature. However, the relationship appears to follow a U shape and not the inverted U of Aghion et al. (2005). Therefore, the results do not support H1A *(The relationship between competition and innovation follows an inverted-U shape)* but do support H1B (*The relationship between competition and innovation follows a U shape*). Moreover, due to all DTF moderation terms being significant in both types of models, the relationship appears to be moderated by a firm's distance to the industry's technological frontier, as suggested by Aghion et al. (2005). Therefore, the results support H2B (*The U-shaped relationship between competition and innovation is moderated by a firm's distance to the industry's technological frontier*). Interestingly, the moderation by a firm's DTF consistently shows that it makes (lagged) competition's relationship with a firm's innovative input less pronounced. In the case of the negative binomial models, it could even follow the inverted U. However, this last observation is tentative, as the results of the Poisson models do not (convincingly) suggest such a relationship for laggard firms.

Nevertheless, it can be said that, since the relationship between lagged competition and a firm's innovative input is less pronounced for laggard firms, competition seems to be less relevant to their R&D expenditure, which makes sense intuitively: For neck-and-neck firms, high levels competition encourages them to innovate (further) to retain their position close to the industry's frontier, which is in line with Smith's (and Arrow's) argument. When competition is low, on the other hand, that position close to the frontier allows them to reap the benefits of low competition, which provides funds that can be subsequently invested in innovation. As such, for low levels of competition, the relationship between lagged competition and a neck-and-neck firm's innovative input follows Schumpeter's theory that innovation is increased by the absence of competition. However, with 'medium' levels of competition, a neck-and-neck firm is neither incentivised to spend on innovation by competitive pressure, nor does the firm have the excess financial means needed to spend on innovation provided by low levels of competition. Consequently, the relationship between lagged competition and a firm's innovative input takes the shape of an inverted U for neck-and-neck firms. For laggard firms, on the other hand, low levels of competition do not provide funds to the extent that they do for neck-and-neck firms and high levels of competition reduce their profitability to a minimum,[27] which makes the relationship between lagged competition and innovative input less pronounced for them. Finally, apart from its influence on the relationship of competition, firms are discouraged from spending on innovation by being further from the frontier, as can be expected.

5.1.3 Input models: High- Vs. Low-Tech

The models that investigated the high- and low-tech samples, reported in Table 4, on the next page, only yielded significant results in the full and the high-tech samples. As such, no comparison can be made with the low-tech sample. Consequently, these results do not support, nor do they lead to a rejection of, H3B (*The U-shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*). Nevertheless, since the coefficients of the high-tech sample are consistently smaller than those of the full samples, there is some tentative support for H3B. The insignificance of the low-tech samples' results can be attributed to the relatively small sample size, as can be seen by the number of observations and firms, reported at the bottom of the Table. With regards to the other main variables, they are all significant, except for the Poisson

[27] Probably superfluously, remember that a firm's distance to the frontier captures a firm's relative profitability.

model of the low-tech sample, and their signs are as expected in all models; lagged sales and lagged profitability have a positive influence on a firm's innovative input whilst lagged firm growth has a negative relationship with a firm's innovative input.

Table 4: Competition Input Models: Split Samples

VARIABLES	(1) NB: FS	(2) NB: HT	(3) NB: LT	(4) P: FS	(5) P: HT	(6) P: LT
Boone	-0.0369***	-0.122***	-0.00915	-0.0636***	-0.0559**	-0.0271
	(0.00633)	(0.00810)	(0.0139)	(0.0216)	(0.0228)	(0.0201)
$Boone^2$	0.000825***	0.00338***	6.29e-05	0.00188***	0.00164**	0.000683
	(0.000195)	(0.000269)	(0.000396)	(0.000706)	(0.000671)	(0.000597)
Ln(Sales)	0.370***	0.188***	0.331***	0.777***	0.749***	0.786***
	(0.0150)	(0.0153)	(0.0346)	(0.0625)	(0.0627)	(0.224)
Ln(Ebitda)	0.110***	0.169***	0.158***	0.125***	0.153***	0.0599
	(0.0131)	(0.0155)	(0.0318)	(0.0469)	(0.0558)	(0.0803)
Growth %	-0.0671***	-0.122***	0.0818*	-0.132***	-0.146**	-0.0530
	(0.0205)	(0.0238)	(0.0465)	(0.0501)	(0.0591)	(0.0933)
DTFD	-0.00316	-0.0127	0.0363*	-0.00497	-0.00423	0.0567
	(0.00943)	(0.0113)	(0.0205)	(0.0256)	(0.0293)	(0.0406)
Observations	10,194	8,288	1,906	10,194	8,288	1,906
No. of Firms	911	752	159	911	752	159
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Robust SE	No	No	No	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

The results of the innovative input models of competition that include interaction with the high-tech dummy are reported in Table 5, on the next page. For robustness, the first two models include the continuous DTF term, whilst the second two include the DTF dummy. With regards to the difference between those models, the estimated coefficients' signs are consistent, and their size is comparable. First, both the negative binomials and the Poisson models fail to produce significant results for the interacted terms, but do give significant estimates for the un-interacted terms. Since those terms reflect the relationship for firms that are low-tech, the interpretation is the following: For low-tech firms, the relationship between lagged competition and a firm's innovative input follows a U shape. However, since the terms moderated by the high-tech dummy fail to produce significant results, no inferences can be made here on the difference in relationship between high- and low-tech firms. Another result that needs to be discussed is the non-zero coefficient of the high-tech dummy in the negative binomial models. In a fixed effects model, unchanging characteristics should return a zero coefficient, as they do in the Poisson model. However, since they are non-zero in the negative binomial models, this confirms what was stated in the methods section: The fixed effects of the negative binomial model do not truly function as fixed effects. Finally, with regards to the other main variables (firm size, profitability, and growth), their signs are as expected.

Table 5: Competition Input Models: High- Vs. Low-Tech Interaction

VARIABLES	(1) NB	(2) P	(3) NB	(4) P
Boone	-0.0424***	-0.0490**	-0.0438***	-0.0515**
	(0.00999)	(0.0219)	(0.00922)	(0.0214)
Boone^2	0.00105***	0.00148**	0.00113***	0.00156**
	(0.000290)	(0.000746)	(0.000263)	(0.000731)
High-Tech	-0.786***		-0.815***	
	(0.109)		(0.109)	
High-Tech * Boone	0.0187	-0.0229	0.0203	-0.0208
	(0.0139)	(0.0275)	(0.0134)	(0.0283)
High-Tech * Boone^2	-0.000763*	0.000605	-0.000838**	0.000527
	(0.000428)	(0.000887)	(0.000410)	(0.000907)
Ln(Sales)	0.370***	0.779***	0.320***	0.752***
	(0.0150)	(0.0621)	(0.0160)	(0.0709)
Ln(Ebitda)	0.110***	0.124***	0.171***	0.150***
	(0.0131)	(0.0468)	(0.0142)	(0.0523)
Growth %	-0.0667***	-0.134***	-0.0591***	-0.128**
	(0.0205)	(0.0497)	(0.0197)	(0.0497)
DTFD	-0.00281	-0.00523		
	(0.00944)	(0.0257)		
DTF			0.194***	0.0897
			(0.0283)	(0.0933)
Observations	10,194	10,194	10,194	10,194
Number of Firms	911	911	911	911
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

5.1.5 Output Models: Unmoderated

The results of the unmoderated innovative output models concerning competition are reported in Table 6, on the next page. First, the basic competition term is only significant in the negative binomial models, where it shows a negative relationship. Second, both the squared and the unsquared term are significant in the negative binomial as well as the Poisson models. However, the signs differ between the models; the squared term is negative in the negative binomial model whilst it is positive in the Poisson model and the unsquared term is positive in the negative binomial model whilst it is negative in the Poisson model. As such, the Poisson models show an inverted U-shaped relationship, while the negative binomial model suggests a U-shaped relationship. This puzzling difference could be the result of a few factors: The doubtful nature of fixed effects in the negative binomial model;[28] counter to literature, the overdispersion could be influencing the coefficients in the Poisson models; and/or other factors, like the missing DTF-moderation or a firm being high- or low-tech. Due to the last possibility, no convincing conclusions can be drawn until those factors are investigated. However, since the Poisson model is preferred when the models contradict, there is some tentative support for H1A *(The relationship between competition and innovation follows an inverted-U shape).*

Finally, lagged firm profitability has a positive and lagged firm growth a negative sign, which was expected. However, the signs of firm's lagged sales contradict in the Poisson and the negative binomial models. Since the Poisson model is preferred when the models contradict, the results again indicate a positive influence of lagged firm sales on innovation. With regards to the results of firm's R&D expenditure, all negative binomial models are significant and show positive signs, which is in line with literature. However, the two Poisson models that include the squared Boone term show a negative relationship between a firm's lagged R&D expenditure and its innovative output. This puzzling result could be caused by complacency, since when a firm already has well-cited patents, it might spend less on R&D. Another cause could lie in omitted variable bias due to the DTF moderation being absent in these models.

[28] Those doubts, mentioned in the methods section, are somewhat confirmed by the non-zero findings for the high-tech dummy, as stated before; since fixed effects models should only show (non-zero) coefficients for characteristics that change and firms do not change their industry, those high-tech dummies should return a zero coefficient (as they do in the Poisson models), but they do not.

Table 6: Competition Output Models: Basic and Squared

VARIABLES	(1) NB: Basic	(2) P: Basic	(3) NB: Basic	(4) P: Basic	(5) NB: Squared	(6) P: Squared	(7) NB: Squared	(8) P: Squared
Ln(RND)	0.311***	-0.131	0.318***	-0.0643	0.226***	-0.140***	0.235***	-0.0755***
	(0.0168)	(0.232)	(0.0168)	(0.233)	(0.0174)	(0.000102)	(0.0173)	(0.000101)
Boone	-0.0411***	-0.00697	-0.0427***	-0.00934	-0.272***	0.106***	-0.273***	0.103***
	(0.00397)	(0.0108)	(0.00394)	(0.0100)	(0.0135)	(5.07e-05)	(0.0135)	(5.04e-05)
$Boone^2$					0.00777***	-0.00351***	0.00776***	-0.00348***
					(0.000426)	(1.55e-06)	(0.000426)	(1.54e-06)
Ln(Sales)	-0.313***	0.614	-0.255***	0.877**	-0.121***	0.618***	-0.0567*	0.876***
	(0.0333)	(0.376)	(0.0298)	(0.354)	(0.0348)	(0.000150)	(0.0316)	(0.000149)
Ln(Ebitda)	0.270***	0.443	0.204***	0.183	0.212***	0.435***	0.137***	0.183***
	(0.0378)	(0.308)	(0.0339)	(0.238)	(0.0376)	(8.44e-05)	(0.0336)	(7.37e-05)
Growth %	-0.200***	-0.387	-0.210***	-0.410	-0.148**	-0.372***	-0.158***	-0.393***
	(0.0613)	(0.249)	(0.0618)	(0.251)	(0.0605)	(0.000123)	(0.0610)	(0.000122)
DTF	0.296***	0.0612			0.291***	0.0417***		
	(0.0807)	(0.432)			(0.0818)	(0.000194)		
DTFD			0.0340	-0.358			0.0159	-0.357***
			(0.0274)	(0.222)			(0.0274)	(5.76e-05)
Observations	9,989	9,989	9,989	9,989	9,989	9,989	9,989	9,989
No. of Firms	859	859	859	859	859	859	859	859
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

5.1.6 Output Models: Moderated

The models of competition and innovative output, moderated by the DTF, can be found in Table 7, on the next page. These models follow the same strategy as the moderated input models: First, the unsquared terms are interacted with the DTF, following Peroni and Ferreira (2012) as well as Berube et al (2012). Second, the squared terms are added and interacted with the DTF as well, following Aghion et al. (2005). Third, both the squared and unsquared term are interacted with the DTF dummy to allow for easier interpretation, which follows Hashimi (2013).

The unsquared models that are interacted with the DTF are significant and give consistent signs in both the negative binomial and the Poisson model. Together, the terms lead to the following interpretation: The relationship between lagged competition and a firm's innovative output is negative for firms that are close to the industry's technological frontier, e.g. neck-and-neck firms. Nonetheless, when their distance to the frontier becomes sufficiently large, e.g. they are a laggard, the effect of lagged competition on a firm's innovative output becomes positive, since the terms moderated by the DTF are positive and larger than the unmoderated terms. Consequently, those models indicate that laggard firms' propensity to obtain (important) patents is increased by higher levels of lagged competition. However, the squared term is missing here, which might be influencing results. Additionally, the relationship between the DTF variable by itself and a firm's innovative output is negative, as expected.

Table 7: Competition Output Models: Moderated

VARIABLES	(1) NB: Mod	(2) P: Mod	(3) NB: Sq & Mod	(4) P: Sq & Mod	(5) NB: Sq & D-Mod	(6) P: Sq & D-Mod
Ln(RND)	0.240***	-0.153	0.162***	-0.200	0.206***	-0.0937
	(0.0175)	(0.236)	(0.0180)	(0.240)	(0.0176)	(0.238)
Boone	-0.125***	-0.123***	-0.413***	-0.268	-0.329***	0.160
	(0.00697)	(0.0427)	(0.0186)	(0.171)	(0.0150)	(0.125)
$Boone^2$			0.0113***	0.00420	0.00925***	-0.00700*
			(0.000641)	(0.00526)	(0.000481)	(0.00425)
DTF	-2.455***	-2.241**	-4.617***	-6.108***		
	(0.191)	(0.910)	(0.361)	(2.274)		
DTF * Boone	0.202***	0.184***	0.599***	0.686**		
	(0.0128)	(0.0707)	(0.0484)	(0.291)		
DTF * $Boone^2$			-0.0163***	-0.0150*		
			(0.00164)	(0.00871)		
DTFD					-1.932***	-0.594
					(0.212)	(0.983)
DTFD * Boone					0.244***	-0.0159
					(0.0281)	(0.148)
DTFD * $Boone^2$					-0.00686***	0.00269
					(0.000901)	(0.00489)
Ln(Sales)	-0.148***	0.570	0.0364	0.564	0.00488	0.868**
	(0.0343)	(0.382)	(0.0360)	(0.369)	(0.0321)	(0.354)
Ln(Ebitda)	0.215***	0.476	0.158***	0.492*	0.119***	0.185
	(0.0371)	(0.311)	(0.0372)	(0.295)	(0.0335)	(0.226)
Growth %	-0.119*	-0.363	-0.0477	-0.303	-0.109*	-0.396
	(0.0607)	(0.251)	(0.0599)	(0.227)	(0.0607)	(0.242)
Observations	9,989	9,989	9,989	9,989	9,989	9,989
Number of Firms	859	859	859	859	859	859
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

The models that include a squared term of competition, moderated by a firm's DTF, have significant moderated terms in both the negative binomial and the Poisson model. However, the unmoderated terms are only significant in the negative binomial model. The unmoderated terms in the negative binomial model follow the quadratic relationship found by the unmoderated quadratic negative binomial model in Table 4. Therefore, they suggest that the relationship between lagged competition and a firm's innovative output for firms at the industry's technological frontier follows a U shape. Furthermore, the competition terms moderated by the DTF show consistent signs in the negative binomial and the Poisson model. The moderated unsquared term is positive and, in the case of the negative binomial model,[29] larger than the unmoderated unsquared term. Moreover, the moderated squared term is negative in both models and slightly larger than the unmoderated term in the negative binomial model.[30] For the negative binomial model, the interpretation is then that the relationship between lagged competition and a firm's innovative output is less pronounced for firms that are further from the industry's technological frontier. Additionally, when the distance to the frontier is sufficiently large, the signs are switched, which amounts to the inverted U as found by Aghion et al. (2005), amongst others. For the Poisson model, such a combination of effects cannot be made due to the insignificance of the unmoderated terms. Nevertheless, the moderated terms form an inverted U-shaped relationship between lagged competition and a firm's innovative output as well. Furthermore, that relationship becomes more pronounced the closer a firm is to the technological frontier, since the DTF moderator is continuous. As such, the results provide support for H2B (*The U-shaped relationship between competition and innovation is moderated by a firm's distance to the industry's technological frontier*). Lastly, the DTF variable by itself is again negative in both models, which indicates that being further from the industry's technological frontier has a negative relationship with a firm's innovative output.[31]

Finally, the models that include the DTF dummy. In the Poisson model, only the squared unmoderated term is significant. In the negative binomial model, on the other hand, all competition terms are significant. The two unmoderated terms give the relationship between lagged competition and a firm's innovative output for neck-and-neck firms, which takes the form a U, since the unsquared term is negative, and the squared term is positive.

[29] It is larger in the Poisson model as well but since that term is insignificant, no comparison should be made.
[30] See the footnote above.
[31] This variable being negative now, whilst it was positive before in models without DTF moderation, is a suggestion that the moderation of lagged competition is indeed needed to capture the relationship correctly.

Consequently, a neck-and-neck firm's propensity to obtain (influential) patents seems to be highest at either high or low levels of competition. For a laggard firm, on the other hand, this relationship between a competition and a firm's innovative output is less pronounced, since the moderated terms have signs opposite to their unmoderated counterparts that are not as large. Notably, this observation aligns with the one made for the moderated input models in 5.1.2. As such, the inference made there is applicable here as well: neck-and-neck firms successfully innovate to retain their position close to the industry's technological frontier when competition is high and succeed in innovating when competition is low due to the funds that low level of competition provides for neck-and-neck firms. At medium levels of competition, on the other hand neither the availability of funds, nor the competitive pressure is causing them to innovate successfully. For laggard firms, these effects are again less pronounced due to their comparatively lower availability of funds when competition is low and lack of funds when competition is high.

In these moderated models, the other main variables are not all significant. Nevertheless, when they are significant, a firm's lagged R&D expenditure, lagged firm profitability and lagged firm growth show the expected signs. However, the signs for the lagged firm sales terms contradict, as they did in the previous Table. As such, the reasoning and conclusion for the contradiction is the same.

To sum up, with regards to DTF moderation, most models found that it significantly moderated the relationship between competition and innovation, as hypothesised by H2A and H2B. Moreover, this moderation was consistent with the moderation found by the innovative input models, in that it makes the relationship between competition and innovation less pronounced. Interestingly, some models provide an indication that being far enough from the industry's frontier could even cause the relationship to take the shape of an inverted U.

5.1.7 Output Models: High- Vs. Low-Tech

Like with the input models, the models that investigated the high- and low-tech samples are reported first, in Table 8, on the next page. There, the negative binomial models feature significant results for the competition terms in both samples. Since the competition terms for the low-tech sample are smaller than those of the high-tech sample, the results indicate that the relationship between lagged competition and a firm's innovative output is less pronounced for low-tech than for high-tech firms. Consequently, those results lead to a rejection of H3B (*The U-shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*). A possible explanation for this might lie in the importance of innovation for high-tech industries, which causes the relationship to be more pronounced there. However, no real conclusions can be made until the interacted models are investigated, as that is a more statistically robust method. Since only the low-tech sample is significant for the Poisson models, no comparison can be made there.

Table 8: Competition Output Models: Split Samples

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	NB: FS	NB: HT	NB: LT	P: FS	P: HT	P: LT
Ln(RND)	0.235***	0.215***	0.285***	-0.0755	-0.0878	0.819**
	(0.0173)	(0.0194)	(0.0431)	(0.234)	(0.253)	(0.398)
Boone	-0.273***	-0.361***	-0.228***	0.103	0.0185	0.400***
	(0.0135)	(0.0157)	(0.0348)	(0.0697)	(0.0965)	(0.0569)
$Boone^2$	0.00776***	0.0110***	0.00580***	-0.00348*	-0.000889	-0.0125***
	(0.000426)	(0.000526)	(0.00102)	(0.00192)	(0.00268)	(0.00249)
Ln(Sales)	-0.0567*	-0.0723**	0.0198	0.876**	0.967**	0.823
	(0.0316)	(0.0345)	(0.0814)	(0.350)	(0.377)	(0.760)
Ln(Ebitda)	0.137***	0.185***	-0.0572	0.183	0.125	0.362
	(0.0336)	(0.0373)	(0.0812)	(0.235)	(0.242)	(0.354)
Growth %	-0.158***	-0.199***	-0.106	-0.393	-0.440*	-0.749
	(0.0610)	(0.0650)	(0.178)	(0.247)	(0.247)	(0.497)
DTFD	0.0159	0.0222	-0.0482	-0.357	-0.426**	-0.115
	(0.0274)	(0.0306)	(0.0629)	(0.220)	(0.215)	(0.219)
Observations	9,989	8,120	1,869	9,989	8,120	1,869
Number of Firms	859	708	151	859	708	151
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	No	No	No
Robust SE	No	No	No	Yes	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

With regards to the other main variables, when they are significant, lagged firm R&D expenditure and lagged firm profitability both feature positive signs, as theorised. Lagged firm growth, on the other hand, has a negative relationship with a firm's innovative output, which is not in line with the expectation. A possibility is that the reasoning for the negative relationship for innovative input, e.g. innovation not being necessary when a firm is growing, is applicable here as well. Finally, the significant results for a firm's lagged sales again contradict, with the Poisson models showing positive signs whilst the negative binomial models display negative signs. Since the Poisson models are preferred when they contradict, a firm's lagged sales seems to have a positive relationship with a firm's innovative output, as was predicted.

The interaction models regarding the difference in relationship of competition between innovative output for high- and low-tech firms can be found in Table 9, on the next page. First, the models that are not moderated by the DTF. In the negative binomial models, all competition terms are significant. The two un-interacted terms reflect low-tech firms and suggest a U-shaped relationship between lagged competition and a firm's innovative output for them. The interacted terms, on the other hand, show the difference in relationship for high-tech firms. Since the signs are both opposite to, and smaller than, the un-interacted terms, their coefficients suggest that the relationship between lagged competition and a firm's innovative output is less pronounced for high-tech firms than it is for low-tech firms. As such, this result supports H3B (*The U-shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*). Here it must again be noted that the high-tech dummy's terms show non-zero coefficients, which is indicative of the non-validity of the fixed effects in the negative binomial models. In the Poisson models, only the model that includes the continuous DTF variable features significant results for all competition terms. There, the un-interacted terms show an inverted U shape, which is in line with H1A (*The relationship between competition and innovation follows an inverted-U shape*). Moreover, the interacted terms feature opposing and smaller signs, which indicates that the relationship between lagged competition and a firm's innovative output is indeed less pronounced for high-tech firms than it is for low-tech firms. Consequently, that result supports H3A (*The inverted-U shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*).

Finally, the other main variables. When they are significant, a firm's lagged R&D expenditure, a firm's lagged size, and lagged firm profitability are all positive, as theorised. Furthermore, lagged firm growth, when significant, has a negative influence on a firm's innovative output, which is in line with previous results. With regards to the DTF terms, the continuous term in the Poisson model has a negative sign whilst the dummy term in the negative binomial model has a positive sign. A possible cause of this contradicting result might lie in the absence of moderation with the term, as stated before.

Table 9: Competition Output Models: High- Vs. Low-Tech Interaction

VARIABLES	(1) NB: Sq	(2) P: Sq	(3) NB: Sq	(4) P: Sq
Ln(RND)	0.193***	-0.0665	0.182***	-0.132
	(0.0178)	(0.234)	(0.0179)	(0.233)
Boone	-0.362***	0.280***	-0.363***	0.226***
	(0.0163)	(0.0835)	(0.0164)	(0.0814)
$Boone^2$	0.00990***	-0.00950***	0.00995***	-0.00766***
	(0.000507)	(0.00303)	(0.000508)	(0.00291)
High-Tech	-2.252***		-2.322***	
	(0.223)		(0.224)	
High-Tech * Boone	0.308***	-0.234*	0.314***	-0.155
	(0.0317)	(0.139)	(0.0318)	(0.152)
High-Tech * $Boone^2$	-0.00829***	0.00788*	-0.00848***	0.00537
	(0.00102)	(0.00452)	(0.00102)	(0.00476)
Ln(Sales)	0.0535	0.889**	-0.0176	0.628*
	(0.0329)	(0.349)	(0.0358)	(0.368)
Ln(Ebitda)	0.0982***	0.170	0.182***	0.424
	(0.0334)	(0.234)	(0.0373)	(0.301)
Growth%	-0.0871	-0.413*	-0.0750	-0.387*
	(0.0607)	(0.241)	(0.0602)	(0.235)
DTFD	0.0184	-0.369*		
	(0.0274)	(0.216)		
DTF			0.337***	0.0123
			(0.0829)	(0.415)
Observations	9,989	9,989	9,989	9,989
Number of Firms	859	859	859	859
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

5.2 Firm Size

5.2.1 Input Models

The results of firm size for the innovative input models can be found in Table 10 below. Lagged firm size has a significant and positive relationship with a firm's innovative input in all basic models. As such this supports H4 (*Firm size has a positive relationship with innovation*). However, when the squared terms are added, since research has suggested that the relationship is non-linear, the Poisson and negative binomial models show differing results. Both negative binomial models have a positive and significant unsquared term of firm size, whilst both Poisson models only feature significant unsquared terms that are positive as well. Since the Poisson model is believed to be more statistically robust, those results are preferred. Nevertheless, since all significant firm size terms are positive, the results again support H4.

Table 10: Size Input Models: Basic and Squared

VARIABLES	(1) NB: Basic	(2) P: Basic	(3) NB: Basic	(4) P: Basic	(5) NB: Sq	(6) P: Sq	(7) NB: Sq	(8) P: Sq
Boone	-0.0360***	-0.0654***	-0.0369***	-0.0636***	-0.0226***	-0.0658***	-0.0224***	-0.0640***
	(0.00630)	(0.0211)	(0.00633)	(0.0216)	(0.00637)	(0.0210)	(0.00639)	(0.0216)
$Boone^2$	0.000822***	0.00194***	0.000825***	0.00188***	0.000451**	0.00194***	0.000430**	0.00189***
	(0.000194)	(0.000691)	(0.000195)	(0.000706)	(0.000197)	(0.000688)	(0.000197)	(0.000703)
Ln(Sales)	0.318***	0.751***	0.370***	0.777***	-0.0265	0.707***	0.00984	0.724***
	(0.0163)	(0.0710)	(0.0150)	(0.0625)	(0.0283)	(0.184)	(0.0278)	(0.188)
$(Ln(Sales))^2$					0.0251***	0.00233	0.0259***	0.00284
					(0.00170)	(0.0105)	(0.00169)	(0.0106)
Ln(Ebitda)	0.167***	0.151***	0.110***	0.125***	0.148***	0.151***	0.0977***	0.125***
	(0.0145)	(0.0522)	(0.0131)	(0.0469)	(0.0143)	(0.0523)	(0.0127)	(0.0469)
Growth %	-0.0587***	-0.125**	-0.0671***	-0.132***	-0.0654***	-0.126**	-0.0734***	-0.132***
	(0.0203)	(0.0501)	(0.0205)	(0.0501)	(0.0202)	(0.0502)	(0.0204)	(0.0502)
DTF	0.194***	0.0898			0.160***	0.0889		
	(0.0294)	(0.0933)			(0.0299)	(0.0945)		
DTFD			-0.00316	-0.00497			-0.00944	-0.00530
			(0.00943)	(0.0256)			(0.00934)	(0.0257)
Observations	10,194	10,194	10,194	10,194	10,194	10,194	10,194	10,194
Number of Firms	911	911	911	911	911	911	911	911
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

With regards to the other main variables, their results are consistent and in line with the previously presented results: The lagged competition terms form a U-shaped relationship, lagged firm profitability indicates a positive relationship, lagged firm growth has a negative influence on a firm's innovative input. Finally, the DTF terms are positive when they are significant, which suggests that laggard firms spend more on R&D in an attempt to catch up with their industry's frontier firms.[32]

To investigate the other size hypotheses, the data is first split into high- and low-tech samples, the results of which can be found in Table 11 below. Since the previous model did not unequivocally show a quadratic relationship, the linear models are included here as well. First, all the unsquared terms are significant and positive in the linear models. Consequently, they indicate a positive and linear relationship between lagged firm size and a firm's innovative input, which supports H4 (*Firm size has a positive relationship with innovation*). Furthermore, the relationship is much more pronounced for the low-tech sample than it is for the high-tech sample in both types of models. Consequently, these results support H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*). However, the confidence intervals of the Poisson models' terms overlap, so that conclusion is tentative.

Table 11: Size Input Models: Split Samples

VARIABLES	(1) NB: HT	(2) NB: LT	(3) P: HT	(4) P: LT	(5) NB:Sq HT	(6) NB:Sq LT	(7) P:Sq HT	(8) P:Sq LT
Boone	-0.122***	-0.00915	-0.0559**	-0.0271	-0.0153*	-0.00447	-0.0552**	-0.0258
	(0.00810)	(0.0139)	(0.0228)	(0.0201)	(0.00874)	(0.0145)	(0.0228)	(0.0202)
Boone^2	0.00338***	6.29e-05	0.00164**	0.000683	7.55e-05	-6.55e-05	0.00161**	0.000646
	(0.000269)	(0.000396)	(0.000671)	(0.000597)	(0.000287)	(0.000412)	(0.000671)	(0.000596)
Ln(Sales)	0.188***	0.331***	0.749***	0.786***	-0.180***	0.280***	0.511**	1.217***
	(0.0153)	(0.0346)	(0.0627)	(0.224)	(0.0198)	(0.0546)	(0.206)	(0.329)
(Ln(Sales))^2					0.0368***	0.00449	0.0128	-0.0216
					(0.00131)	(0.00378)	(0.0114)	(0.0209)
Ln(Ebitda)	0.169***	0.158***	0.153***	0.0599	0.110***	0.148***	0.154***	0.0598
	(0.0155)	(0.0318)	(0.0558)	(0.0803)	(0.0140)	(0.0327)	(0.0563)	(0.0802)
Growth %	-0.122***	0.0818*	-0.146**	-0.0530	-0.104***	0.0789*	-0.146**	-0.0430
	(0.0238)	(0.0465)	(0.0591)	(0.0933)	(0.0225)	(0.0467)	(0.0592)	(0.0988)
DTFD	-0.0127	0.0363*	-0.00423	0.0567	-0.0150	0.0346*	-0.00388	0.0634
	(0.0113)	(0.0205)	(0.0293)	(0.0406)	(0.0104)	(0.0206)	(0.0296)	(0.0405)
Observations	8,288	1,906	8,288	1,906	8,288	1,906	8,288	1,906
Number of Firms	752	159	752	159	752	159	752	159
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Robust SE	No	No	Yes	Yes	No	No	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

[32] However, as noted before, the DTF moderation of competition is missing here, which might be causing this conflicting result.

For the models that include a squared term of lagged firm size, only the high-tech sample of the negative binomial model has both size terms significant. In it, the unsquared term shows a negative relationship, whilst the squared term shows a positive relationship. Together, those create a somewhat U-shaped relationship between lagged firm size with a firm's innovative input, since it decreases until the squared term takes over around 2.5.[33] In the other models that include squared firm size, only the unsquared firm size terms are significant. Furthermore, they are all positive, which supports H4 (*Firm size has a positive relationship with innovation*). Since the term is much larger for the low-tech sample than the high-tech sample in the Poisson model, the results provide support for H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*) as well. Nevertheless, before any real conclusions are made, this is further investigated using interaction effects, since those are considered statistically superior at showing a difference in relationships, in this case between high-and low-tech firms. Moreover, since the models split between high- and low-tech samples again did not convincingly show a quadratic relationship between lagged firm size and a firm's innovative input, the linear models are included there as well. But first, the results of the other main variables in these split samples: When the competition terms are significant, they indicate a U-shaped relationship, like the input models before. Moreover, most firm profitability terms are positive, which is in line with both literature and previous results. Furthermore, the growth terms are all negative, which is in line with the expectation, except for the positive term in the negative binomial model that investigates the low-tech sample. Finally, the two DTF dummies that are significant are positive, which again suggests that laggard firms spend more on R&D in an attempt to catch up with their industry's frontier.[34]

The results of the second strategy to identify the difference in relationships between high- and low-tech firms for lagged firm size and a firm's innovative input, the use of interaction effects, can be found in Table 12, on the next page. First, since high-tech is a dummy, the terms that are not interacted with it represent the low-tech sample. Both the negative binomial and the Poisson models' lagged firm size terms are fully significant for the linear

[33] Ln(Sales) ranges from ~ 1.2 to 12.5.

[34] Nevertheless, as noted before, this might be due to the DTF moderation of lagged competition not being included here.

models. All their un-interacted terms are positive, which therefore suggests a positive relationship between a firm's lagged sales and its innovative input for low-tech firms. Therefore, those results support H4 (*Firm size has a positive relationship with innovation*). Furthermore, all their interacted terms are positive as well, which indicates that the positive relationship between lagged firm size and a firm's innovative input is more pronounced for high-tech firms. Consequently, these results do not support H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*).

Table 12: Size Input Models: High- Vs. Low-Tech Interaction

VARIABLES	(1) NB	(2) P	(3) NB	(4) P	(5) NB: Sq	(6) P: Sq	(7) NB: Sq	(8) P: Sq
Boone	-0.0294***	-0.0509***	-0.0291***	-0.0492***	-0.0243***	-0.0494***	-0.0235***	-0.0477**
	(0.00664)	(0.0185)	(0.00669)	(0.0189)	(0.00656)	(0.0182)	(0.00661)	(0.0185)
$Boone^2$	0.000634***	0.00152**	0.000604***	0.00146**	0.000505**	0.00148**	0.000462**	0.00142**
	(0.000204)	(0.000593)	(0.000205)	(0.000602)	(0.000201)	(0.000581)	(0.000202)	(0.000589)
Ln(Sales)	0.280***	0.568***	0.327***	0.599***	0.260***	1.149***	0.275***	1.144***
	(0.0192)	(0.113)	(0.0180)	(0.114)	(0.0440)	(0.340)	(0.0422)	(0.344)
$(Ln(Sales))^2$					0.00226	-0.0282	0.00456	-0.0265
					(0.00309)	(0.0197)	(0.00301)	(0.0201)
High-Tech	-0.894***		-0.911***		1.101***		1.091***	
	(0.107)		(0.107)		(0.157)		(0.157)	
High-Tech * Ln(Sales)	0.0550***	0.192**	0.0622***	0.187*	-0.508***	-0.621	-0.474***	-0.593
	(0.0154)	(0.0978)	(0.0151)	(0.101)	(0.0559)	(0.387)	(0.0544)	(0.395)
High-Tech * $(Ln(Sales))^2$					0.0355***	0.0405*	0.0335***	0.0390*
					(0.00371)	(0.0222)	(0.00365)	(0.0228)
Ln(Ebitda)	0.164***	0.154***	0.108***	0.128***	0.168***	0.155***	0.114***	0.130***
	(0.0145)	(0.0525)	(0.0130)	(0.0469)	(0.0145)	(0.0533)	(0.0130)	(0.0473)
Growth %	-0.0593***	-0.111**	-0.0679***	-0.118**	-0.0630***	-0.109**	-0.0714***	-0.116**
	(0.0203)	(0.0512)	(0.0206)	(0.0515)	(0.0202)	(0.0516)	(0.0204)	(0.0519)
DTF	0.188***	0.104			0.179***	0.106		
	(0.0298)	(0.0960)			(0.0294)	(0.0979)		
DTFD			-0.00481	0.00274			-0.00454	0.00471
			(0.00944)	(0.0258)			(0.00934)	(0.0260)
Observations	10,194	10,194	10,194	10,194	10,194	10,194	10,194	10,194
Number of Firms	911	911	911	911	911	911	911	911
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes	No	Yes	No	Yes

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable

All independent variables are lagged

Moving on to the models that include squared terms of lagged firm size, for the un-interacted terms, e.g. those that represent low-tech firms, only the unsquared versions are positive, which suggests that the relationship between lagged firm size and a firm's innovative input is linear and positive for low-tech firms. However, for the interacted terms, e.g. those that capture the relationship for high-tech firms, the unsquared terms are negative when they are significant, and the squared terms are all positive and significant. Together with the significant un-interacted terms, the negative binomial model thus indicates a somewhat U-shaped relationship between lagged firm size and a firm's innovative input for high-tech firms, since the unsquared terms taken together are negative whilst the squared terms are positive.[35] For the Poisson models, on the other hand, the terms show an increasingly positive relationship for high-tech firms. As such these results do not support H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*).

Finally, the other main variables again show that the relationship between lagged competition and a firm's innovative input takes the shape of a U, that the influence of lagged firm profitability is positive, that lagged firm growth has negative terms, and that the DTF, when it is significant, shows that laggard firms spend more on R&D in an attempt to come closer to their industry's frontier.[36]

5.2.2 Output Models

The results of the basic models of firm size for the innovative output of a firm can be found in Table 13, on the next page. Here, both the negative binomial and the Poisson models give significant results for firm size in both the basic model and the model that includes the squared term. However, the signs are inconsistent in both types of models. First, the negative binomial basic models show a negative linear relationship between lagged firm size and a firm's innovative output, whilst the Poisson models show a positive linear relationship. In the models that are expanded with the squared term, the signs found differ as well. For the negative binomial models, the relationship between lagged firm size and its innovative output seems to take the shape of an inverted U, since the unsquared terms are negative, and the squared terms are positive. In the Poisson model, on the other hand, the relationship seems to take the shape of a U, as the unsquared terms are negative whilst the squared terms are positive. This puzzling divergence could be the result of a few factors; it could be caused by the apparently invalid nature of fixed effects in the negative binomial model, it could be the result of differences between high- and low-tech firms that are differently captured by the models, or both. Regardless, since the squared terms are significant in both models, the relationship between lagged firm size and a firm's innovative output seems to be non-linear.

[35] The squared term again takes over around 2.5, so the relationship is largely positive.
[36] Nevertheless, the same observation as previous footnotes is applicable here as well, DTF moderation of lagged competition is missing in these models, to this could be causing this conflicting result.

However, since the results conflict regarding the relationship, finding either a U or an inverted U, H4 *(Firm size has a positive relationship with innovation)* is not supported.

Finally, when significant, the other main variables show the following relationships: It is positive for lagged R&D expenditure, as theorised; for competition, the results of the negative binomial models suggest a U shape whilst the Poisson models find an inverted U shape; lagged firm profitability shows a positive relationship, as expected; lagged firm growth has a negative influence on a firm's innovative output; and the continuous DTF term is positive in the negative binomial models whilst the DTF dummy is positive in the Poisson model.

Table 13: Size Output Models: Basic and Squared

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	NB: Basic	P: Basic	NB: Basic	P: Basic	NB: Sq	P: Sq	NB: Sq	P: Sq
Ln(RND)	0.226***	-0.140	0.235***	-0.0755	0.191***	-0.0952	0.199***	-0.0303
	(0.0174)	(0.234)	(0.0173)	(0.234)	(0.0184)	(0.232)	(0.0183)	(0.235)
Boone	-0.272***	0.106	-0.273***	0.103	-0.221***	0.132*	-0.222***	0.129*
	(0.0135)	(0.0735)	(0.0135)	(0.0697)	(0.0160)	(0.0728)	(0.0160)	(0.0712)
$Boone^2$	0.00777***	-0.00351*	0.00776***	-0.00348*	0.00633***	-0.00415**	0.00631***	-0.00413**
	(0.000426)	(0.00196)	(0.000426)	(0.00192)	(0.000494)	(0.00196)	(0.000494)	(0.00200)
Ln(Sales)	-0.121***	0.618*	-0.0567*	0.876**	-0.293***	3.713**	-0.232***	4.025**
	(0.0348)	(0.368)	(0.0316)	(0.350)	(0.0450)	(1.673)	(0.0428)	(1.688)
$(Ln(Sales))^2$					0.0161***	-0.158*	0.0164***	-0.162**
					(0.00269)	(0.0827)	(0.00269)	(0.0810)
Ln(Ebitda)	0.212***	0.435	0.137***	0.183	0.193***	0.377	0.120***	0.136
	(0.0376)	(0.300)	(0.0336)	(0.235)	(0.0375)	(0.297)	(0.0336)	(0.227)
Growth %	-0.148**	-0.372	-0.158***	-0.393	-0.121**	-0.361	-0.131**	-0.379
	(0.0605)	(0.241)	(0.0610)	(0.247)	(0.0606)	(0.248)	(0.0610)	(0.255)
DTF	0.291***	0.0417			0.279***	0.00625		
	(0.0818)	(0.418)			(0.0819)	(0.431)		
DTFD			0.0159	-0.357			0.0112	-0.361*
			(0.0274)	(0.220)			(0.0274)	(0.209)
Observations	9,989	9,989	9,989	9,989	9,989	9,989	9,989	9,989
Number of Firms	859	859	859	859	859	859	859	859
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

Subsequently, the models are run with the sample split between high- and low-tech firms, which can be found in Table 14 below. First, the models that only include a linear term of lagged firm size. In the negative binomial model, the low-tech sample has a negative sign, whilst the low-tech sample has a positive sign in the Poisson model. This divergence could be the result of the lack of a squared term. However, when the squared term is added, the negative binomial and Poisson model again differ. In the negative binomial model, the unsquared terms are negative whilst the squared terms are positive for both the high- and the low-tech sample. Since their confidence intervals overlap, no inferences can be made about the difference between high- and low-tech firms on their basis. In the Poisson model, only the results of the high-tech sample are significant, which could be a result of the smaller sample size for the low-tech sample. For the high-tech sample, the results together suggest a decreasingly positive relationship between lagged firm size and a firm's innovative output, since the maximum value of the logarithm of sales is 12.5, which is at before the squared term takes over. However, due to the size of the confidence intervals, the relationship could take the shape of an inverted U as well. Regardless, these results provide little support for H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*).

Table 14: Size Output Models: Split Samples

VARIABLES	(1) NB: HT	(2) NB: LT	(3) P: HT	(4) P: LT	(5) NB:Sq HT	(6) NB:Sq LT	(7) P:Sq HT	(8) P:Sq LT
Ln(RND)	0.215***	0.285***	-0.0878	0.819**	0.187***	0.210***	-0.0228	0.812**
	(0.0194)	(0.0431)	(0.253)	(0.398)	(0.0202)	(0.0481)	(0.259)	(0.385)
Boone	-0.361***	-0.228***	0.0185	0.400***	-0.287***	-0.130***	0.0337	0.398***
	(0.0157)	(0.0348)	(0.0965)	(0.0569)	(0.0208)	(0.0445)	(0.0971)	(0.0576)
Boone^2	0.0110***	0.00580***	-0.000889	-0.0125***	0.00880***	0.00314**	-0.00114	-0.0124***
	(0.000526)	(0.00102)	(0.00268)	(0.00249)	(0.000673)	(0.00127)	(0.00270)	(0.00249)
Ln(Sales)	-0.0723**	0.0198	0.967**	0.823	-0.248***	-0.220**	4.710***	-0.0364
	(0.0345)	(0.0814)	(0.377)	(0.760)	(0.0474)	(0.105)	(1.705)	(2.143)
(Ln(Sales))^2					0.0164***	0.0235***	-0.192**	0.0411
					(0.00301)	(0.00667)	(0.0835)	(0.102)
Ln(Ebitda)	0.185***	-0.0572	0.125	0.362	0.165***	-0.0958	0.0535	0.355
	(0.0373)	(0.0812)	(0.242)	(0.354)	(0.0373)	(0.0808)	(0.228)	(0.351)
Growth %	-0.199***	-0.106	-0.440*	-0.749	-0.162**	-0.107	-0.441*	-0.744
	(0.0650)	(0.178)	(0.247)	(0.497)	(0.0652)	(0.176)	(0.254)	(0.494)
DTFD	0.0222	-0.0482	-0.426**	-0.115	0.0221	-0.0637	-0.444**	-0.117
	(0.0306)	(0.0629)	(0.215)	(0.219)	(0.0306)	(0.0631)	(0.197)	(0.220)
Observations	8,120	1,869	8,120	1,869	8,120	1,869	8,120	1,869
Number of Firms	708	151	708	151	708	151	708	151
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	No	No	Yes	Yes	No	No
Robust SE	No	No	Yes	Yes	No	No	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

For the other main variables, their relationships are consistent and as expected, with the exception of competition and the DTF. For competition, the Poisson models again suggest an inverted U (when significant), whilst the negative binomial models suggest a U shape. For the DTF dummy, the signs are negative when significant, which could be the result of moderation by it being absent in these models, as stated before.

Finally, as with the innovative input models, the difference between high and low-tech firms for the relationship of lagged firm size and a firms' innovative output is tested, of which the results are reported in Table 15, on the next page. Since the previous results did not unequivocally show a quadratic relationship, the basic model is interacted with the high-tech dummy as well. In all models, the terms that are not interacted with the high-tech dummy show the results for the low-tech sample. First, all basic models feature fully significant size terms, but show conflicting signs in the negative binomial and the Poisson model. In the negative binomial model, a low-tech firm's lagged size seems to take a negative relationship with a firm's innovative output. Furthermore, the interaction term is positive and larger than the un-interacted term, which suggest that, for high-tech firms, the relationship between a firm's lagged size and its innovative output takes a linearly positive relationship. Nevertheless, for the model that includes the continuous DTF variable, the confidence intervals overlap. In the linear Poisson models, on the other hand, the un-interacted terms are positive, which suggests a positive relationship for low-tech firms, whilst the interacted term is negative and smaller, which suggests that the positive linear relationship found is less pronounced for high-tech firms. These conflicting results could again be the result of the difference in models.[37] Since the Poisson model is preferred when the models contradict, these results provide some support for H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*). However, it could also be that the squared term is needed to model the relationship, the results of which are analysed next.

[37] Again, note the significant and non-zero coefficient for the high-tech dummy in the negative binomial models, which should be zero in a fixed effects model, like it is in the Poisson models.

Table 15: Size Output Models: High- Vs. Low-Tech Interaction

VARIABLES	(1) NB	(2) P	(3) NB	(4) P	(5) NB: Sq	(6) P: Sq	(7) NB: Sq	(8) P: Sq
Ln(RND)	0.209***	-0.119	0.218***	-0.0520		-0.0614	0.184***	0.00692
	(0.0176)	(0.237)	(0.0175)	(0.240)		(0.240)	(0.0184)	(0.247)
Boone	-0.163***	0.0653	-0.163***	0.0480		0.0781	-0.0837***	0.0599
	(0.0165)	(0.0785)	(0.0165)	(0.0672)		(0.0771)	(0.0193)	(0.0662)
$Boone^2$	0.00473***	-0.00232	0.00470***	-0.00190		-0.00255	0.00242***	-0.00210
	(0.000506)	(0.00210)	(0.000507)	(0.00182)		(0.00206)	(0.000587)	(0.00179)
Ln(Sales)	-0.213***	1.528***	-0.152***	2.046***		-0.906	-0.513***	-0.839
	(0.0356)	(0.423)	(0.0325)	(0.439)		(1.921)	(0.0519)	(1.989)
$(Ln(Sales))^2$						0.110	0.0333***	0.130
						(0.0895)	(0.00371)	(0.0931)
High-Tech	-1.606***		-1.590***				-3.439***	
	(0.148)		(0.148)				(0.274)	
High-Tech * Ln(Sales)	0.225***	-0.901***	0.225***	-1.156***		5.171*	0.936***	5.537**
	(0.0184)	(0.253)	(0.0183)	(0.259)		(2.748)	(0.0779)	(2.698)
High-Tech * $(Ln(Sales))^2$						-0.296**	-0.0528***	-0.325**
						(0.137)	(0.00543)	(0.134)
Ln(Ebitda)	0.160***	0.405	0.0898***	0.149		0.322	0.0592*	0.0777
	(0.0374)	(0.296)	(0.0335)	(0.228)		(0.290)	(0.0334)	(0.216)
Growth %	-0.0940	-0.411*	-0.103*	-0.434*		-0.415*	-0.0706	-0.432*
	(0.0603)	(0.234)	(0.0607)	(0.240)		(0.238)	(0.0602)	(0.246)
DTF	0.271***	-0.0382				-0.114		
	(0.0822)	(0.416)				(0.431)		
DTFD			0.0115	-0.394*			0.00515	-0.412**
			(0.0273)	(0.211)			(0.0273)	(0.195)
Observations	9,989	9,989	9,989	9,989		9,989	9,989	9,989
Number of Firms	859	859	859	859		859	859	859
Year FE	Yes	Yes	Yes	Yes		Yes	Yes	Yes
Industry FE	Yes	No	Yes	No		No	Yes	No
Robust SE	No	Yes	No	Yes		Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

First, the absence of estimates for the negative binomial model that includes the continuous DTF variable is the result of an error with the statistical software. Several attempts were made to obtain estimates, but those did not succeed. In the quadratic negative binomial model that is estimated, the significant un-interacted terms together form a U-shaped relationship, since the unsquared term is negative whilst the squared term is positive. Therefore, those results suggest that the relationship between lagged firm size and a firm’s innovative output takes the shape of a U for low-tech firms. The interacted terms are both significant as well and have opposite signs compared to the un-interacted terms. Moreover, since they are larger than their counterparts, the interacted terms suggest that, for high-tech firms, the relationship between a firm’s lagged size and its innovative output takes the shape of an inverted U. Interestingly, that relationship is found for high-tech firms in the Poisson models as well, since the interacted unsquared terms are positive, whilst the interacted squared terms are negative. Nevertheless, in the Poisson models, the un-interacted terms did not produce significant results. Consequently, no definitive conclusions can be made with regards to H5

(*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*), on the basis of these results. For the other main variables, their results are in line with those of Table 14 and, as such, the same observations apply here.

5.3 Firm Profitability

5.3.1 Input Models

For the relationship between lagged firm profitability and a firm's innovative input, the results of both the basic models and the split samples can be found in Table 16, on the next page. The basic models all return significant estimates and have consistent signs. Since they indicate that there is a positive relationship between a firm's lagged profitability and its innovative input, the results support H6 *(Firm profitability has a positive relationship with innovation).* For the split samples, all firm profitability terms are significant except in the low-tech sample of the Poisson model. Moreover, in the negative binomial models the coefficient for the low-tech sample is smaller than the coefficient for the high-tech sample, which suggests that the relationship between lagged firm profitability and a firm's innovative input is more pronounced for high-tech firms. Therefore, the results provide support for H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*). In the split sample Poisson models, only the term of the high-tech sample is significant, which again is likely to be attributable to the lower sample size. Therefore, no real comparison can be made with the low-tech sample. Nevertheless, since the coefficient of the full sample is smaller than the coefficient of the high-tech sample, this is a suggestion that H7 is indeed supported. However, since the confidence intervals overlap slightly, this observation is tentative. For the other main variables, their results are consistent across models and samples as well as in line with previous results and literature, with the exception of the competition terms, which are consistent across models and samples and in line with previous results but diverge from most literature.

Table 16: Profit Input Models: Basic and Split Samples

VARIABLES	(1) NB: Basic	(2) P: Basic	(3) NB: Basic	(4) P: Basic	(5) NB: HT	(6) NB: LT	(7) P: HT	(8) P: LT
Boone	-0.0360***	-0.0654***	-0.0369***	-0.0636***	-0.122***	-0.00915	-0.0559**	-0.0271
	(0.00630)	(0.0211)	(0.00633)	(0.0216)	(0.00810)	(0.0139)	(0.0228)	(0.0201)
Boone^2	0.000822***	0.00194***	0.000825***	0.00188***	0.00338***	6.29e-05	0.00164**	0.000683
	(0.000194)	(0.000691)	(0.000195)	(0.000706)	(0.000269)	(0.000396)	(0.000671)	(0.000597)
Ln(Sales)	0.318***	0.751***	0.370***	0.777***	0.188***	0.331***	0.749***	0.786***
	(0.0163)	(0.0710)	(0.0150)	(0.0625)	(0.0153)	(0.0346)	(0.0627)	(0.224)
Ln(Ebitda)	0.167***	0.151***	0.110***	0.125***	0.169***	0.158***	0.153***	0.0599
	(0.0145)	(0.0522)	(0.0131)	(0.0469)	(0.0155)	(0.0318)	(0.0558)	(0.0803)
Growth %	-0.0587***	-0.125**	-0.0671***	-0.132***	-0.122***	0.0818*	-0.146**	-0.0530
	(0.0203)	(0.0501)	(0.0205)	(0.0501)	(0.0238)	(0.0465)	(0.0591)	(0.0933)
DTF	0.194***	0.0898						
	(0.0294)	(0.0933)						
DTFD			-0.00316	-0.00497	-0.0127	0.0363*	-0.00423	0.0567
			(0.00943)	(0.0256)	(0.0113)	(0.0205)	(0.0293)	(0.0406)
Observations	10,194	10,194	10,194	10,194	8,288	1,906	8,288	1,906
No. of Firms	911	911	911	911	752	159	752	159
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	Yes	No	No
Robust SE	No	Yes	No	Yes	No	No	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

As with firm size and competition, the inclusion of a dummy for high-tech firms is subsequently tested, the results of which are given in Table 17, on the next page. Again, the result of the term that is not interacted represents the relationship between a firm's lagged profitability and its innovative input for low-tech firms. This term is only significant in the negative binomial models, where it is positive. The interaction term is significant and positive in both types of models, which indicates that the relationship between a firm's lagged profitability and its innovative input is more pronounced for high-tech firms. Since this is in line with the results of the split samples, the evidence is fairly convincing. Consequently, it can be concluded that there is sufficient support for H7 *(The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries).* As with the previous models, all other main variables show results that are consistent with this research's expectation and relevant literature, except for the competition terms, which, although consistent with previous results, are not in line with most literature.

Table 17: Profit Input Models: High- Vs. Low-Tech Interaction

VARIABLES	(1) NB	(2) P	(3) NB	(4) P
Boone	-0.0315***	-0.0498***	-0.0312***	-0.0480**
	(0.00653)	(0.0181)	(0.00658)	(0.0187)
Boone^2	0.000692***	0.00148**	0.000661***	0.00142**
	(0.000200)	(0.000589)	(0.000202)	(0.000604)
Ln(Sales)	0.324***	0.728***	0.376***	0.752***
	(0.0163)	(0.0707)	(0.0149)	(0.0627)
Ln(Ebitda)	0.130***	0.00987	0.0675***	-0.0122
	(0.0193)	(0.0739)	(0.0179)	(0.0665)
High-Tech	-0.836***		-0.850***	
	(0.103)		(0.103)	
High-Tech * Ln(Ebitda)	0.0411***	0.172***	0.0494***	0.171***
	(0.0141)	(0.0628)	(0.0140)	(0.0644)
Growth %	-0.0605***	-0.116**	-0.0693***	-0.123**
	(0.0203)	(0.0499)	(0.0206)	(0.0499)
DTF	0.187***	0.0977		
	(0.0297)	(0.0969)		
DTFD			-0.00426	0.00527
			(0.00943)	(0.0259)
Observations	10,194	10,194	10,194	10,194
Number of Firms	911	911	911	911
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

5.3.2 Output Models

The results of firm profitability in the innovative output models can be found in Table 18, on the next page, where both the basic model and the split samples are included. The only profitability terms that are significant are in the basic model and the high-tech sample of the negative binomial models. As before, the insignificance of the low-tech samples can likely be attributed to the smaller sample size. The full sample results indicate that a firm’s lagged profitability has a positive relationship with a firm’s innovative output. Therefore, those results support H6 (*Firm profitability has a positive relationship with innovation*). The result for the high-tech sample in the negative binomial model is positive as well. Since it is considerably larger than the result for the corresponding full sample, this is a tentative indication that the relationship between a firm’s lagged profitability and its innovative output is more pronounced in high-tech industries. Therefore, these results provide some provisional support for H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*). However, since the low-tech samples' and the Poisson models' results are insignificant, the interaction effects will first be analysed before any conclusion are made.

Table 18: Profit Output Models: Basic and Split Samples

VARIABLES	(1) NB: Basic	(2) P: Basic	(3) NB: Basic	(4) P: Basic	(5) NB: HT	(6) NB: LT	(7) P: HT	(8) P: LT
Ln(RND)	0.226***	-0.140	0.235***	-0.0755	0.215***	0.285***	-0.0878	0.819**
	(0.0174)	(0.234)	(0.0173)	(0.234)	(0.0194)	(0.0431)	(0.253)	(0.398)
Boone	-0.272***	0.106	-0.273***	0.103	-0.361***	-0.228***	0.0185	0.400***
	(0.0135)	(0.0735)	(0.0135)	(0.0697)	(0.0157)	(0.0348)	(0.0965)	(0.0569)
$Boone^2$	0.00777***	-0.00351*	0.00776***	-0.00348*	0.0110***	0.00580***	-0.000889	-0.0125***
	(0.000426)	(0.00196)	(0.000426)	(0.00192)	(0.000526)	(0.00102)	(0.00268)	(0.00249)
Ln(Sales)	-0.121***	0.618*	-0.0567*	0.876**	-0.0723**	0.0198	0.967**	0.823
	(0.0348)	(0.368)	(0.0316)	(0.350)	(0.0345)	(0.0814)	(0.377)	(0.760)
Ln(Ebitda)	0.212***	0.435	0.137***	0.183	0.185***	-0.0572	0.125	0.362
	(0.0376)	(0.300)	(0.0336)	(0.235)	(0.0373)	(0.0812)	(0.242)	(0.354)
Growth %	-0.148**	-0.372	-0.158***	-0.393	-0.199***	-0.106	-0.440*	-0.749
	(0.0605)	(0.241)	(0.0610)	(0.247)	(0.0650)	(0.178)	(0.247)	(0.497)
DTF	0.291***	0.0417						
	(0.0818)	(0.418)						
DTFD			0.0159	-0.357	0.0222	-0.0482	-0.426**	-0.115
			(0.0274)	(0.220)	(0.0306)	(0.0629)	(0.215)	(0.219)
Observations	9,989	9,989	9,989	9,989	8,120	1,869	8,120	1,869
Number of Firms	859	859	859	859	708	151	708	151
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	Yes	No	No
Robust SE	No	Yes	No	Yes	No	No	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

Next, the models that include the interaction effect of the high-tech dummy are reported in Table 19, on the next page. First, the negative binomial models both feature significant and positive results for the interaction effect. However, only the un-interacted term in the model that includes the DTF dummy is significant. Since it is negative and smaller than the interacted term, the results indicate a negative relationship between a firm's lagged profitability and its innovative output for low-tech firms and a positive relationship for high-tech firms. Therefore, the results of the negative binomial model do not support H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*). Second, the Poisson models. Like with the negative binomial models, only the model that includes the DTF dummy features significant estimates for both the interacted and un-interacted terms. The un-interacted term is positive, which thus suggests a positive relationship between a firm's lagged profitability and its innovative output for low-tech firms. The interacted term, on the other hand, is negative and smaller than the un-interacted term, which implies that the relationship is less pronounced for high-tech firms. Nevertheless, since the confidence intervals overlap, it could even be that the relationship is negative for high-tech firms. Regardless, the Poisson models do not provide support for H7 either. With regards to the other main variables, the results of Table 19 largely follow the previous Tables when the estimates are significant.

Table 19: Profit Output Models: High- Vs. Low-Tech Interaction

	(1)	(2)	(3)	(4)
VARIABLES	NB	P	NB	P
Ln(RND)	0.215***	-0.134	0.223***	-0.0659
	(0.0175)	(0.234)	(0.0174)	(0.235)
Boone	-0.188***	0.0854	-0.187***	0.0678
	(0.0157)	(0.0777)	(0.0157)	(0.0674)
Boone^2	0.00540***	-0.00290	0.00536***	-0.00246
	(0.000485)	(0.00208)	(0.000486)	(0.00183)
Ln(Sales)	-0.0413	0.639*	0.0150	0.918***
	(0.0352)	(0.370)	(0.0319)	(0.351)
Ln(Ebitda)	-0.0168	0.734**	-0.0833**	0.661**
	(0.0422)	(0.303)	(0.0382)	(0.300)
High-Tech	-1.243***		-1.233***	
	(0.130)		(0.130)	
High-Tech * Ln(Ebitda)	0.216***	-0.324	0.218***	-0.522*
	(0.0193)	(0.246)	(0.0192)	(0.275)
Growth %	-0.116*	-0.389*	-0.124**	-0.417*
	(0.0603)	(0.236)	(0.0607)	(0.242)
DTF	0.256***	0.0144		
	(0.0821)	(0.418)		
DTFD			0.0144	-0.384*
			(0.0273)	(0.214)
Observations	9,989	9,989	9,989	9,989
Number of Firms	859	859	859	859
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

To sum up, there is some evidence that the relationship between a firm's profitability and its innovative output is positive. Consequently, H6 *(Firm profitability has a positive relationship with innovation)* is tentatively supported. The difference in relationship between high- and low-tech firms, on the other hand, shows diverging results in the different models. In the split samples of the negative binomial models, there was some modest support for H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*). However, the results of the interaction effects indicated another relationship, both in the negative binomial and the Poisson model. Since those models differed as well, a real conclusion cannot be made. However, since the Poisson model seems to be more statistically robust,[38] this research suspects the relationship between a firm's lagged profitability and its innovative output to be positive for both high- and low-tech firms, with the relationship being more pronounced for low-tech firms. As such, H7 is not supported. A potential reason for this might be the relatively large knowledge increase required to innovate in low-tech industries, mentioned before; since the amount of research (and thus R&D expenditure) required to innovate is larger, the funds provided by profitability are more influential to innovate successfully, e.g. obtain a patent, in low-tech industries.

5.4 Firm Growth

5.4.1 Input Models

The results of the input models regarding firm growth, including the split samples, can be found in Table 20, on the next page. In the basic models, the growth terms are all significant and have negative coefficients. Consequently, they show that the relationship between a firm's lagged growth and its innovative input seems to be negative. As such, those results support H8 *(Firm growth has a negative relationship with innovative input).* The results of the split samples are significant for the high-tech samples in both types of models, but only significant for the low-tech sample in the negative binomial model, which is likely attributable to the smaller sample size of low-tech firms. In the negative binomial model, the high-tech sample has a negative sign, whilst the low-tech sample has a positive sign. Therefore, the results suggest a negative relationship between lagged firm growth and a firm's innovative input for high-tech firms and a positive relationship for low-tech firms. Consequently, these results do not support H10 (*The negative relationship between firm growth and innovative*

[38] Again, see the significant and non-zero high-tech dummy in the negative binomial models.

input is more pronounced in low-tech industries than in high tech industries). Additionally, although the coefficient of the high-tech sample is larger than that of the full sample for the Poisson models, their confidence intervals overlap, so no inferences can be made concerning that difference. Finally, all other main variables give significant estimates, with the exception of the low-tech samples. Moreover, those that are significant are in line with previous results: The relationship of lagged competition with a firm's innovative input takes a U shape and lagged firm size as well as lagged profitability have a positive influence.

Table 20: Growth Input Models: Basic and Split Samples

VARIABLES	(1) NB: Basic	(2) P: Basic	(3) NB: Basic	(4) P: Basic	(5) NB: HT	(6) NB: LT	(7) P: HT	(8) P: LT
Boone	-0.0360***	-0.0654***	-0.0369***	-0.0636***	-0.122***	-0.00915	-0.0559**	-0.0271
	(0.00630)	(0.0211)	(0.00633)	(0.0216)	(0.00810)	(0.0139)	(0.0228)	(0.0201)
Boone2	0.000822***	0.00194***	0.000825***	0.00188***	0.00338***	6.29e-05	0.00164**	0.000683
	(0.000194)	(0.000691)	(0.000195)	(0.000706)	(0.000269)	(0.000396)	(0.000671)	(0.000597)
Ln(Sales)	0.318***	0.751***	0.370***	0.777***	0.188***	0.331***	0.749***	0.786***
	(0.0163)	(0.0710)	(0.0150)	(0.0625)	(0.0153)	(0.0346)	(0.0627)	(0.224)
Ln(Ebitda)	0.167***	0.151***	0.110***	0.125***	0.169***	0.158***	0.153***	0.0599
	(0.0145)	(0.0522)	(0.0131)	(0.0469)	(0.0155)	(0.0318)	(0.0558)	(0.0803)
Growth %	-0.0587***	-0.125**	-0.0671***	-0.132***	-0.122***	0.0818*	-0.146**	-0.0530
	(0.0203)	(0.0501)	(0.0205)	(0.0501)	(0.0238)	(0.0465)	(0.0591)	(0.0933)
DTF	0.194***	0.0898						
	(0.0294)	(0.0933)						
DTFD			-0.00316	-0.00497	-0.0127	0.0363*	-0.00423	0.0567
			(0.00943)	(0.0256)	(0.0113)	(0.0205)	(0.0293)	(0.0406)
Observations	10,194	10,194	10,194	10,194	8,288	1,906	8,288	1,906
Number of Firms	911	911	911	911	752	159	752	159
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	Yes	No	No
Robust SE	No	Yes	No	Yes	No	No	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

The results of the models that include the interaction effects of being high-tech are subsequently given in Table 21, on the next page. The growth terms of the negative binomial models are all significant. Since the interaction terms have a negative coefficient, whilst the terms that are not interacted have a smaller positive coefficient, the results indicate that the relationship between lagged firm growth and a firm's innovative input is positive in low-tech industries whilst it is negative in high-tech industries. However, the Poisson models show a negative relationship between a firm's lagged growth and its innovative input for low-tech firms and no significant estimates for high-tech firms. These results conflict, which makes drawing conclusions on their basis ill-advised. Consequently, these results provide no support for, nor do they reject H10 *(The negative relationship between firm growth and innovative input is more pronounced in low-tech industries than in high tech industries).* Moreover, the negative binomial model's results again feature a non-zero coefficient for the high-tech dummy, unlike the Poisson model, which is indicative of non-validity of the negative binomial model's fixed effects. As such, where the models conflict, the Poisson model is generally preferred. However, since the Poisson model failed to produce sufficient evidence in these models, no real conclusion on the difference in relationship between high- and low-tech firms can be drawn here. Nevertheless, it seems that H8 *(Firm growth has a negative relationship with innovative input)* is supported. Finally, all other main variables are significant, and their estimates are consistent with previous results.

Table 21: Growth Input Models: High- Vs. Low-Tech Interaction

	(1)	(2)	(3)	(4)
VARIABLES	NB	P	NB	P
Boone	-0.0357***	-0.0655***	-0.0366***	-0.0637***
	(0.00630)	(0.0211)	(0.00633)	(0.0216)
Boone^2	0.000819***	0.00194***	0.000822***	0.00188***
	(0.000194)	(0.000691)	(0.000195)	(0.000706)
Ln(Sales)	0.316***	0.751***	0.369***	0.778***
	(0.0162)	(0.0713)	(0.0150)	(0.0628)
Ln(Ebitda)	0.169***	0.151***	0.112***	0.125***
	(0.0145)	(0.0522)	(0.0131)	(0.0468)
Growth %	0.0882**	-0.130**	0.0852*	-0.139**
	(0.0438)	(0.0631)	(0.0447)	(0.0627)
High-Tech	-0.760***		-0.751***	
	(0.0999)		(0.0993)	
High-Tech * Growth %	-0.179***	0.00557	-0.185***	0.00930
	(0.0481)	(0.0823)	(0.0490)	(0.0827)
DTF	0.194***	0.0898		
	(0.0294)	(0.0935)		
DTFD			-0.00436	-0.00499
			(0.00942)	(0.0256)
Observations	10,194	10,194	10,194	10,194
Number of Firms	911	911	911	911
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

5.4.2 Output Models

The results of growth in the innovative output models are reported in Table 22 below. First, for the basic models, only the negative binomial models feature significant estimates for firm growth, where the signs are negative. Consequently, those results suggest a negative relationship between lagged firm growth and a firm's innovative output. As such, these results provide no support for H9 *(Firm growth has a positive relationship with innovative output).* Moving on to the split samples, only the high-tech samples yield significant results for the growth terms, which are negative. Since the low-tech samples' estimates are not significant and the confidence intervals of the growth estimates for the high-tech sample and the corresponding full sample in the negative binomial model overlap, no conclusions can be drawn with regards to H11 (*The positive relationship between firm growth and innovative output is more pronounced in low-tech industries than in high-tech industries*). Therefore, the models with interaction terms of the high-tech dummy will subsequently be analysed to see if the difference in relationship is indeed supported.

Table 22: Growth Output Models: Basic and Split Samples

VARIABLES	(1) NB: Basic	(2) P: Basic	(3) NB: Basic	(4) P: Basic	(5) NB: HT	(6) NB: LT	(7) P: HT	(8) P: LT
Ln(RND)	0.226***	-0.140	0.235***	-0.0755	0.215***	0.285***	-0.0878	0.819**
	(0.0174)	(0.234)	(0.0173)	(0.234)	(0.0194)	(0.0431)	(0.253)	(0.398)
Boone	-0.272***	0.106	-0.273***	0.103	-0.361***	-0.228***	0.0185	0.400***
	(0.0135)	(0.0735)	(0.0135)	(0.0697)	(0.0157)	(0.0348)	(0.0965)	(0.0569)
Boone^2	0.00777***	-0.00351*	0.00776***	-0.00348*	0.0110***	0.00580***	-0.000889	-0.0125***
	(0.000426)	(0.00196)	(0.000426)	(0.00192)	(0.000526)	(0.00102)	(0.00268)	(0.00249)
Ln(Sales)	-0.121***	0.618*	-0.0567*	0.876**	-0.0723**	0.0198	0.967**	0.823
	(0.0348)	(0.368)	(0.0316)	(0.350)	(0.0345)	(0.0814)	(0.377)	(0.760)
Ln(Ebitda)	0.212***	0.435	0.137***	0.183	0.185***	-0.0572	0.125	0.362
	(0.0376)	(0.300)	(0.0336)	(0.235)	(0.0373)	(0.0812)	(0.242)	(0.354)
Growth %	-0.148**	-0.372	-0.158***	-0.393	-0.199***	-0.106	-0.440*	-0.749
	(0.0605)	(0.241)	(0.0610)	(0.247)	(0.0650)	(0.178)	(0.247)	(0.497)
DTF	0.291***	0.0417						
	(0.0818)	(0.418)						
DTFD			0.0159	-0.357	0.0222	-0.0482	-0.426**	-0.115
			(0.0274)	(0.220)	(0.0306)	(0.0629)	(0.215)	(0.219)
Observations	9,989	9,989	9,989	9,989	8,120	1,869	8,120	1,869
Number of Firms	859	859	859	859	708	151	708	151
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	Yes	No	No
Robust SE	No	Yes	No	Yes	No	No	Yes	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

Finally, the results of the models of growth that include interaction effects are given in Table 23 below. Since none of the relevant terms are significant, so no conclusions can be made on their basis. Nevertheless, the lack of significant results is suspected to be due to one or both of the following reasons: First, the sample size for low-tech firms is considerably smaller, which reduces the significance of estimates. Second, it could be that firm growth does not significantly influence a firm's innovative output for low-tech firms.

Table 23: Growth Output Models: High- Vs. Low-Tech Interaction

VARIABLES	(1) NB	(2) P	(3) NB	(4) P
Ln(RND)	0.226***	-0.139	0.235***	-0.0746
	(0.0174)	(0.233)	(0.0174)	(0.234)
Boone	-0.272***	0.106	-0.273***	0.103
	(0.0135)	(0.0734)	(0.0135)	(0.0697)
$Boone^2$	0.00777***	-0.00351*	0.00777***	-0.00348*
	(0.000426)	(0.00195)	(0.000426)	(0.00192)
Ln(Sales)	-0.122***	0.618*	-0.0569*	0.877**
	(0.0349)	(0.368)	(0.0317)	(0.351)
Ln(Ebitda)	0.212***	0.435	0.137***	0.182
	(0.0376)	(0.300)	(0.0337)	(0.235)
Growth %	-0.115	-0.423	-0.144	-0.516
	(0.162)	(0.444)	(0.164)	(0.475)
High-Tech	-0.149*		-0.121	
	(0.0847)		(0.0843)	
High-Tech * Growth %	-0.0375	0.0544	-0.0161	0.130
	(0.172)	(0.475)	(0.174)	(0.496)
DTF	0.292***	0.0421		
	(0.0818)	(0.418)		
DTFD			0.0159	-0.358
			(0.0274)	(0.221)
Observations	9,989	9,989	9,989	9,989
Number of Firms	859	859	859	859
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Robust SE	No	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

5.5 Full Models

5.5.1 Full Output Models

To investigate whether the relationships found hold up when all additions to the basic model are included simultaneously, a full model is estimated with the full sample that includes DTF dummy interaction, with split samples, and with interaction effects. The resulting estimates are given in Table 24 below.

Table 24: Full Input Models

VARIABLES	(1) NB: Full	(2) P: Full	(3) NB: Full HT	(4) NB: Full LT	(5) P: Full HT	(6) P: Full LT	(7) Full & Interacted	(8) Full & Interacted
Boone	-0.0378***	-0.0978***	-0.0153*	-0.00447	-0.0552**	-0.0258	-0.0125	-0.0236
	(0.00838)	(0.0265)	(0.00874)	(0.0145)	(0.0228)	(0.0202)	(0.0114)	(0.0207)
Boone^2	0.000711***	0.00268***	7.55e-05	-6.55e-05	0.00161**	0.000646	0.000254	0.000739
	(0.000264)	(0.000835)	(0.000287)	(0.000412)	(0.000671)	(0.000596)	(0.000327)	(0.000640)
DTFD * Boone	0.0295***	0.0655**						
	(0.0108)	(0.0293)						
DTFD * Boone^2	-0.000551	-0.00162*						
	(0.000345)	(0.000886)						
High-Tech							1.117***	
							(0.161)	
High-Tech * Boone							-0.00712	-0.0369
							(0.0148)	(0.0288)
High-Tech * Boone^2							-3.31e-05	0.00105
							(0.000449)	(0.000881)
Ln(Sales)	0.0235	0.732***	-0.180***	0.280***	0.511**	1.217***	0.269***	1.309***
	(0.0280)	(0.185)	(0.0198)	(0.0546)	(0.206)	(0.329)	(0.0465)	(0.363)
(Ln(Sales))^2	0.0249***	0.00133	0.0368***	0.00449	0.0128	-0.0216	0.00541*	-0.0271
	(0.00171)	(0.0104)	(0.00131)	(0.00378)	(0.0114)	(0.0209)	(0.00323)	(0.0208)
High-Tech * Ln(Sales)							-0.472***	-0.799*
							(0.0594)	(0.417)
High-Tech * (Ln(Sales))^2							0.0325***	0.0399*
							(0.00383)	(0.0233)
Ln(Ebitda)	0.0999***	0.133***	0.110***	0.148***	0.154***	0.0598	0.0981***	-0.0181
	(0.0127)	(0.0472)	(0.0140)	(0.0327)	(0.0563)	(0.0802)	(0.0301)	(0.0927)
High-Tech * Ln(Ebitda)							0.0211	0.181*
							(0.0320)	(0.105)
Growth %	-0.0717***	-0.126**	-0.104***	0.0789*	-0.146**	-0.0430	0.0973**	-0.0428
	(0.0204)	(0.0493)	(0.0225)	(0.0467)	(0.0592)	(0.0988)	(0.0468)	(0.0848)
High-Tech * Growth %							-0.203***	-0.0983
							(0.0513)	(0.104)
DTFD	-0.301***	-0.547**	-0.0150	0.0346*	-0.00388	0.0634	-0.00513	0.00767
	(0.0813)	(0.215)	(0.0104)	(0.0206)	(0.0296)	(0.0405)	(0.00933)	(0.0260)
Observations	10,194	10,194	8,288	1,906	8,288	1,906	10,194	10,194
Number of Firms	911	911	752	159	752	159	911	911
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	Yes	No	No	Yes	No
Robust SE	No	Yes	No	No	Yes	Yes	No	Yes

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both Xtnbreg [NB] and Xtpoisson [P] models have R&D Expenditure as the dependent variable
All independent variables are lagged

First, the full sample models that include the DTF dummy interaction. The un-interacted terms of lagged competition, e.g. those that represent neck-and-neck firms, are both significant and form a U-shaped relationship between lagged competition and a firm's innovative input, in both types of models. Since the interacted terms have opposing signs and smaller coefficients in both types of models, they indicate that the relationship between lagged competition and a firm's innovative input is less pronounced for firms that are laggards. Nonetheless, since the confidence intervals of those estimates overlap, the relationship could even take the shape of an inverted U for laggard firms. Regardless, these results are in line with previous ones. However, they do not support H1A (*The relationship between competition and innovation follows an inverted-U shape*), but do support H1B (*The relationship between competition and innovation follows a U shape*), since the relationship found follows a U shape. Moreover, they support H2B (*The U-shaped relationship between competition and innovation is moderated by a firm's distance to the industry's technological frontier*). Next, the estimates for sales suggest a quadratically positive relationship between lagged firm size and a firm's innovative input in the negative binomial model, whilst the relationship found is linear and positive in the Poisson model. As such, they both support H4 (*Firm size has a positive relationship with innovation*). With regards to lagged firm profitability, both models yield a positive and significant estimate, which confirms H6 (*Firm profitability has a positive relationship with innovation*). For lagged firm growth, both the negative binomial and the Poisson model find a significant and negative relationship, which supports H8 (*Firm growth has a negative relationship with innovative input*). Finally, for the DTF dummy, both models suggest a negative relationship with a firm's innovative input, which is in line with the expectation that being further from the frontier discourages firms from spending on R&D.[39]

Second, the models that investigate the split samples. For the competition terms, only the high-tech sample of the Poisson model yields significant estimates for both. Together, they suggest that the relationship between lagged competition and a firm's innovative input takes the shape of a U. However, since the low-tech sample did not produce significant results, which can probably be attributed to the smaller sample size, no comparison can be made. Consequently, the results provide no support for H3B (*The U-shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*). For firm size, the results of the Poisson model both show a positive and linear relationship, with the estimate for the low-tech sample being considerably larger, which supports H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*). In the negative binomial models, on the other

[39] This is as expected; since DTF moderation is included here, the DTF dummy is negative here, instead of the positive estimates obtained when the moderation is not included in the models.

hand, a U-shaped relationship is found for the high-tech sample, whilst the low-tech sample's result suggests a linearly positive relationship with a firm's innovative input. As such, those results provide no support for H5. Considering lagged firm profitability, both samples' estimates are significant only in the negative binomial model. Since they are both positive, H6 (*Firm profitability has a positive relationship with innovation*) is supported. Moreover, the coefficient estimated for the low-tech sample is larger than that of the high-tech sample, which suggests a more pronounced relationship for low-tech firms. However, the confidence intervals of those estimates overlap, so that observation is tentative. Regardless, the results do not support H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*). Finally, for lagged firm growth, both the negative binomial model and the Poisson model find a significant and negative relationship with a firm's innovative input, which supports H8 (*Firm growth has a negative relationship with innovative input*). Nevertheless, since the negative binomial model's estimate for the low-tech sample is significant and positive, whilst the Poisson model's estimate for the low-tech sample is insignificant, the results do not provide support for H10 (*The negative relationship between firm growth and innovative input is more pronounced in low-tech industries than in high tech industries*).

Third, the models that include interaction with the high-tech dummy for all main variables. It must again be noted that the high-tech dummy's estimate is non-zero in the negative binomial model, which attests to the invalid nature of its fixed effects. No significant estimates are obtained for the competition terms, which is thought to be the result of the absence of the DTF interaction, which significantly shaped the relationship in previous models. Regardless, these estimates provide no support for H3B (*The U-shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*). For lagged firm size, the terms are all significant in the negative binomial model. Since the un-interacted terms are both positive, they suggest an increasingly positive relationship with a firm's innovative input for low-etch firms. For high-tech firms, on the other hand, the linear term becomes negative, whilst the squared term becomes larger. Consequently, they jointly describe a U-shaped relationship between lagged firm size and a firm's innovative input. However, in the Poisson model, the linear un-interacted term is positive and significant, whilst the interacted squared term is positive, and the other terms are insignificant. Accordingly, the Poisson model suggests that lagged firm size has a linear and positive relationship with a firm's innovative input for low-tech firms, whilst the relationship is increasingly positive for high-tech firms. Therefore, no support for H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*) is found here. Moving on to firm profitability, the negative binomial model finds a significant and positive relationship only for low-tech firms, whilst the Poisson model finds the same relationship, but then only for high-tech firms. Since both find a positive relationship, there is some support for H6 (*Firm profitability has a positive relationship with innovation*), but since they are different models, no comparison can be drawn that would allow inferences regarding H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*). Finally, lagged firm growth is significant in the negative binomial models only, where the un-interacted term is positive whilst the interacted term is negative and larger. Consequently, that model suggests that, for low-tech firms, the relationship between lagged firm growth and a firm's innovative input is positive, whilst it is negative for high-tech firms. As such, no support is found here for H8 (*Firm growth has a negative relationship with innovative input*), nor for H10 (*The negative relationship between firm growth and innovative input is more pronounced in low-tech industries than in high tech industries*).

5.5.2 Full Output Models

The results of the full output models can be found in Table 25, on the next page. As with the full input model above, first the models that include DTF dummy moderation for the competition terms. Lagged R&D expenditure shows a positive and significant relationship with a firm's innovative output, as expected. However, this term is insignificant in the Poisson model. Moving on to the competition terms, they are only all significant in the negative binomial model. There, the relationship takes the shape of a U for neck-and-neck firms. Furthermore, the signs for the moderated terms, e.g. those that represent laggard firms, have opposite signs and are smaller than the unmoderated terms. As such, they indicate that the parabolic relationship between lagged competition and innovative output is indeed less pronounced for laggard firms than for neck-and-neck firms. Since the terms are significant, they provide support for H2B (*The U-shaped relationship between competition and innovation* *is moderated by a firm's distance to the industry's technological frontier*). For the firm size terms, the negative binomial and the Poisson model differ. In the negative binomial model, the relationship takes the shape of a U, whilst the relationship is decreasingly positive in the Poisson model. Therefore, those results do not unequivocally support H4 (*Firm size has a positive relationship with innovation*). For lagged firm profitability, only the negative binomial model has a significant estimate, where it is positive, which supports H6 (*Firm profitability has a positive relationship with innovation*). Finally, neither of the models has a significant estimate for lagged firm growth. Consequently, no conclusions can be made with regards to H9 (*Firm growth has a positive relationship with innovative output*). Nevertheless, it could be that firm growth does not significantly influence a firm's innovative output, since it often returns insignificant estimates.

Table 25: Full Output Models

VARIABLES	(1) NB: Full	(2) P: Full	(3) NB: Full HT	(4) NB: Full LT	(5) P: Full HT	(6) P: Full LT	(7) NB: Sq & Mod	(8) P: Sq & Mod
Ln(RND)	0.189***	-0.0498	0.187***	0.210***	-0.0228	0.812**	0.181***	0.0155
	(0.0183)	(0.238)	(0.0202)	(0.0481)	(0.259)	(0.385)	(0.0185)	(0.247)
Boone	-0.296***	0.186	-0.287***	-0.130***	0.0337	0.398***	-0.112***	0.185**
	(0.0185)	(0.127)	(0.0208)	(0.0445)	(0.0971)	(0.0576)	(0.0304)	(0.0890)
$Boone^2$	0.00833***	-0.00779*	0.00880***	0.00314**	-0.00114	-0.0124***	0.00312***	-0.00637*
	(0.000570)	(0.00435)	(0.000673)	(0.00127)	(0.00270)	(0.00249)	(0.000870)	(0.00327)
DTFD * Boone	0.220***	-0.00653						
	(0.0292)	(0.145)						
DTFD * $Boone^2$	-0.00618***	0.00261						
	(0.000930)	(0.00485)						
High-Tech							-3.518***	
							(0.303)	
High-Tech * Boone							0.0426	-0.155
							(0.0415)	(0.140)
High-Tech * $Boone^2$							-0.00104	0.00531
							(0.00126)	(0.00458)
Ln(Sales)	-0.0970**	4.102**	-0.248***	-0.220**	4.710***	-0.0364	-0.379***	-0.686
	(0.0458)	(1.694)	(0.0474)	(0.105)	(1.705)	(2.143)	(0.0806)	(2.123)
$(Ln(Sales))^2$	0.00891***	-0.166**	0.0164***	0.0235***	-0.192**	0.0411	0.0332***	0.133
	(0.00286)	(0.0816)	(0.00301)	(0.00667)	(0.0835)	(0.102)	(0.00472)	(0.0866)
High-Tech * Ln(Sales)							0.780***	5.356*
							(0.105)	(2.815)
High-Tech * $(Ln(Sales))^2$							-0.0527***	-0.327**
							(0.00621)	(0.127)
Ln(Ebitda)	0.111***	0.139	0.165***	-0.0958	0.0535	0.355	-0.0690	-0.139
	(0.0335)	(0.219)	(0.0373)	(0.0808)	(0.228)	(0.351)	(0.0715)	(0.372)
High-Tech * Ln(Ebitda)							0.152**	0.220
							(0.0759)	(0.405)
Growth %	-0.0988	-0.384	-0.162**	-0.107	-0.441*	-0.744	-0.0307	-0.718
	(0.0608)	(0.249)	(0.0652)	(0.176)	(0.254)	(0.494)	(0.160)	(0.504)
High-Tech * Growth %							-0.0504	0.290
							(0.172)	(0.546)
DTFD	-1.741***	-0.702	0.0221	-0.0637	-0.444**	-0.117	0.00738	-0.416**
	(0.221)	(0.958)	(0.0306)	(0.0631)	(0.197)	(0.220)	(0.0274)	(0.193)
Observations	9,989	9,989	8,120	1,869	8,120	1,869	9,989	9,989
Number of Firms	859	859	708	151	708	151	859	859
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	Yes	No	No	Yes	No
Robust SE	No	Yes	No	No	Yes	Yes	No	Yes

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Both Xtnbreg [NB] and Xtpoisson [P] models have the CWPS as the dependent variable
All independent variables are lagged

In the split sample models, the significant lagged R&D expenditure terms are all positive, which confirms expectations and is in line with literature. For the lagged competition terms, the negative binomial models both show a U-shaped relationship. Moreover, since the terms for the low-tech sample are considerably smaller than those of the high-tech sample, these results provide no support for H3B (*The U-shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*). A possibility is that, due to the importance of R&D for high-tech firms, the relationship is more pronounced there. In the Poisson model, on the other hand, only the low-tech sample has significant estimates for the lagged competition terms, so no comparison can be made with the high-tech sample. For the lagged firm size terms, both samples feature significant estimates in the negative binomial model. However, since their confidence intervals overlap, no assessment of their difference should be made. In the Poisson model, only the high-tech sample has significant estimates for the firm size terms, which is likely attributable to the smaller sample size for low-tech firms. Consequently, these results provide no support for H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*). The lagged firm profitability variable is only significant in the negative binomial model's high-tech sample, where it is positive, so no inferences can be made about the difference between high- and low-tech firms. Therefore, no conclusions regarding H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*) can be made. Finally, the lagged firm growth estimates are significant of the high-tech samples only, where their sign is negative. Since the low-tech samples did not produce significant results, no comparison can be made here either. Hence, these results do not allow for inferences about H11 (*The positive relationship between firm growth and innovative output is more pronounced in low-tech industries than in high-tech industries*).

Lastly, the models that include interaction with the high-tech dummy for the main variables. First, the lagged R&D expenditure term is significant in the negative binomial model only, where it is positive, as theorised. Second, only the un-interacted competition terms are significant. Moreover, the relationship they describe is different, since the negative binomial model suggests a U-shaped relationship whilst the Poisson model's relationship between lagged competition and a firm's innovative output has the shape of an inverted U. Since the

Poisson model is preferred due to its suspected statistical superiority, these results provide some tentative support for H1 (*The relationship between competition and innovation follows an inverted-U shape*). Nevertheless, since the interacted terms are insignificant, this observation is provisional. Additionally, no statements can be made with regards to H3A (*The inverted-U shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*) due to the insignificance of the interacted terms. Considering the lagged firm size terms, the negative binomial model suggests a U-shaped relationship for low-tech firms and an inverted U shape for high-tech firms. The Poisson model echoes that relationship for high-tech firms, but failed to produce significant estimates for low-tech firms, which could be caused by the smaller sample size. Regardless, the results do not support H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*). For lagged firm profitability, only the interacted term in the negative binomial model is significant. Furthermore, since it is positive, it provides some support for supports H6 (*Firm profitability has a positive relationship with innovation*), but due to the insignificance of the un-interacted term H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*) is not supported. Finally, the lagged firm growth terms are significant in neither model, which does not provide a basis for observations regarding the relationship with a firm's innovative output in these models.

6. Conclusion

This research has aimed to shed light onto the complex relationship between firm-level innovation and its determinants, with a special focus on competition. In doing so, both firms' innovative in- and output was investigated using different models to increase robustness. This chapter first discusses the research's findings and sets out their implications for firms and policy makers. Next, the limitations of this research are discussed. Finally, it ends with possible suggestions for future research.

6.1 Summary and discussion of findings

6.1.1 Competition and innovative input

First, the unmoderated relationship between competition and a firm's innovative input. The models consistently showed that a quadratic term of competition needs to be included to capture the relationship. Nevertheless, the shape of the relationship found was a U which supports H1B (*The relationship between competition and innovation follows a U shape*) and not the inverted U that was hypothesised by H1A *(The relationship between competition and innovation follows an inverted-U shape).* This difference is suspected to be caused by other researchers' use of a regular regression model with the dependent variable in a logarithm, a strategy which can cause inaccurate estimates, since a count data models should be used, as set out before. Moreover, Aghion et al. (2005)'s research investigated innovative output, not innovative input. Another possibility is that the differing results lie in the nature of the US manufacturing industries, as both other studies that analyse US data (Hashimi, 2013 and Correa & Ornaghi, 2014) do not find an inverted U either. Finally, both those studies are at the industry level, whilst this study is at the firm level, which could be another reason for the diverging results, since neither of them finds a U-shaped relationship. Regardless, the finding of U-shaped relationship instead of an inverted U has some implications for competition policy, as situations of medium competition were generally preferred by competition authorities so far. This relationship, on the other hand, would lead them to support either very low or very high levels of competition. Since very low competition has negative consequences for consumers, it can be expected that those authorities will pursue situations of very high competition if they base their policy on this research.

Second, with regards to moderation by a firm's DTF, both the negative binomial and Poisson models showed a U-shaped relationship as well. Moreover, all three model specifications found that the relationship was moderated by the DTF, which confirmed H2B (*The U-shaped relationship between competition and innovation is moderated by a firm's distance to the industry's technological frontier*). Concretely, they suggested that being further from the industry's technological frontier makes the relationship between competition and innovation less pronounced. As such, it is concluded that competition is less influential in deciding innovative input for a laggard firm than it is for a neck-and-neck firm. This is theorised to be the result of firms being encouraged or even forced to innovate by high levels of competition, which is in line with Smith (1776) and Arrow (1962), whilst low levels of competition lead to the increased funds that can be used for innovation, which follows Schumpeter (1942). When competition is at 'medium levels', on the other hand, they neither have the excess funds of low competition, nor the motivation caused by high levels of competition. This effect is then more pronounced for neck-and-neck firms than for laggard firms since low levels of competition provide neck-and-neck firms with more funds than laggard firms, whilst at high levels of competition, neck-and-neck firms have more to lose, and laggard firm barely make a profit to spend on innovation. A consequence of this finding would be that laggard firms might need to be supported to increase total R&D expenditure. However, such support might create uneconomical incentives for firms, which might even thereby distort competition in the market. Consequently, that possibility is probably more theoretical than practical.

Third, the investigation of the difference in relationship between high- and low-tech firms yielded few concrete observations. However, some of the results did suggest that the relationship might indeed be more pronounced for low-tech firms than for high-tech firms. Nevertheless, the interaction effects models did not confirm this. Therefore, some support was found for H3B (*The U-shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*), but it was not overwhelming. This result was somewhat puzzling, since most research suspected differences between high- and low-tech firms. However, this research suspects those differences to exist, partly attributing the lack of consistent and/or significant findings to the smaller sample size for low-tech firms. Another suspected cause is differences between specific industries within the high- and low-tech groups. If that is the case, the results would fail to show significant results for the difference between high- and low-tech firms, since there is no relationship that fits either entire group. Nevertheless, another explanation is that the relationship does not differ between high- and low-tech firms, since they are enabled by the funds low levels of competition provides, e.g. Schumpeter's (1942) reasoning, and encouraged to innovate by high levels of competition, which is in line with Smith (1776) and Arrow (1962), with neither influence dominating at medium levels of competition.

6.1.2 Competition and innovative output

First, the unmoderated models of competition and innovative output. The unmoderated models supported theory in finding a quadratic relationship. Although both quadratic models were significant, the relationship they described differed; the negative binomial model shows a U-shaped relationship, whilst the Poisson model shows an inverted U-shaped relationship. Since the Poisson model is believed to be more statistically accurate, it is preferred over the negative binomial model when they differ. As such, the results did provide some support for H1A *(The relationship between competition and innovation follows an inverted-U shape)*, but it was not overwhelmingly convincing. This divergence from competition's relationship with innovative input might lie in the difference and relation between innovative in- and output: Whilst spending on R&D (e.g. innovative input) is affected by lagged competition in the way previously described, for innovative output other factors come in to play, such as the tournament-nature of obtaining patents,[40] which, combined with the relationship found for innovative input, favours situations of medium levels of competition: With high levels of competition, due to the amount of firms in the market and intensity of competition, other firms might be 'first past the post' which makes the R&D expenditure on the potential patent in question redundant. When combined with the high spending on R&D, this leads to a reduced likelihood to obtain a well-cited patent for individual firms, as the probability to successfully patent for an individual firm is not only a function of an individual firms' R&D expenditure, but that of the market's total R&D expenditure as well. When competition is low, on the other hand, all firms that are able to spend on R&D do so, as found by the

[40] When a patent is obtained by firm A, firm B cannot apply for it anymore, due to patents being exclusive.

innovative input models, which likewise reduces each individual firm's likelihood of obtaining the patent. When competition is at medium levels, spending on R&D is relatively low, which increases the likelihood of obtaining a well-cited patent for individual firms. However, since the negative binomial model produced a diverging relationship, this inference is tentative. Interestingly, this might suggest that, for competition authorities, their strategy of allowing oligopolies to exist might be the correct one when aiming to maximise successful and influential innovation. However, this result only relates to individual firms' innovative output and does not capture the total amount of citation weighted patents in an industry. As such, further research is required to make any definitive observations regarding that consideration for competition authorities. What can be said by combining this result with that of the relationship between competition and innovative input, is that a firm might be most successful if it aims to operate in markets with medium levels of competition, since then most firms' R&D expenditure is lowest, and then increase its own R&D spending, since that level of competition is most advantageous for an individual firm's innovative output. However, additional research is needed here as well to confirm this suspicion.

Second, the output models that were moderated by a firm's DTF. The support for DTF moderation was quite convincing, as in the input models, which therefore confirms H2A (*The inverted-U shaped relationship between competition and innovation is moderated by a firm's distance to the industry's technological frontier*). This aligns with intuition, as a firm's reaction to industry competition, as captured by Boone's indicator, is necessarily shaped by its relative position in that industry, as measured by the DTF. Moreover, most evidence pointed towards the relationship being less pronounced for laggard firms, regardless of its shape, which is once again in line with the results of the input models and thus follows the same reasoning. An implication of the consistently significant DTF moderation in these models (as well as the innovative input models) is that any future research that aims to assess the relationship between competition and innovation must include a measure of DTF. Furthermore, for policy makers with regards to competition, an evaluation of the industry in question's technological differences would seem essential to include. Moreover, for M&A approval, the merger's effect on the DTF make-up of the relevant industry would be vital to incorporate.

Third, the models that investigated the difference in relationship between high- and low-tech firms were not fully significant, but produced some interpretable results, nevertheless. Both the split sample models and the interaction models generally suggested that the relationship between lagged competition and innovative output is more pronounced in low-tech industries than in high-tech industries, which supports H3A (*The inverted-U shaped relationship between competition and innovation is more pronounced in low-tech industries than in high-tech industries*). This result is attributed to two circumstances: First, low-tech industries are more neck-and-neck than high-tech industries. Since the relationship between competition and innovation is more pronounced for neck-and-neck firms, as concluded above, it then follows that the relationship is more pronounced for low-tech firms than for high-tech firms. Second, in low-tech industries, a relatively large knowledge increase is required to innovate. As such, the relationship of competition with innovation is more pronounced for low-tech firms than for high-tech firms, since the risk of other firms being first past the post is then larger due to the longer process of successfully innovating. Consequently, it follows that competition policy would then be more influential in low-tech industries, which thus calls for differing policies for high- and low-tech industries.

6.1.3 Firm size

First, the relationship between firm size and innovative input. The models did not unequivocally show that a quadratic term needs to be included to capture the relationship. However, this was partly due to differences between high- and low-tech firms, which the subsequent models analysed. Nevertheless, since the relationship was consistently positive, there was support for H4 *(Firm size has a non-linear positive relationship with innovation).* With regards to the models that analysed the split samples and those that included the high-tech dummy, there was fairly convincing evidence that the relationship does indeed differ between high- and low-tech industries. However, some models found support for H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*), whilst other did not. As such, the expectation that the relationship is more pronounced for low-tech firms since they focus more on process innovation, as concluded by Fontenele et al. (2016), which provides benefits relative to the scale of production, is not supported but not rejected either. The conflicting results, both with each other and literature, could have few different reasons: the smaller sample size for low-tech firms; other research often having considerably more observations of large than small firms due to data availability; a moderating factor that is not included in the model; and/or differences between specific industries. For the moderating factor, a possibility is that it is moderated by competition, as suggested by Acs & Audretsch (1987), or other industry characteristics, as suggested by Becheikh, Landry, and Amara (2006).

Second, the relationship between firm size and innovative output. The two types of models both found that including a quadratic term significantly captures the relationship, but showed differing signs. Nevertheless, neither of them suggested a consistently positive relationship, so there was no support for H4 *(Firm size has a positive relationship with innovation*) with regards to innovative output. The relationship was subsequently investigated for high- and low-tech firms, as that was suspected to shape the relationship. Indeed, the results suggested that the relationship differed between high- and low-tech firms. However, that difference was not consistent in the different types of models, with some suggesting the shape of an inverted U and others indicating a U shape. One fairly consistent result was that, for low-tech firms, the relationship takes the shape of a U. However, since this was not backed by the Poisson model, this is not convincingly supported. Another somewhat consistent result was that, for high-tech firms, the relationship takes the shape of an inverted U. Regardless, H5 (*The positive relationship between firm size and innovation is more pronounced for low-tech firms than for high-tech firms*) was not convincingly supported. Finally, as with the input models, the diverging result could be the result of the smaller sample size for low-tech firms, other research often having considerably more observations of large than small firms due to data availability; and/or differences between specific industries. Another possibility is that the relationship is moderated by competition, as suggested by Acs & Audretsch (1987), or another industry characteristic altogether (Becheikh, Landry, and Amara, 2006). Regardless, since the relationship appears to be more complicated than a simple linear one, more research would be required to design innovation-maximising policy with regards to firm size.

6.1.4 Firm profitability

First, the relationship between profitability and innovative input. The results consistently suggested that profitability does indeed have a positive relationship with innovative input. Consequently, there was support for H6 *(Firm profitability has a positive relationship with* *innovation).* The reasoning for this lies in the funds profitability provides, which can then be invested in innovation. The relationship was subsequently analysed for high- and low-tech firms, using both split samples and interaction effects, to see if there was a difference. In doing so, the results convincingly suggested that the relationship was less pronounced for low-tech firms, which provides evidence for H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*). Consequently, the expectation that the relationship is positive but less pronounced for low-tech industries than for high-tech industries due to low-tech firms only innovating out of necessity, as theorised by Audretsch (1995) and Branch (1974), seems to be correct. However, additional data on the motivation for innovation would be needed to confirm it.

Second, the output models for profitability. Again, there was support for H6 *(Firm profitability has a positive relationship with innovation).* Moreover, the difference between high- and low-tech firms was analysed there as well. Interestingly, for innovative output, there was no support for H7 (*The positive relationship of firm profitability and innovation is less pronounced in low-tech industries than in high-tech industries*), with the Poisson model's interaction effects even finding the opposite, that the difference in relationship is reversed, more pronounced for low-tech firms. As stated in the corresponding results section, this might be the result of the relatively large knowledge increase required to innovate in low-tech industries (Audretsch and Acs, 1991), which makes other firms' innovative input more relevant for a firm's innovative output than the funds needed to innovate. Regardless, since profitability seems to increase both innovative in- and output, these results provide support for tax schemes that allow for profits to go untaxed if they are subsequently invested in innovation, as many nations already do.

6.1.5 Firm growth

As above, the relationship of firm growth with innovative input is discussed first. Here, the results convincingly suggested a negative relationship between firm growth and innovative input. This was expected due to innovation being required for growth, which makes innovation less needed when a firm already is growing. As such, there was support H8 *(Firm growth has a negative relationship with innovative input).* When the relationship was examined for high- and low-tech firms, the relationship seemed to be positive for low-tech firms, and negative for high-tech firms. However, the Poisson model, which is believed to be more accurate, did find a negative relationship for low-tech firms as well. Regardless, the results do not support H10 *(The negative relationship between firm growth and innovative input is more pronounced in low-tech industries than in high tech industries).* The complacency that leads firms to reduce innovative effort when they are growing, suggested by Etro (2005), makes intuitive sense. However, for society at large, it would probably be more beneficial if firms did not reduce their innovative effort when they are growing. A possible policy implication would then be to incentivise firms to keep innovating when they are experiencing growth, for example with a method similar to the tax scheme described in the firm profitability section above.

In the models that scrutinised the relationship with innovative output, the relationship found was negative as well. Consequently, no support for H9 *(Firm growth has a positive relationship with innovative output)* was provided. This can probably be attributed to Etro's (2005) reasoning for the negative relationship for innovative output, in that innovating is less required when a firm is already growing. When this relationship was subsequently investigated for high- and low-tech firms, most models failed to give significant results to the extent that real conclusions could be drawn. Therefore, there was no support for H11 (*The positive relationship between firm growth and innovative output is more pronounced in low-tech industries than in high-tech industries*), which was hypothesised on the basis of the lower-growth nature of low-tech industries, which causes growth to have more pronounced effects when it is present. Since that theoretical consideration seems to be robust, the lack of significant results that confirm it is not attributed to that relationship not being present, but to the smaller sample size for low-tech firms, which makes it harder for the comparison to significantly show a difference. Nevertheless, another explanation is that the relationship does in fact not differ, since both high- and low-tech firms suffer from complacency with regards to innovation when they are experiencing growth.

6.2 Limitations

This research, like all research, does have some limitations that need to be mentioned. First, due to a lack of data on specific types of costs, some proxies had to be used to create the

Distance-To-Frontier measure. Although the measure captured what it needed to and behaved as it should, not having the data (to construct a measure) of TFP is a limitation, nevertheless. Moreover, data on specific costs, specifically firms' average variable cost, would have allowed Boone's indicator to be constructed without the use of proxies as well, which would have improved its robustness. Second, this research suffered from a discrepancy in the number of observations for its high- and low-tech samples, with a ratio of about 4 to 1, respectively . Consequently, some of the low-tech analysis, whether with samples or interaction effects, produced some insignificant results, which made a comparison with the high-tech firms impossible in those instances. Third, endogeneity was a real concern for this study, as innovation, especially successful innovation, in turn affects firms' competitive situation, size, profitability, and growth. To reduce the potential bias this creates, lags were used for all analyses. Nevertheless, the research could have been more robust if instrumental variables were alternatively used. However, no clear choices presented themselves. Fourth, to estimate certain variables, firms that had a negative Ebitda were deleted, which, although consistent with literature, could have caused selection bias.

Another limitation of this study is the use of naics-3 as an industry demarcation for the construction of a variety of variables. Whilst a more detailed level of naics was available, this reduced the observations for each industry to such an extent that the variables constructed would be biased or insignificant. A reason for this is that the data only includes manufacturing companies that are publicly listed, which reduces the sample size. Furthermore, the sole use of publicly listed firms is a limitation in itself, since it might cause selection bias. However, the data that is used is often not available for companies that are not publicly listed. Additionally, the statistical models used somewhat limited this study. The negative binomial model, which is supposedly the correct model to use, does not truly use fixed effects, as extensively noted throughout this study. Consequently, its estimates sometimes diverged from the Poisson model, which seems to be more statistically robust regardless of the overdispersion present in the data. Where both types of models aligned, the evidence was clear. However, they did not consistently produce the same results, which is a limitation.

Finally, multicollinearity was a challenge in this study. For example, firm growth was taken as a percentage to reduce this issue there. Nevertheless, as Goldberger (1991) and Woolridge (2020) consider, multicollinearity is in itself not an assumption-violating or catastrophic problem. It can cause standard errors to become larger than they would otherwise, which reduces the significance of results. Since most results were significant and standard errors were quite small, it can be concluded that multicollinearity did not pose a substantial problem. However, it could have contributed to the insignificance of the results for the industry analysis, which makes it a limitation that needed to be mentioned, regardless.

6.3 Suggestions for future research

As suggestions for future research, the first would be to combat the limitations mentioned above. Therefore, future research should feature data on specific types of costs, which would make the Distance-To-Frontier measure and Boone's indicator more reliable, as well as a larger number of observations for low-tech firms, which would likely increase the significance of the results for those firms. Furthermore, the identification and utilisation of viable instrumental variables is recommended, as that would improve the robustness of the analysis by providing an alternative method to combat endogeneity, besides the use of lags. Additionally, the creation of a negative binomial model that does properly include fixed effects would be a suggestion for future research, as that would improve the robustness of the estimates found. Moreover, if there is trustworthy data of non-listed firms available, including it would not only reduce selection bias and increase the sample size and thus be likely to improve the significance and robustness of results, especially for the low-tech sample, but allow for a more detailed level of the naics codes and thereby industries to be analysed as well, which would improve the construction of some of the measures.

Second, the addition of inventor information to the innovative output models would help the models explain a larger portion of the variance of innovative output. Therefore, future research should aim to include that information, as it was beyond the already considerable scope of this masters' thesis to do so. Third, due to the web-like structure of effects in this field, the use of models that allow for such entanglement of correlation, like for example a simultaneous equation model, could be a valuable addition to the body of research on this topic.

Fourth, future research should investigate the relationship between both innovative in- and output and their determinants separately for specific industries, instead of generalising with high- and low-tech industries, since industry characteristics are influential in determining those relationships. Moreover, it is suspected that this approach would clarify some of the conflicting results found, as those are believed to be the result of the high- and low-tech oversimplification. Doing so would allow policy makers to tailor their policy to specific industries with a scientific basis.

Finally, adding a measure of industry-wide R&D expenditure to the innovative output models could help capture the theorised effect of more industry-wide R&D spending on an individual firm's innovative output, since an individual firm's probability of obtaining a (well-cited) patent is believed to decrease with industry wide R&D spending. Moreover, such research would allow firms to see if the strategy described in 6.1.2 is indeed optimal.

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Annexes

Annex 1: Industry classification and frequency

naics3	Industry	Freq.	Percent	Cum.
	High-Tech industries			
325	Chemical	2,398	18.25	18.25
333	Machinery (excluding electrical)	2,240	17.05	35.3
334	Computers and electronic products	4,491	34.18	69.48
335	Electrical equipment, appliances, and components	781	5.94	75.42
339	Miscellaneous manufactured commodities	861	6.55	81.97
Subtotal:		10,771	81.97	
	Low-Tech industries			
322	Paper products	312	2.37	84.34
326	Plastic & Rubber	216	1.64	85.98
332	Fabricated metal products	682	5.19	91.17
336	Transportation equipment	1,160	8.83	100
Total:		13,141	100	