CentER

Discussion Paper

No. 2010–52

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By Erik Brouwer, Henry van der Wiel

May 2010

ISSN 0924-7815

TILBURG UNIVERSITY

Competition and innovation: Pushing productivity up or down?*

Erik Brouwer† and Henry van der Wiel‡

May 26, 2010

Abstract

This paper examines the relationship between competition, innovation and productivity for the Netherlands. We use industry level data aggregated from micro data as well as moments from firm level data for the period 1996-2006. We match innovation data from Community Innovation Survey with accounting data to link innovative activities with performance at the industry level. We find strong evidence for a positive impact of competition on Total Factor Productivity (TFP) at the industry level. Competition directly increases TFP by reducing X-inefficiencies and removing inefficient firms from markets, but also through more innovation. Nonetheless, there exists an inverted U-curve between competition and innovation for the Netherlands, at least for manufacturing industries. Yet, our results indicate that a negative effect of competition on productivity through lower innovation expenditures arises only at very high levels of competition.

Keywords: competition, innovation, profit elasticity, productivity

JEL classification: D40, L16, O31

*Financial support from NWO (grant numbers 453.03.606 and 472.04.031) is gratefully acknowledged. Thanks to Jan Boone, Roel van Elk, Bert Minne and Ruud Okker for their comments on earlier versions of this paper. We are also grateful to Rob Alessie for his excellent econometric advice. The data analysis reported in this document was carried out at the Centre for Policy Related Statistics of Statistics Netherlands. The views expressed in this document are those of the authors and do not necessarily reflect the policy of Statistics Netherlands.

†PricewaterhouseCoopers, Department of Economics, Tilburg University, CentER and Tilec. Email: e.brouwer@uvt.nl.

‡Department of Economics, Tilburg University, CentER and CPB. Email: hvdw@cpb.nl.

1. Introduction

This paper examines the relationship between competition, innovation and productivity at the industry level for the Netherlands. In the view of the endogenous growth theory (see *e.g.*, Romer (1990), Aghion and Howitt (1992) and Aghion and Howitt (2006)), competition and innovation are interrelated and as such seen as important determinants for productivity and in that way contributing to sustained economic growth. And economic growth is a fundamental driver of improving the living standards of the population (*i.e.* the welfare level).

For the Netherlands, this relationship is especially interesting since for many years its performance on productivity growth is relatively poor in an international (and historical) perspective, particularly compared to the US, pushing the Netherlands back in its top-ranking with regard to the level of productivity (see e.g., van der Wiel (2001), Gelauff, Klomp, Raes and Roelandt (2004), Kegels, Peneder and van der Wiel (2008) and van der Wiel, Creusen, van Leeuwen and van der Pijll (2008)). In that respect, it is not surprising that Dutch policy intends to foster productivity by using policy measures that aim to stimulate either innovation or competition to realize higher welfare.

However, as Nickell (1996) already mentioned more than ten years ago, the theoretical and empirical evidence that competition improves the productivity performance are not overwhelming. Moreover, the study by Aghion, Bloom, Blundell, Griffith and Howitt (2005) for the UK finds that the relationship between competition and innovation is an inverted U. In that case, a trade-off between both drivers of productivity may exist and innovation policy and competition policy can be at odds with each other when focussed on realizing higher productivity: stimulating competition beyond a certain level might then have a negative effect on innovation, and subsequently on productivity. But empirical evidence is scarce. State of the art research on the empirical relation between competition and innovation as Aghion et al. (2005) did for the UK has not been done for Dutch industries yet, let alone the impact on productivity. Hence, we do not know whether there exists an inverted U curve for the Netherlands, and if so, which industries have competition intensities beyond the innovation maximizing level.

This paper picks up this ambiguous connection between competition and innovation, and relates it to Dutch productivity. We apply an empirical framework that is comparable with Nickell (1996), Griffith, Redding and van Reenen (2004) and Griffith, Harrison and Simpson (2006).

We start from the idea of a production function taking on board views from the endogenous growth theory. Hence, our framework includes the impact competition and innovation have on productivity performance. In the vein of the convergence literature, the distance to the global frontier – as being the highest attainable productivity – level may also be relevant because this may signal potentials for productivity growth through (costless) technology transfers or knowledge spillovers. Recent studies from, for instance, Griffith et al. (2004) and Conway, Rosa, Nicoletti and Steiner (2006) emphasize the importance of technology transfers and the effect of product market regulations on the international diffusion of productivity shocks given the distance to the frontier. Moreover, our framework both explains changes in competition and innovation, and it provides insight in how the interaction mechanism between competition and innovation works in practice knowing that they are endogenous.

We use data from two sources. First, we employ industry level data from the Production Survey (PS) for more than 150 3-digit SIC-industries directly based on aggregated Dutch firm level data covering almost the whole Dutch economy over the period 1993-2006.[1] Second, we employ innovation indicators from six consecutive Community Innovation Surveys (CIS) covering the period 1996-2006. Moreover, the industry level data is augmented with information from firm level data on variances. Industry averages are sums ignoring firm heterogeneity within an industry, while this is increasingly seen as important in the endogenous growth literature (see *e.g.*, Bartelsman and Doms (2000) and Aghion and Howitt (2006)). As we have firm level data at our disposal, we add measures of variances between firms to our analysis at the industry level to take heterogeneity of firms into account. An example is the distance to the frontier.

To some extent, the ambiguous message from the empirical literature on the relationship between competition and innovation is related to the difficulty in measuring both concepts and the availability of adequate data. Moreover, from a modeling perspective, both competition and innovation are endogenous and this complicates estimation of their impact on productivity. Other factors may determine competition and innovation like policy measures and macro economic shocks. Additionally, competition may affect innovation as well, but innovation may also change the market structure and the degree of competition through product differentiation. Hence, we have reverse causality and encounter endogeneity problems. We address these problems using Generalized Methods of Moments (GMM). This estimation technique exploits

[1] For a number of industries, we use 4-digit SIC-industries.

lagged explanatory variables as instruments to cope with endogeneity.

Our main findings are the following. We show that competition and to a lesser extent innovation are good for productivity. But here it is important to take into account the relationship between competition and innovation. We provide support for the view that there exists an inverted U-curve between competition and innovation for the Netherlands, at least for the manufacturing sector. This corresponds with findings of Aghion et al. (2005). As there can be a trade-off between both, our findings have implications for policy because competition and innovation might be in conflict. However, we show that the overall results indicate that a negative effect of competition on productivity through lower innovation arises only at very high levels of competition. Hence when it comes to productivity, more intense competition is almost always better.

This study contributes to the (empirical) literature in different ways. First, it examines the existence of an inverted-U curve between competition and innovation for the Netherlands. Besides the study of Aghion et al. (2005), empirical evidence for such inverted U-curve is scarce.[2] Second, compared to Aghion et al. (2005), we use better measures for competition and innovation. Aghion et al. (2005) applies the price cost margin (PCM) and patent citation as indicators for competition and innovation respectively. Both indicators have severe shortcomings. We use the profit elasticity (PE) and the innovation rate as those indicators are more robust (see *e.g.*, Boone, van Ours and van der Wiel (2007), Kleinknecht, van Montfoort and Brouwer (2002) and Brouwer (2007)). Moreover, our study analyzes the entire economy, whereas Aghion et al. (2005) only look at manufacturing industries. We also have data for other industries like services. Third, we explicitly consider the effect of competition and innovation on productivity, since the latter is one of the main goals for policy makers as productivity is directly related to welfare. As far as we are aware of, there is no comparable study in this respect. Finally, we control for possible feedback mechanism from innovation to competition taking account of other explanatory variables.

The structure of this paper is as follows. Section 2 gives a brief theoretical background of the relationship between competition, innovation and productivity. The empirical framework,

[2]See Creusen, Minne and van der Wiel (2006b) for an analysis of the inverted-U curve for only the Dutch retail trade.

econometric specification and endogeneity problems are discussed in section 3. Next, section 4 introduces the data sources and the key variables in question. It also presents some descriptive statistics. Section 5 contains the results of estimating the relationship between competition, innovation and productivity. This section also examines the robustness of these results with respect to our competition indicator. Finally, section 6 summarizes the main findings and sketches policy implications.

2. Theoretical and empirical background

2.1. Theoretical background competition and innovation

Traditional views competition and innovation

Let us first have a closer look at the separate effects of competition and innovation on productivity. In theory, investments in R&D create new technologies and new products, both generating higher productivity, or stated otherwise: more value added per worker (see *e.g.*, Grossman and Helpman (1991), Cameron (1998), Griliches (1998) and Cameron and Trivedi (2005)). The general finding in empirics is that innovation is good for productivity (see, inter alia, van Leeuwen (2009)).

The intensity of competition is also important for economic growth (see *e.g.*, Geroski (1990) and Nickell (1996)). This can be found in theory and empirics.[3] The story goes as follows. Competition on product markets is generally seen as generating lower prices for consumers and higher quality. Competitive pressure stimulates firms to operate efficiently by, for instance, *cutting the fat out* of their organizations. Or, more intense competition forces inefficient firms to leave the market. It brings product prices in line with their marginal costs, lowering the rents of producers and increasing consumer surplus. Vigorous product market competition may therefore result in higher productivity as resources and output are allocated to their most productive use.

However, taking into account the interplay between (product market) competition and innovation, economic theory does not predict the shape of this relationship nor how competition

[3] Exceptions are Scharfstein (1988) and Martin (1993), they argue that competition leads to an increase in managerial slack, and hence lowers productivity.

affects productivity and economic growth through innovation. Whether or not competition raises innovation is an ongoing debate and a challenging research topic since Schumpeter's remarks in two famous books, dividing the theoretical strands into two camps. The first strand consists of those that argue that competition is bad for innovation (see Schumpeter (1942)). The second strand claims that competition is good for innovation (see Schumpeter (1934)).

According to Schumpeter (1942) fiercer competition generates less R&D, reducing the rate of innovation and hence economic growth. The intuition is that because the expectation of high profits drives innovation, an increase in competition will discourage innovation if it results in lower profits. The Industrial Organization literature of product differentiation and monopolistic competition supports this strand (see Salop (1979) and Dixit and Stiglitz (1977)). Using a Schumpeterian endogenous growth model, Aghion and Howitt (1992) show that an increase in product market competition has a negative effect on productivity growth by reducing the monopoly rents that reward innovation (see also Romer (1990) and Grossman and Helpman (1991)). Examples of empirical studies that support this negative correlation are Hamberg (1964), Mansfield (1964), Kraft (1989), Porter (1990) and Symeonidis (2001).

The view that competition is good for innovation, is theoretically supported by studies from Schumpeter (1934), Arrow (1962) and Scherer (1980). In this strand, it is thought that competition stimulates an incumbent to innovate otherwise the firm is forced to leave the market and the potential entrant will win the race. This entrant will win this race if the replacement effect (Arrow (1962)) for the incumbent is stronger than its efficiency effect.[4] When innovating the incumbent monopolist replaces her own profits while the potential entrant has no pre profits to replace at all. Aghion and Howitt (1999) show these mechanisms in a theoretical model. More intense competition raises innovation activities, because it reduces incumbent's pre-innovation profits more than it lowers its post innovation profits. The empirical evidence for this second strand is larger than for the first strand. We refer to studies like Geroski (1990), Nickell (1996), Blundell, Griffith and van Reenen (1995), Blundell, Griffith and van Reenen (1999) and Carlin, Schaffer and Seabright (2004) that find a positive relationship between competition and innovation (or productivity).

[4] When the monopolist does not innovate, he loses his current monopoly profits. This gives an incentive for the monopolist to innovate.

Recent view: nonlinear relation competition and innovation

Having both a positive and a negative relationship in the literature, the third strand in the debate is predictable: the connection between competition and innovation can be characterized as an inverted U-shape. Reconciling theory and empirical evidence, Aghion et al. (2005) develop a model where low (high) levels of competition have a positive (negative) effect on innovation.[5]

The intuition behind this inverted-U is as follows. There are two types of competition effects on innovation: escape competition effect and Schumpeterian effect.

In case of low levels of competition, the escape competition effect dominates. While preinnovation profits are reduced, increasing competition will raise the incentive of neck-and-neck firms to innovate because firms become the single front technology if they innovate. But if competition further intensifies, the balance between the two effects changes and the Schumpeterian effect (*i.e.* fiercer competition generates less R&D) will start to dominate, generating the negative part of the inverted-U curve between competition and innovation. Further increases in competition reduce the (post)innovation rents for laggard firms to become neck-and-neck with the leader again.

Hence, the inverted-U relationship arises due to a change in the composition of firms. Initially when competition is low, industries are most often leveled. So if competition increases industries become more frequently unleveled, whereas the chance that they become leveled again reduces as for laggards it is increasingly difficult and costly to catch up. Stated otherwise, when competition is really fierce hardly any industry will remain leveled. Consequently, as the innovation rate is lower in unleveled situations, beyond some level of competition, innovation will decline, generating the inverted U. Moreover, Aghion et al. (2005) add the idea of neck-and-neck industries (or firms) where the difference in performance is small across firms as they have the same technology, whereas in 'leader-follower' industries firms have different technologies and, hence, different productivity levels. Due to more neck-and-neckness, the inverted U becomes steeper as the escape competition is larger.

Such inverted U-curve between competition and innovation can also occur in another way as there can be a trade-off between process and product innovation as well when competition is raised (see Boone (2000b)). At the industry level, this may then generate an inverted U-curve

[5]Note that it was Scherer (1967) who for the first time came up with the idea of an inverted-U relationship.

if total innovation expenditures (*i.e.* process and product outlays) are considered.

Boone (2000b) shows that a rise in competition may raise industrywide efficiency through more process innovation. But, this may reduce product variety or the number of products introduced to the market: less product innovation. The reason is that when competition becomes more intense, inefficient firms are forced to leave the market as a result of the selection effect of competition and lower costs of opponents (higher efficiency level from process innovation). This reduces the product variety (or product innovations) in this market. Moreover, more competition reduces profits and makes it for some firms less attractive to introduce a new product. Hence, a trade off may occur between process and product innovations at the aggregate level.

There are, however, two possibilities that may overturn this trade off. First, firms could also escape competition by product differentiation, and hence creating their own niches (see also van der Wiel (2010)). Second, lower profits due to more competitive pressure could act as a wake up call for managers. To avoid bankruptcy, managers have to look for new products that can generate additional profits. Hence, although process innovation is applied industrywide, innovation expenditures with respect to product innovation might go up as well in that particular industry.

The empirical evidence for an inverted U-shape between competition and innovation is scarce.[6] Besides Aghion et al. (2005), only Scott (1984) and Kilponen and Santavirta (2007) found significant evidence in favor of this form. For instance, the latter examines this relationship for the manufacturing companies in Finland between the years 1990 and 2001. In contrast, tested on a data set of Swedish firms, Tingvall and Poldahl (2006) find that the inverted-U relationship relation between competition and R&D is by PCM. Further, using firm level data Creusen, Minne and van der Wiel (2006b) tested the inverted U-shape for the Dutch retail trade but their results also rejected this view. Finally, Griffith et al. (2006) find no evidence for an inverted U-curve looking at an unbalanced panel of nine countries and 12 two-digit manufacturing industries over the period 1987-2000.

The following summarizes this section. Positive as wells as negative effects from competition on innovation can be found in theory and empirics, while recent literature suggests an inverse U relation between competition and innovation. Consequently, the implications for produc-

[6] Below in subsection 2.3, we show that this finding might also depend on the indicators used for competition and innovation.

tivity are similar: effects can be positive and negative. But recent theory indirectly provides indications that fiercer competition is always good for productivity. As a matter of fact, from Aghion, Blundell, Griffith, Howitt and Prantl (2006) one can deduct that a decline in innovation expenditures (of incumbents) in an industry can go hand in hand with higher aggregate productivity of that particular industry. The reason is that after intensifying competition, the least efficient domestic firm has no incentive anymore to imitate or to innovate due to the large productivity gap to the technological frontier. So the innovation expenditures of that industry decline. Yet it can be proved that aggregate productivity of that industry rises (see Kocsis, Lukach, Minne, Shestalova, Zubanov and van der Wiel (2009)). The reason is the entry of a foreign leader with the highest productivity level in that particular industry. That foreign firm replaces the least efficient domestic firm increasing aggregate productivity, but this entry is not seen (in statistics) as an innovation.

2.2. Further extension endogenous growth literature: distance to frontier

Following up on the fundamentals of earlier work of Aghion and Howitt (see Aghion and Howitt (1992) and Aghion and Howitt (1999)), the idea has been postulated that the distance to the technological frontier (*i.e.* the technology giving the highest possible level of output given the inputs) matters for countries or industries. For example, Aghion and Howitt (2006) describe a model where the growth performance of a country (or industry) also depends on its proximity to the technological frontier and what both innovation and competition mean in this respect.

A similar story can be told for the interaction between entry and the distance to the frontier. In this model (see Aghion et al. (2006)), entry threat is an exogenous parameter which measures the probability that a (foreign) firm enters the (home) market. The results of this model are the following. The impact of entry on innovation is non-uniform across firms and industries. Higher threat of entry leads to higher innovation expenditures and higher productivity growth of incumbents, which are already highly efficient (*i.e.* firms close to the frontier). These firms innovate more to prevent entry. However, increased entry (threat) discourages less efficient incumbents (*i.e.* firms far below the frontier) to spend on innovation. The reason for the heterogeneity in the incumbents' response to the entry threat is simple: while the costs of innovation are the same for all firms, the market leaders have a higher chance of retaining their leadership in the face of entry than the laggards have of gaining it.

2.3. Empirical issues

Linking competition, innovation and productivity is not only from a theoretical perspective an unsettled issue. Dealing with it in practice is a challenging case too and still in its infancy. The ambiguous empirical results with regard to competition and innovation may partly be related to doubtful indicators for competition and innovation. Two questions are highly ranked on the research agenda: (i) How to measure competition?, and (ii) how to measure innovation?

In the empirical literature, competition is often measured with variables like concentration, profitability, price cost margins (see *e.g.*, Domowitz, Hubbard and Petersen (1986), Blundell et al. (1995), Blundell et al. (1999), Nickell (1996), and Aghion et al. (2005)). Boone (2000a) and Boone et al. (2007) have shown that these competition measures are not monotone in competition. When competition intensifies due to more aggressive interaction between firms, the industry PCM may rise suggesting less competition. The reason is that PCM increases as a result of the reallocation of market shares from inefficient firms (with low mark ups) to efficient firms (with high mark ups). This paper uses, therefore, the profit elasticity (PE) as indicator for competition. This measure relates the firm's profit to its efficiency that can be captured by average variable costs. The intuition behind this indicator is that inefficient firms are punished more severely in terms of their profits when competition intensifies. This measure of competition is monotone for different parameterizations of competition (see *e.g.*, Boone et al. (2007) and Boone, van Ours and van der Wiel (2010)).

This paper employs the innovation intensity – innovation expenditures over employees – as indicator for the innovation activities instead of, for instance, R&D expenditures or patents. We do not use the R&D measure as this measure does not cover all the innovative efforts of firms.[7] The definition of innovation expenditures we use, is much wider than the one for R&D that is often used in the studies mentioned above. Our innovation indicator consists of, amongst others, costs of patent application, wages of R&D personnel, exploitation costs, and capital expenditure on buildings and equipment for R&D.

The same limitations pertains to the number of (applied for) patents or cited patents as indicator for innovation. This indicator is for example used in Aghion et al. (2005) and Kilponen and Santavirta (2007). The problem, here, is that not every innovative firm applies for a patent due to, amongst others, high costs of application and the desire to keep the innovation

[7] In our data set, the R&D expenditures are not even half as much as the innovation expenditures.

secret. This shortcoming is particularly relevant in non-manufacturing industries that we want to analyze as well. Innovations in (particular) services can hardly be patent. Hence, these industries should then be excluded from further analysis if an innovation measure based on patents is used or these industries are seen as non innovating industries in the analysis and, consequently, underestimating the extent of innovation.[8]

Finally, the studies from Tingvall and Poldahl (2006) and Aghion et al. (2005) illustrate that the results of the inverted U-shaped relation between competition and innovation can be sensitive to either the choice of competition measures or the innovation indicator. Tingvall and Poldahl (2006) find strong support for the inverted-U relationship using the Herfinfahl index (H). However, if this concentration indicator is replaced by PCM, then they do not find support for this form. Similarly, Aghion et al. (2005) do not find a statistically significant inverted U-shape when they use R&D-expenditures as indicator for innovation. Below we test the sensitivity of our results for using different competition measures.

3. Econometric specifications

3.1. Empirical framework

The basic idea in our framework is that both competition and innovation are major determinants of productivity, and productivity is one of the main goals for policy as productivity is the direct link to welfare.[9]

Our empirical model consists of components of studies from Nickell (1996), Griffith et al. (2004) and Griffith et al. (2006). It integrates the views of existing literature such as the two faces of R&D, the convergence debate and the existence of firm level heterogeneity in productivity.

We start with a production function taking on board mechanisms from endogenous growth

[8]For instance, Kilponen and Santavirta (2007) excluded the industries without any US patents.

[9]Similar to innovation and competition, human capital (or human skills) may have an impact on productivity. Seen as another input factor in the production process, human capital might help to speed up technology absorption and stimulating innovation. Sianesi and van Reenen (2003) provide a comprehensive overview of empirical studies on the effects of human capital on growth. However, in this paper, we ignore human capital as driver of productivity, because we have no data on human capital.

theory that both innovation and competition matter for economic growth. Therefore, in contrast to Nickell (1996) who focuses on the impact of competition on productivity, our model also includes the impact of innovation on productivity performance. As Griffith et al. (2004), we take into account views from the convergence literature and the role of the so called two faces of R&D (see also Cohen and Levinthal (1989)), where convergence between countries/industries depends on the absorption capacity of knowledge spillovers.[10] Finally, as competition and innovation are both endogenous variables, we explain these variables separately in our model.[11]

Productivity equation

Assume that each industry j produces in period t according to a standard neoclassical production technology

$$Y_{jt} = AF(L, K) = A_{jt} K_{jt}^{\alpha} L_{it}^{\beta} \tag{1}$$

where Y is (real) output, K denotes capital, L is labor, and A indicates total factor productivity (TFP). We assume that the elasticities of capital and labor (*i.e.* α and β) exhibit diminishing marginal returns to the accumulation of each factor alone and these elasticities are constant over time and across industries.[12] A is allowed to increase over time. Taking the natural logarithm, we write equation (1) as a decomposition of labor productivity (LP) growth into contributions of the capital intensity, the shifts in the industry's size (in terms of employed staff) and A[13]

$$\Delta lp_{jt} \equiv \Delta y_{jt} - \Delta l_{jt} = \Delta a_{jt} + \alpha \left(\Delta k_{jt} - \Delta l_{jt}\right) + \left(\alpha + \beta - 1\right) \, \Delta l_{jt} \tag{2}$$

Note that the parameter on industry size (*i.e.* labor) determines whether the firms in industry j can benefit from increasing economies of scale (*i.e.* if $\alpha + \beta - 1 > 0$).

The view of the endogenous growth theory that innovation and competition matter for growth enters our equation through A (see *e.g.*, Romer (1990), Griliches (1998), Aghion and Howitt (1992), Nickell (1996), Griffith et al. (2004) and Aghion et al. (2006)).[14] Taking a closer look

[10]Notice that Griffith et al. (2004) neglect competition issues.

[11]Competition determines innovation. But there may also be reverse causality as innovation may affect competition.

[12]That is: $\alpha, \beta \in < 0, 1 >$.

[13]Lower case letters mean logarithm of the variables concerned.

[14]In the endogenous growth literature, there is an ongoing debate about semi- versus endogenous growth theory (*i.e.* Schumpeterian growth theory). Roughly speaking, according to the semi endogenous growth

at the determinants of A (or TFP), we assume that industries may enhance their productivity growth in four ways.

First, based on theory, we expect that fierce competition forces firms in a particular industry to reduce 'X inefficiencies', and consequently affects productivity in the short term (see for instance Nickell (1996), for an overview). Weak competition makes managers and employees lax, or even seduces managers and employees to shirk.

Second, based on the convergence literature, the Schumpeterian growth theory takes into account the distance to the technological frontier as a measure of the potential for technology transfer. The larger the distance is the further firms lie behind the frontier and the greater the potential of productivity growth through technology transfers within an industry. For instance, Griffith et al. (2004), Conway et al. (2006) and van der Wiel et al. (2008) empirically show that the distance to the frontier matters for productivity growth. We examine whether or not this 'gap'(=g) also affects growth rates of TFP.

Third, innovation might have a direct impact on the rate of TFP growth by conducting R&D to develop new process technologies and/or new products (so called first face of R&D). Although, knowledge has the characteristics of a public good (knowledge spillovers), changes in TFP require real resources in terms of R&D (and human capital) to exploit those knowledge spillovers, but also to generate knowledge in the first place.

Finally, it can be argued that the ability of a firm (or industry) to benefit from knowledge spillovers depends on its own level of R&D activities and the distance behind the technological frontier. This idea is developed by Cohen and Levinthal (1989), who established the concept of the 'two faces of R&D'. In fact, R&D activities play two roles. On the one hand, R&D activities generate innovations. On the other hand, R&D improves the ability of a firm to identify, assimilate and exploit outside knowledge. Cohen and Levinthal (1989) label this as the learning or absorptive capacity of the firm. The absorptive capacity is largely a function of the firm's level of prior knowledge (see also Griffith et al. (2004)).

Going back to our model and include the preceding elements, we first assume that A depends on the stock of knowledge (S) and the intensity of competition (C). Industries with a larger (R&D)

models one should estimate a productivity equation in levels, whereas according to the endogenous growth theory one should estimate growth rates. See Madsen (2008) for a further discussion and why (time-series) evidence is more favorable for the Schumpeterian growth theory using growth rates.

knowledge stock or more intense competition have a higher level of TFP. Taking logarithms and differencing with regard to time, the rate of A depends on the growth rate of S and the change in C and X

$$\Delta a_{jt} = \nu_0 \Delta s_{jt} + \nu_1 \Delta c_{jt-1} + \nu_2 \Delta x_{jt-1} \tag{3}$$

with $\nu_0 > 0$, $\nu_1 > 0$ and X is a vector of control variables which (in theory) may include other (exogenous) explanatory variables that affect TFP-growth like non-technological innovations or spillovers from outside the industry. We assume that competition and those other determinants do not directly affect TFP but with a lag. In doing so, we also eliminate already some of the endogeneity bias in our framework.

Combining equations (3) and (A.2, see appendix A) gives an expression for TFP which depends on competition as well as innovation, and on a vector of control variables

$$\Delta a_{jt} = \mu_1 \, IR_{jt-1} + \nu_1 \, \Delta c_{jt-1} + \nu_2 \Delta x_{jt-1} \tag{4}$$

where IR is innovation intensity. Implementing equation (4) in the productivity equation (2), we obtain:

$$\Delta lp_{jt} = \mu_1 IR_{jt-1} + \nu_1 \Delta c_{jt-1} + \nu_2 \Delta x_{jt-1} + \alpha \left(\Delta k_{jt} - \Delta l_{jt} \right) + \left(\alpha + \beta - 1 \right) \Delta l_{jt} \tag{5}$$

Finally, we include the distance to the frontier and the second face of R&D to this equation. Summarizing we have:

$$\begin{aligned} \Delta lp_{jt} &= \mu_1 IR_{jt-1} + \nu_1 \Delta c_{jt-1} + \delta_1 g_{jt-1} + \delta_2 g_{jt-1} IR_{jt-1} + \delta_3 g_{jt-1} \Delta c_{jt-1} + \nu_2 \Delta x_{jt-1} \\ &+ \alpha \left(\Delta k_{jt} - \Delta l_{jt} \right) + \left(\alpha + \beta - 1 \right) \Delta l_{jt} + T_t + \varepsilon_{jt} \end{aligned} \tag{6}$$

where $g = ln(A_f/A)$. This term captures the gap and in that sense the potential technology transfers from the technological frontier (A_f).[15] To estimate this equation, we add an error term (ε_{jt}) to this equation assuming that this is serially uncorrelated. Moreover, we include time dummies T to control for macroeconomics shocks that affect TFP in all industries.

Innovation equation

[15] The pace of this catch up depends on the size of the estimated coefficient δ. For instance, patents may hamper spillovers and lower this coefficient.

What determines innovation? According to Tingvall and Poldahl (2006), there is no explicit theoretical model with preferred explanatory variables. From section 2 we infer that competition is important. The degree of competitive pressure affects the amount of investment in innovation. Following Aghion et al. (2005) the nonlinear relation between competition and innovative effort can be estimated by regressing the innovation rate of each industry on a quadratic function of competition intensity in the respective industry. Then the equation for the innovation rate for industry j in period t is

$$IR_{jt} = \varphi_1 C_{jt-1} + \varphi_2 C_{jt-1}^2 + \varphi_3 W_{jt-1} + T_t + \psi_{jt} \tag{7}$$

with W being other determinants of innovation like policy measures in the form of subsidies and the possibilities of cooperation between firms. We use lags as we assume that the impact of our explanatory variables takes some time to affect innovation. We also add an error term (ψ) and time dummies to this equation.

Theory provides some guidance for the parameters φ_1 and φ_2 as discussed in section 2. If $\varphi_1 > 0$ then for ΔC close to zero, the dominant effect is escape competition: firms innovate more when competition intensifies. In contrast, $\varphi_1 < 0$ then for ΔC close to zero, the Schumpeter effect dominates the effect of competition on innovation. In this case, competition discourages the innovative efforts of an industry as (laggard) firms find it difficult to reap the benefits of these efforts. But following Aghion et al. (2005) this relationship may also be nonlinear with $\varphi_1 > 0$ and $\varphi_2 < 0$.[16] If competition is low then competition is conducive to IR, whereas if competition is high then competition may discourage IR.

Competition equation

Given the complexity of modeling competition, our aim here is to estimate a simple equation relating competition to a number of determinants at the industry level.[17] We model competition as follows

$$C_{jt} = \lambda_1 IR_{jt-1} + \lambda_2 IR_{jt-1}^2 + \lambda_3 Z_{jt-1} + T_t + \zeta_{jt} \tag{8}$$

with Z a vector of other explanatory variables discussed below. Theory has put forward several (exogenous) determinants of competition (see *e.g.*, Tirole (1988), Cabral (2000) and Boone

[16] The downward sloping part of the inverted U-shape occurs beyond the level of C where: $2\varphi_2 C > \varphi_1$.

[17] As far as we know, empirical research that may serve as a reference is scarce (see Creusen, Minne and van der Wiel (2006a) for one of the exceptions).

(2000a)). Some of these determinants are related to market structure of industries and conduct of firms. Given our available data, Z includes variables that are linked to strategic entry barriers such as advertising costs and number of firms that enter and exit the market.[18]

We put I into equation (8) to take account of a possible feedback mechanism from innovation back to the intensity of competition at the industry level. The idea is that the higher the competition intensity in an industry, the higher the incentive for firms to reduce the competition intensity by differentiating their products from that of their competitors by creating niches. Hence, when the outlays for product innovation increase, this may eventually have a negative effect on the degree of competition. We use a one year lag as to take into account that our innovation indicator is an input measure and does not directly affect the extent of competition.

3.2. Industry averages and heterogeneity of firms

As explained below, this paper uses industry level data to limit the complexity of the econometric model. These industry data are averages based sums from firm level data.

However, we do not completely ignore information based on firm level data because it is well known that firms are heterogenous in their innovative efforts (see *e.g.*, Bartelsman and Doms (2000), van der Wiel and van Leeuwen (2003), Bartelsman, Haltiwanger and Scarpetta (2004) and van Leeuwen (2009)). This paper therefore links firm level data to industry level data to take account of the possibility of different responses of firms instead of assuming a representative firm response within an industry.[19] First, we already discussed the importance of the distance to the frontier as driver of industry's productivity growth. Having firm level data at our disposal, we can consider the relevance of this issue. Second, we also control for variances in efficiency per industry. More precisely, we add the variance of the average variable costs as control variable to the innovation equation (7) and to the productivity equation (6). The reasoning is that, at high levels of competitions, firms will adopt or use the existing technology quicker/better if the variation is small than when it is large (*i.e.* reducing X-inefficiencies).[20] Moreover, we relate this difference in efficiency to the extent to which industries are neck-and-neck. Aghion et al. (2005) argue that when industries are more neck-and-neck (*i.e.* lower

[18]Notice that these variables are not exogenous themselves.

[19]This is an interesting field for further research. As firm level data is most often confidential, statistical offices could add moments of variables based on firm level data without violating confidentiality. This opens a new dimension for research at the industry level.

[20]We do not include this variable into the competition equation due to probably high collinearity.

variance in efficiency across firms, or stated otherwise, firms operate at similar technological levels) the more positive the effect of competition on innovation. If variance is high, then an increase in competition will have a stronger negative effect on innovation. All in all, the peak of inverted U will be higher and occurs at a higher level of competition.[21]

3.3. Econometric issues

One difficulty in analyzing the relationship between competition and innovation is that both factors are not exogenous. In fact, competition might even be endogenous due to reverse causality with innovation. To illustrate, innovation can affect competition in two ways. First, high R&D-investments can reduce entry as if other firms have to follow this they form a barrier to entry thereby reducing competition (see Sutton (1991)). Second, innovation can take the form of product differentiation thereby reducing competition by creating niches and by making goods less perfect substitutes (see Boone (2000b)).

The study of Aghion et al. (2005) uses a set of policy instruments to cope with the endogeneity of competition due to innovation. These instruments (*e.g.*, privatization, EU Single Market Program, and Monopoly and Merger Commission investigations) are based on the introduction of policy changes across industries. These changes are likely exogenous because they are not related to innovation performance. Unfortunately, a similar data set with policy changes is currently not available for the Netherlands. We need another approach.

We use GMM estimation technique to cope with endogeneity problems. GMM exploits lagged explanatory variables as instruments after the equation has been differenced to eliminate unobserved fixed effects. To be more precise, our model consists of the three earlier mentioned equations: productivity, innovation and competition in equations (6), (7) and 8 respectively. These equations are estimated in first differences and all right hand side variables in our model are lagged with one year. Subsequently, the endogenous variables on the right hand side are instrumented with all the exogenous variables of the model including the second and third lagged of the endogenous variables themselves. Of course every instrument is the same for each endogenous variables on the right side. The first-stage regressions, where we estimate the

[21] Aghion et al. (2005) state that the fraction of sectors with neck-and-neck competitors is itself endogenous, depending upon equilibrium innovation intensities. But, in our view, lower variance could also be the result of intensifying competition selecting the best performing firms from inefficient firms and making the difference between the remaining firms smaller.

endogenous variables on the right hand side with the instruments, are tested with the Hansen's J test (test of over identifying restriction) and the GMM C statistic (test of endogeneity).

GMM estimation technique is to be preferred above for instance IV-techniques in the following situations. In case of heteroskedasticity the IV-estimates of the standard errors are inconsistent, and also the tests for endogeneity and overidentifying restrictions are then invalid (see Baum, Schaffer and Stillman (2003)). When facing heteroskedasticity of unknown form, GMM is the estimation approach. GMM makes use of the orthogonality conditions to allow for efficient estimation in the presence of heteroskedasticity of unknown form (see Hansen (1982)). One of the advantages of GMM is also that it can estimate the coefficients in a model without solving the model analytically (Verbeek (2004)). Therefore we can estimate our three equations separately.

For this analysis, we use industry level data instead of firm level data because we are then able to estimate our complete model with fixed effects regressions and instruments using GMM. We see this analysis as a first step to analyze firm level data in future research. An analysis of that type encounters a number of (econometric) challenges to deal with that we now can circumvent using industry level data. For instance many firms do not innovate at all, because of that a Tobit or Heckman model combined with two fixed effects regression equations for the other two equations is required. Also estimating a fixed effect Tobit is not that easy as extra assumptions are needed. Finally, at the firm level we have many missing observations for innovation mainly because all firms below 50 employees are sampled in the innovation survey (see below) and there is not much of a chance that a firm is present in the sample for the entire observed period.[22]

4. Data description

4.1. Data sources

We use a number of data sources. The most important ones are: Production Survey (PS) and Community Innovation Survey (CIS). Both sources are surveys from Statistics Netherlands and based on firm level data. Below, we briefly describe these two main sources of information in more detail.

[22]Moreover, firms above 50 employees might be missing due to non response.

PS

Data on, for instance, labor productivity is derived from PS, produced by Statistics Netherlands on a yearly basis. Data from PS is available for the years 1993 to 2006.[23] The PS is a sampled survey; only firms with more than 20 employees are included in the sample each year. For smaller firms, sampling fractions decrease, and consequently most smaller firms will have gaps in the data for several years. Moreover, Statistics Netherlands apply a rotating sample method to reduce the administrative burden of (small) firms. This also reduces consecutive observations of firms.

CIS

Data on innovation expenditures has been gathered from the Dutch section of CIS. CIS is a European harmonized questionnaire, held every two years, containing questions about innovative activities in enterprizes. Our innovation data covers the period 1996-2006. In fact, we use six consecutive CIS-surveys: *i.e.* CIS2 for 1994-1996, CIS2,5 for 1996-1998, CIS3 for 1998-2000, CIS3,5 for 2000-2002, CIS4 for 2002-2004, and CIS2005 for 2004-2006. CIS samples firms below 50 employees. Firms with less than ten employees are not included.

A main advantage of CIS is that after merging with PS one can directly relate firms' innovation activities to their performance and input factors. Yet CIS has shortcomings that limit the options for research. We mention the most important ones. First, the number of observations in CIS is low compared to that of PS due to a more limited sampling technique including different threshold for sampling (*i.e.* 50 versus 20 employees). This narrows the matching with PS. Additionally, CIS contains industries that are not present in PS and vice versa. This reduces the number of industries that can be examined. Second, CIS suffers from lower response rates and the responses can be selective as it is most likely that innovative firms are more inclined to respond than firms that do not innovate. Finally, CIS does not capture all issues of innovation. For example, information on human capital formation is not included.[24] Also, new firms entering the market are initially not included in the sample, while these firms may enter the market because they are innovative.

Taking the caveats of our sources for granted, after aggregating firm level data to industry level data, we merged the two data sources at the 3 (and sometimes 4) digit SIC-code in order

[23] Data for the industries transport and telecom only covers the period 2000-2006.

[24] Some European countries like Finland do take human capital issues into account.

to obtain information over the period 1996-2006, and in order to be able to construct lagged exogenous variables that we need for our estimation technique later on. Because we do not have CIS data in odd years, we lose observations. To keep enough observations, we interpolate the innovation data which may reintroduce some endogeneity.[25]

4.2. Variables

This subsection discusses the definitions of our dependent variables and the explanatory variables respectively that we use for estimating the equations for productivity, innovation and competition.

Labor productivity

Labor productivity is defined as gross value added per employee, and is derived from PS.

Innovation intensity

The expenditure on innovation divided by the number of employees is used as a measure of the innovation intensity of an industry.[26] As explained in equation (A.2), we use a ratio and this ratio comes from CIS. The innovation expenditures consist of the total costs of both contracted R&D and intramural R&D, including wages, exploitation costs, and capital expenditure on buildings and equipment for R&D.[27]

Measures of competition

With the data at hand there are several routes open for measuring competition. In this paper we use PE, (see Boone et al. (2007)). This measure results from an econometric specification that relates profits to efficiency captured by the average variable costs. This regression is applied to firms belonging to one and the same market (or industry). The parameter of this regression measures PE and comparing this parameter over time enables us to make inferences on changes in competition. The main idea of PE is that fiercer competition enables efficient firms to earn

[25] We use a linear interpolation. Besides having less observations, if we do not interpolate it is hardly possible to use GMM as we need observations for the years t, $t-1$ and $t-2$.

[26] We do not use sales in the denominator because, it turned out that the sales from CIS were not reliable. An alternative not applied here is to use the sales from the PS.

[27] Although the difference between product and process innovation expenditures can be important from a theoretical perspective (see Boone (2000b)), we cannot distinguish between both concepts as CIS does not provide separate figures for either product or process innovation expenditures.

relatively higher profits than their inefficient competitors. PE measures the percentage fall in a firm's profits in response to a 1 percentage increase in the firm's cost per unit of output.

An alternative measure for the extent of competition is the PCM. This measure refers to the firm's ability to set its prices above its marginal costs. This paper defines PCM at the industry level as gross profits as a proportion of total sales. Gross profits is value added minus total wages and the costs of intermediate inputs.

Both competition measures are based on firm level data from PS.

Physical capital

Physical capital is an input factor in the production process that determines output (see equation (1)). Unfortunately, time series for this type of capital are scarce, particularly at the firm level. Indeed, as we use an unbalanced panel data set based on a sample, it is very hard to construct a capital input measure for each firm in the data set as firms are not present in all consecutive years. Therefore, we employ an alternative indicator at the industry level. We aggregate all the depreciation expenditures within an industry. In fact, we use the depreciation rate (*i.e.* depreciation expenditures over gross value added) as measure for the capital intensity as can be deducted from equation (4). Figures originate from PS.

Non-technological innovations

Non-technological innovations in CIS are defined as changes in strategy, management, organization, or marketing. This type of innovation can enhance the performance of a firm or an industry. Particularly, firms may realize higher productivity gains if they simultaneously do technological and non-technological innovations (see Hempell, van Leeuwen and van der Wiel (2004)) than doing either technological or non technological innovation suggesting that those innovations are complementary. Put differently, technological innovations might be a necessary condition for improving the performance of a firm, but not a sufficient condition.

CIS provides only discrete data (yes or no) and no data on outlays for non technological innovations. We employ the percentage of firms (as percentage of total number of firms in an industry) that implement a non-technological innovation.

Distance to the frontier

The distance to the frontier (g) can be a determinant for productivity as explained in section

2. Due to data availability, for this study we limit ourselves to data for the Netherlands.[28] In theory, the highest productivity level of all firms in a given Dutch industry represents the (national) frontier. However, defined in such way this definition for the frontier is very sensitive to the presence of outliers in the data. To reduce this sensitivity, we look at the highest quartile in the labor productivity distribution in each 3-digit SIC class instead of the highest single labor productivity level of one particular firm in that industry. The productivity level of these firms in this quartile will be taken as the frontier and this level is related to the average productivity level of the industry to measure the (average) distance to the technological frontier. We expect positive estimated coefficients for g, including the interaction terms that captures the second face of R&D.

Cooperation

This explanatory variable comes from CIS. Firms are asked whether or not they cooperate with other firms with respect to their innovation activity. The variable we use is defined as the percentage of firms (as percentage of total number of firms) that reported cooperation.

Efficiency difference

As discussed in section 3.2, we want to test the importance of within industry variation. More precisely, we use the variance in average variable costs (variable costs over revenues) as indicator for differences in (cost) efficiency. Variable costs include wages and costs for intermediate inputs. If the variance is low, it points to small differences in performance across firms.

To some extent, this indicator is comparable to the variable that measures the distance to the frontier as they both measure differences within an industry. High values for both indicates large variation. But two distinctions are the following. First, this measure of efficiency difference uses the average variable costs, whereas the distance to the frontier is based on labor productivity. Second, if the distribution of the average variable costs is not normal (so not bell-shaped, with a peak at the mean) then these measures may provide different information. Relatively low variance can go together with a relatively large gap. Ignoring statistical outliers due to measurement issues, this means that most firms in this particular industry are relatively

[28]Ideally, the global technological frontier is needed for our analysis to incorporate the idea of the distance to the frontier as potential determinant for higher productivity. The global frontier can be defined as the highest productivity level of an individual firm in the world. This definition is not feasible in practice, because we do not have worldwide micro data at our disposal.

inefficient, while a limited number of firms are relatively efficient.

Funding

A government subsidy such as a R&D subsidy aims to stimulate innovation. Such subsidies reduce the innovation costs and help to internalize externalities. Our variable is based on the question in CIS whether or not the firm received a subsidy for its innovation activities. We use a ratio: the number of firms receiving a subsidy over the total number of firms (including non innovative firms) in the 3/4 digit SIC-code.[29]

Advertising costs

Advertisement expenses can form an entry barrier (see Sutton (1991)). For example, high advertisement expenditures may signal to potential entrants that they need a lot of advertisement to promote their products. However, high advertisement costs can also be a sign of intense competition in an industry (see *e.g.*, Creusen, Minne and van der Wiel (2006a)). Through advertising firms try to make their products known to people, more transparent (*i.e.* promoting its features), so consumers will buy their product instead of products of their competitors. This indicator, expressed as ratio advertising costs over revenues, is derived from PS.

Cost disadvantage ratio

The cost disadvantage ratio is an indicator for entry barriers caused by economies of scale.[30] Economies of scale act as an entry barrier for new firms to enter the market if small firms have a cost disadvantage compared to big firms.

The cost disadvantage ratio in this paper is defined as the ratio between the market shares of small and medium firms and the market shares of the large firms. More precisely, it is the ratio of the average labor productivity (defined as value added per worker) of the smallest firms responsible for 50 percent of the turnover in a market over the average labor productivity of the largest firms responsible for the remaining 50 percent of the turnover in a market. A low level of this ratio indicates economies of scale. This ratio comes from PS.

Turbulence

[29] We do not have (sufficient) data on the amount of innovation subsidies.

[30] Nonetheless, prudence is called when using this indicator. Firms could also produce higher output in case of constant returns to scale because those firms are more efficient.

The turbulence indicator is defined as the number of firms that actually enter plus the number of firms that actually exit an industry related to the overall number of firms active in this industry. Although not necessarily directly related to competition, a high level of turbulence indicates that there are a lot of firms entering and/or leaving the market reflecting intense competition. This indicator is based on data from the General Business Register (ABR).

GDP

We use the change in real Gross Domestic Product (GDP) in the competition equation as a crude proxy for an increase in market demand.[31] The idea is that in a booming economy, demand (temporarily) exceeds supply. Then competing firms can set their prices above marginal cost and gain high profits without being impeded by competitors' price-cutting. Hence, excess demand is expected to weaken competition among firms. This GDP-measure (we use the index) is based on data from the National Accounts of Statistics Netherlands.

Table 1: Descriptive statistics: Total economy

	Obs	Mean	Std. Dev.	Min	Max
Innovation intensity	1210	3.782	9.345	0.000	222.100
Competition (PE)	1179	5.341	3.781	-1.140	38.823
Labor productivity	1179	84.300	108.436	10.860	1044.185
Efficiency difference	1179	0.018	0.012	0.001	0.085
Non-technological innovations	1210	0.410	0.202	0.000	1.000
Log capital intensity	1179	1.715	0.827	-0.999	6.049
Number of employees	1179	17830	31217	45	249267
Turbulence	980	0.150	0.065	-0.005	0.529
Advertising costs	1027	0.009	0.013	0.000	0.127
Disadvantage ratio	1179	0.788	0.919	-14.640	18.879
GDP index	1207	131.553	7.286	115.103	142.276
Distance to frontier	1197	0.041	0.291	-2.138	1.125
Cooperation	1210	0.163	0.144	0.000	0.811
Funding	1210	0.175	0.184	0.000	1.000

Note: Based on regression sample for equation (6).

[31] We have no aggregate data for industry revenues per 3 digit industry. Moreover, such data probably enhances endogeneity issues more than using GDP.

Table 2: Descriptive statistics: Manufacturing

	Obs	Mean	Std. Dev.	Min	Max
Innovation intensity	745	5.430	11.520	0.009	222.100
Competition (PE)	738	6.632	3.934	-0.043	38.823
Labor productivity	738	64.586	46.800	18.197	537.201
Efficiency difference	738	0.014	0.009	0.001	0.065
Non-technological innovations	745	0.475	0.195	0.000	1.000
Log capital intensity	738	1.896	0.681	-0.435	4.650
Number of employees	738	6936	8237	105	55612
Turbulence	660	0.132	0.054	-0.005	0.450
Advertising costs	666	0.009	0.012	0.000	0.125
Disadvantage ratio	738	0.856	0.933	-6.293	18.879
Distance to frontier	743	0.014	0.300	-2.138	1.125
Cooperation	745	0.216	0.150	0.000	0.811
Funding	745	0.259	0.186	0.000	1.000

Note: Based on regression sample for equation (6).

4.3. Descriptive statistics

Tables 1 to 3 show descriptive statistics of the key variables we want to use in section 5. We present figures for the total economy, but also for manufacturing and services. We distinguish between these two sectors as there might be differences between manufacturing and services. For instance, industries in manufacturing are often more exposed to foreign competition than industries in services (*e.g.*metal industry versus retail trade).[32] Indeed, Creusen, Minne and van der Wiel (2006b) find evidence for the Netherlands that competition is stronger in the manufacturing industry than in services. Additionally, the exact meaning of innovation activities is less clear in services than in manufacturing. For example, innovation in services tends to be organizational or client oriented rather than of a technological nature which is less difficult to define and measure.

Comparing the descriptive statistic of tables 1 – 3, there are substantial differences between both sectors. Despite the fact that the innovation intensity, level of competition, funding, co-

[32]Exceptions are transport and aviation.

Table 3: Descriptive statistics: Services

	Obs	Mean	Std. Dev.	Min	Max
Innovation intensity	465	1.143	1.848	0.000	22.483
Competition (PE)	441	3.180	2.208	-1.140	14.117
Labor productivity	441	117.290	161.459	10.860	1044.185
Efficiency difference	441	0.025	0.013	0.001	0.085
Non-technological innovations	465	0.306	0.168	0.000	0.842
Log capital intensity	441	1.414	0.952	-0.999	6.049
Number of employees	441	36060	44307	45	249267
Turbulence	320	0.188	0.068	0.056	0.529
Advertising costs	361	0.008	0.014	0.000	0.127
Disadvantage ratio	441	0.675	0.885	-14.640	5.716
Distance to frontier	454	0.085	0.272	-0.819	0.903
Cooperation	465	0.076	0.079	0.000	0.528
Funding	465	0.041	0.057	0.000	0.421

Note: Based on regression sample for equation (6).

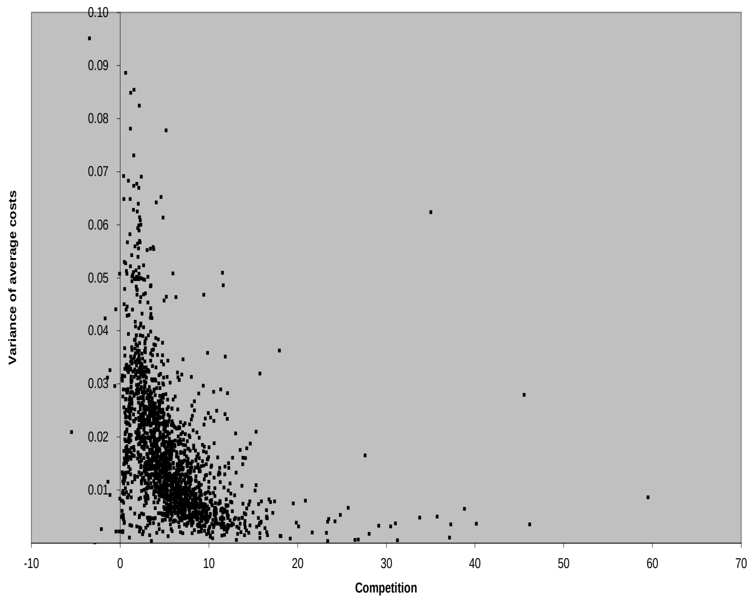
operation and capital intensity are all higher in the manufacturing industry, labor productivity is higher in services, particularly in wholesale trade, renting of automobiles and other transport equipment. Differences in the remaining variables are less pronounced between the manufacturing industry and the services sector. With respect to labor productivity and its key drivers, variances within the services sector are larger for labor productivity and capital intensity, but smaller for the innovation intensity and competition (according to the standard deviation).[33]

Finally, we correlate our indicator for efficiency differences (*i.e.* the variance of variable average costs) within an industry with the degree of competition to check whether the prediction of Aghion et al. (2005) is visible using simple correlations. They argue that the share of neck-

[33]We obtain negative results for turbulence, disadvantage ratio and distance to frontier. These observations do not affect the estimates because there are only a few of them. The explanation for these observations are as follows. The disadvantage ratio can be negative if the value added for an industry is negative. The distance to the frontier can become negative if the distribution of firms has a long tail where the average labor productivity is larger than that of the 75th percentile. The negative result for turbulence is due to data problems related to a lack of consistent time series.

and-neck industries (small variance of costs) will decline as competition increases. Translated to our situation, one would expect a positive correlation: more competition goes together with larger variances in variable costs suggesting less neck-and-neck industries. Figure 1 shows the result. We find a negative correlation, suggesting that the prediction of Aghion et al. (2005) is not right. A possible explanation for our finding is that as competition increases, inefficient firms leave the market and that reduces the variance. In the next section, we put the prediction of Aghion et al. (2005) to a further test taking account of other variables including industry and time fixed effects that might distort this correlation.

Figure 1: Competition and efficiency differences



5. Empirical results

5.1. Explaining productivity

This section begins with addressing the research question to what extent competition and innovation enhance the productivity performance in the Netherlands.[34] Our starting point is equation (6) where we relate labor productivity to competition, innovation, distance to the

[34]Results not reported in this section are available on request.

frontier, capital intensity and economies of scale.[35] As discussed in section 3 other explanatory variables captured by the control vector X may also contribute to a better productivity performance (*i.e.* higher TFP). Therefore, we tested other variables, but they were not significant. For instance, we added to our specification the following explanatory variables: non-technological innovations, the variance of efficiency, the interaction between non-technological innovation and innovation intensity, and the interaction between the variance in efficiency and innovation intensity.

Table 4 presents the econometric results with respect to the estimated labor productivity equation.[36] As discussed, we are particularly interested in the underlying sources of TFP. In general, these findings provide mixed evidence of explaining TFP-growth.

First, we discuss the impact of innovation and competition on productivity. Both explanatory variables seem to be drivers of productivity growth, at least for the total economy. Our empirical results confirm the assertion that competition may directly stimulate firms to attain higher productivity levels by reducing X-inefficiencies and/or removing inefficient firms. This is the case in columns (1) to (4), but not for services. In addition, the general idea that innovation is an important driver behind productivity growth is supported as well (see column 1). However, this result is not statistically significant if we control for other regressors. This result is in line with van der Wiel et al. (2008), who also did not find a significantly positive effect of R&D on the growth of TFP for the Netherlands. A reason for this finding could be that part of the (process) innovation is embodied in physical capital, already picked up by our capital intensity indicator.

Next, we do not find support for the view that the distance to the frontier itself acts as a driver of productivity at the industry level due to 'costless' technology transfers. Remarkably, the interaction of this variable with competition has a negative (but very limited) effect on productivity, suggesting the Schumpeterian effect dominates. More competition seems to induce

[35] As we estimate our equations in first differences unobserved industry heterogeneity is controlled for as long as this unobserved heterogeneity is constant over time.

[36] The tables report two tests: the Hansen's J statistic and the GMM S statistics. The former tests the validity of the instruments used, and rejection implies that the instruments are not valid. We find p-values larger than 0.05 in all cases, so our instruments are both relevant and valid. The p-value of the GMM S statistics is in almost all cases larger than 0.05, implicating that we cannot reject the null hypothesis that our variables are exogenous. One exception is variant 1 in table 4. Finally, we use the robust standard errors to calculate the t-values in all tables.

Table 4: Labor productivity

	(1)	(2)	(3)	(4)	(5)
Explanatory variables	Total	Total	Total	Manufact.	Services
Competition (-1)	0.0129***	0.00979**	0.0106***	0.0141***	0.00942
	(3.14)	(2.23)	(2.85)	(4.04)	(0.94)
Innovation intensity (-1)	0.00358**	0.00229	0.00133	0.000909	0.00144
	(1.98)	(1.53)	(0.81)	(0.48)	(0.19)
Distance Frontier (-1)		-0.0309	-0.0242	-0.0394	0.00325
		(-1.07)	(-0.57)	(-0.45)	(0.08)
Distance Frontier*comp (-1)			-0.0266*	-0.0390***	-0.0469
			(-1.65)	(-2.72)	(-0.90)
Distance Frontier*innov (-1)			-0.00341	-0.00370	-0.0129
			(-0.37)	(-0.28)	(-0.51)
Log capital intensity (-1)		0.291***	0.301***	0.274***	0.258***
		(9.47)	(9.72)	(8.46)	(5.25)
Economies of scale (-1)		-0.0188	-0.0124	0.0188	-0.155***
		(-0.82)	(-0.54)	(0.70)	(-4.75)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No
Hansen's J	0.6969	0.5098	0.3198	0.3001	0.3107
GMM C statistic	0.0396	0.6585	0.7991	0.5345	0.7330
Observations	1005	759	759	498	261

Note: Robust z-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The values reported for the Hansen's J test are the p-values for the null hypothesis of instrument validity. The values reported for GMM C (difference-in-Sargan test) statistics are the p-values for the null hypothesis whether variables are exogenous.

firms to abstain from technology transfers from the global frontier. Apparently, the costs of imitating global technologies are too high and they cannot be recovered in times of fierce competition. Another explanation is that with intense competition there might be less spillovers available as firms (in other countries) are more inclined to keep their information secret.

As expected, capital intensity positively and significantly correlates with labor productivity in all cases. With regard to the existence of economies of scale, although not significant, the results are in line with what is found in the literature. There is one exception, the coefficient is negative and significantly different from zero for services, suggesting substantial decreasing economies of scale on average.[37]

To conclude, we find evidence for a positive effect of competition on productivity, whereas the positive coefficient for innovation is weakly significant. These are partial effects of competition and innovation. Which of these two sources eventually drives productivity is to be determined. We consider next the effect of competition on innovation. After that, we take into account that innovation can also influence competition.

5.2. Explaining innovation

We start with explaining innovation using equation (7). For the control variable W we include the following explanatory variables: distance to the frontier, cooperation, efficiency difference and funding. Table 5 shows the results for the total Dutch economy (see column 1-3), manufacturing (column 4) and services (column 5) respectively.

Starting with the results for the total Dutch economy, table 5 clearly illustrates that it matters whether one takes into account other explanatory variables for innovation. In terms of variables used, columns (1) and (2) are to a large extent directly comparable to the approach of Aghion et al. (2005), whereas column (3) shows the results of equation (7) when one also includes other explanatory variables that might affect innovation. Aghion et al. (2005) use only competition, competition squared and year effects in their regressions, but ignore the potential impact of other determinants.[38]

Ignoring non-linearity, we find a positive and significant impact of competition on innovation (see column (1)). Extending our analysis and taking account of non-linearity, we do not find significant evidence for an inverted U-curve relationship between competition and innovation for the Netherlands when neglecting other explanatory variables (see column (2)). However, conditional on those other variables, we come up with a statistically significant inverted U-curve

[37] This is in contrast with findings of Kox, van Leeuwen and van der Wiel (2010), but they limit their analysis to the (European) business services. Moreover, they differentiate within industries and find increasing returns to scale but mainly for small firms.

[38] They use other determinants but these determinants are only included as instruments for competition coping with the endogeneity problem (*i.e.* policy instruments (see section 3.3) and other instruments like import rate).

Table 5: Innovation

	(1)	(2)	(3)	(4)	(5)
Explanatory variables	Total	Total	Total	Manufacturing	Services
Competition (-1)	0.677*	-0.113	0.198**	0.175*	-0.120
	(1.88)	(-0.18)	(2.08)	(1.67)	(-0.64)
Competition (-1) squared		0.0271	-0.00696**	-0.00652*	0.0160
		(0.90)	(-2.31)	(-1.94)	(0.84)
Distance to frontier (-1)			0.180	0.291	-0.314
			(0.59)	(0.74)	(-1.40)
Cooperation (-1)			0.978	0.565	0.449
			(0.57)	(0.30)	(0.27)
Efficiency difference (-1)			6.574	1.453	7.971*
			(0.73)	(0.12)	(1.62)
Funding (-1)			-0.213	-0.309	-0.363
			(-0.19)	(-0.25)	(-0.14)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No
Hansen's J	0.9683	0.7138	0.6332	0.5850	0.9438
GMM C statistic	0.0911	0.5109	0.3808	0.5051	0.2750
Observations	1210	1210	822	558	264

Note: Robust z-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The values reported for the Hansen's J test are the p-values for the null hypothesis of instrument validity. The values reported for GMM C (difference-in-Sargan test) statistics are the p-values for the null hypothesis whether variables are exogenous.

(see column (3)). So, more competition initially leads to higher innovation and then to lower innovation expenditures per employee.[39] Looking at the data more closely, it turns out that 3 percent of the observations have competition intensities beyond the innovation maximizing level, mainly located in the manufacturing industry. Therefore, differentiating between manufacturing

[39]Notice that this result could be related to a different sample as the number of observations differs between column (2) and column (3) of table 5. This different sample is due to missing observations for the other explanatory variables. We checked for this argument. The inverted U-curve is also present if we run the variant reported in column (2) on the smaller sample, yet the shape is less steep.

and services, it turns out that this macro finding rests upon the conditions in the manufacturing industry. There is no evidence for an inverted U-curve in Dutch services, whereas the outcome for the Dutch manufacturing is significant at the 10 percent significance level.[40] The latter corresponds with Aghion et al. (2005) as they only analyzed UK manufacturing.

The coefficients of the other explanatory variables are not significant, except for the indicator on differences in efficiency within an industry.[41] This indicator correlates positively and significantly with the innovation intensity for services at the 10 percent confidence level. So high variance in variable costs correlates with more innovation, while one would expect a negative correlation: firms innovate to escape their competitors that have more or less the same efficiency level. An explanation for this finding might be that lagging firms in services still have enough incentives to catch up due to low levels of competition in this sector of the economy. The descriptive statistics show that competition is less intense in services than in manufacturing. Appendix B contains additional estimations where we consider a subsample of our data investigating the theoretical predication in Aghion et al. (2005) that the inverted U shape relationship between competition and innovation should be steeper in more neck-and-neck industries (*i.e.* industries with less variance in costs or industries closer to frontier). This prediction is, however, not consistent with our data.

The absence of significant determinants explaining innovation in services underlines the common view that innovation is hard to measure in services, even with the availability of CIS.

Interestingly from a policy perspective, we do not find evidence for a positive impact of an innovation subsidy to stimulate innovation. The coefficient of funding is not significant at any confidence interval. This finding suggests that if we distinguish between stimulating innovation by either competition or by innovation subsidies then it makes more sense for policy makers to use the former as this policy option appears to be the most promising one.

Apparently, competition is the most important determinant of innovation and this determinant is not always conducive to the innovation expenditures. Taking the outcome for manufacturing, the competition intensity in terms of PE that maximizes the innovation level is approximately

[40]Our results for services are in line with Creusen, Vroomen, van der Wiel and Kuypers (2006). They found no evidence for an inverted U in the Dutch retail trade.

[41]We tested also non technological innovations as additional control variable, but this variable was not significant either.

13. This implicates that ten percent of the manufacturing industries operated at least one year beyond this maximal level in the period 1996-2006. When competition becomes too fierce it may therefore have a negative effect on productivity via lower innovation expenditures. However, combining the estimation results presented in table 4 and table 5 by replacing innovation for competition and other explanatory variabels in the labour productivity equation, it turns out that this negative effect is at levels of competition that are far beyond levels observed in general.[42] Hence when it comes to productivity, more intense competition is always better.[43]

5.3. Explaining competition

After examining whether competition affects the size of innovation expenditures, this subsection investigates this causality the other way round by estimating equation (8).

The idea behind this alternative channel from innovation to competition is that (product) innovation leads to more product variety (or more product differentiation). This creates (new) niches in markets with lower intensity of competition as a consequence (see also Boone (2000b)). Or, high levels of innovation expenditures form an entry barrier reducing the degree of competitive pressure (see Sutton (1991)). GDP, the disadvantage ratio, turbulence indicator (*i.e.* the ratio of death and birth of enterprizes over the number of active enterprizes in an industry) and advertising costs are included as control variables into equation (8).

Table 6 presents the results for five variants. For both the total economy (columns 1-3) and services (column 5), the empirical evidence for this feedback mechanism from innovation back to competition appears to be absent.[44] But in manufacturing, this mechanism is present and statistically significant at the 5 percent level. Hence, more innovation will initially lead to more intense competition, but beyond some level of innovation, more innovation expenditures will have a negative effect on measured competition in the Dutch manufacturing industry. Looking at our data set, this happens occasionally. It turns out that there were three manufacturing

[42] For the total economy, this level of PE is almost 600, and for the manufacturing industry with 1200 even much higher.

[43] Estimation of the reduced form of the labor productivity equation supports these findings for a large range of PE values.

[44] It can be argued that longer time lags than one year are needed for this channel because innovation will not directly have implications for the intensity of competition. Due to the limited number of observations we cannot take more lags into consideration without losing significance.

Table 6: Competition

	(1)	(2)	(3)	(4)	(5)
Explanatory variables	Total	Total	Total	Manufacturing	Services
Innovation intensity (-1)	-0.0671	-0.0112	0.300	0.506**	-0.358
	(-1.25)	(-0.12)	(1.62)	(2.50)	(-1.57)
Innovation intensity (-1) squared		-0.000260	-0.00209*	-0.00341**	0.0126
		(-0.49)	(-1.72)	(-2.57)	(0.54)
GDP (-1)			-0.00509	0.0216	-0.0442
			(-0.07)	(0.22)	(-0.90)
Disadvantage ratio (-1)			-0.505	-0.618	0.174
			(-1.34)	(-1.59)	(1.37)
Turbulence (-1)			3.116	1.662	7.212**
			(0.79)	(0.36)	(2.44)
Advertising costs (-1)			-32.52	-29.48	-30.52**
			(-1.47)	(-1.00)	(-2.18)
Year dummies	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No
Hansen's J	0.6013	0.6551	0.6942	0.6515	0.9336
GMM C statistic	0.3369	0.4171	0.5300	0.4348	0.0456
Observations	944	944	696	433	263

Note: Robust z-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The values reported for the Hansen's J test are the p-values for the null hypothesis of instrument validity. The values reported for GMM C (difference-in-Sargan test) statistics are the p-values for the null hypothesis whether variables are exogenous.

industries that were beyond this level in the period 1996-2006.[45] These industries consist of a relatively small number of firms. So, these industries are concentrated and entry might be hindered due to high levels of innovation that act as entry barrier.

Looking at the other explanatory variables, the coefficient of advertising costs is negative and (weakly) significant for services.[46] Apparently, higher advertising costs reduce the intensity

[45] The industries are: extraction of crude petroleum and natural gas (SIC 111), manufacture of office machinery and computers (SIC 300) and manufacture of aircraft and spacecraft (SIC 353).

[46] We also tested an alternative indicator for measuring changes in conduct as explanatory variable for com-

of competition as these costs are used as strategic weapon to lower product substitutability and to raise an entry barrier.[47] Finally, the coefficient of the turbulence indicator is positive and significant at the five percent level for services. Thus, higher turbulence correlates positively with competition. More entry or more firms leaving the market signals more intense competition.

To wrap up. We find (weak) evidence for the manufacturing industry that beyond some 'maximal' innovation level there may exist a negative feedback mechanism from innovation to the development of competition. However, these innovation levels are very high relative to mean values.

5.4. Robustness of results

Finally, this subsection focuses on the robustness of our findings using PCM as indicator for competition.[48] Our preferred measure for competition is PE. As discussed in Boone et al. (2007), this indicator is more robust with respect to the development of competition over time than other traditional indicators like PCM and concentration rates such as H.

At the industry level we find a negative correlation between PCM and PE as one would expect. Nevertheless, in approximately 40 percent of all observations, PCM suggests a rise (fall) in competition, whereas PE points to a fall (rise) in competition. Hence, these two competition measures differ and this may have consequences for our findings if we use PCM instead of PE. Besides measurement errors, this discrepancy between PCM and PE is due to the reallocation effect of market shares from inefficient to efficient firms (see Boone et al. (2007)).

To check the robustness of our results for productivity and the inverted U curve, we use PCM as alternative indicator for competition instead of PE. Tables 7 and 8 report the results of this

petition. Following Creusen, Minne and van der Wiel (2006a), we add a count dummy to the equation that is based on the knowledge that PE and PCM only differs in the interpretation of the change in competition in case of a change in conduct (see Boone et al. (2007)). This additional dummy did not differ significantly from zero in the estimates.

[47]Remind that in theory, advertising costs may also have a positive impact on competition because it may increase market transparency.

[48]PCM is a better measure for competition than H as H will always be wrong in case (inefficient) firms are forced to leave the industry due to more aggressive behavior by firms (see Boone et al. (2007)). This increase in H due to more intense competition goes against the traditional interpretation that a fall in H points to more intense competition.

Table 7: Labor productivity: Robustness check of PE as competition indicator

	(1)	(2)	(3)	(4)	(5)	(6)
Explanatory variable	Total	Manufact.	Services	Total	Manufact.	Services
Innovation intensity (-1)	0.00177	0.000907	0.00291	0.00125	0.000948	0.000602
	(1.07)	(0.49)	(0.41)	(0.77)	(0.51)	(0.08)
PE (-1)				0.00950**	0.0120***	0.00883
				(2.46)	(3.49)	(0.90)
PCM (-1)	-0.389	-0.752	-0.240	-0.0441	-0.149	-0.0267
	(-0.96)	(-1.39)	(-0.62)	(-0.14)	(-0.37)	(-0.08)
Distance Frontier	-0.0116	0.0169	0.0196	-0.0110	-0.0185	-0.000850
	(-0.26)	(0.18)	(0.49)	(-0.27)	(-0.21)	(-0.02)
Distance Frontier*comp	-0.000863	-0.00467	-0.0355	-0.0196	-0.0242	-0.0434
	(-0.04)	(-0.25)	(-0.70)	(-1.12)	(-1.42)	(-0.82)
Distance Frontier*innov	-0.00548	-0.0119	-0.0265	-0.00569	-0.00551	-0.0105
	(-0.55)	(-0.79)	(-1.13)	(-0.62)	(-0.40)	(-0.44)
Log capital intensity (-1)	0.289***	0.258***	0.233***	0.301***	0.268***	0.254***
	(8.39)	(6.98)	(5.15)	(9.17)	(7.89)	(5.19)
Economies of scale (-1)	-0.0121	0.0217	-0.151***	-0.0114	0.0215	-0.155***
	(-0.53)	(0.84)	(-4.56)	(-0.50)	(0.83)	(-4.62)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	No	No	No
Hansen's J	0.6742	0.5807	0.5516	0.2760	0.1881	0.3450
GMM C statistic	0.9473	0.9881	0.2503	0.9708	0.8463	0.7771
Observations	759	498	261	759	498	261

Note: Robust z-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The values reported for the Hansen's J test are the p-values for the null hypothesis of instrument validity. The values reported for GMM C (difference-in-Sargan test) statistics are the p-values for the null hypothesis whether variables are exogenous.

robustness check. Starting with the results for labor productivity in table 7, the coefficients for PCM are negative in almost all cases as one would expect (*i.e.* lower PCM signals fiercer competition and this has a positive effect on productivity). But none of these coefficients are

Table 8: Innovation: Robustness check of PE as competition indicator

	(1)	(2)	(3)	(4)	(5)
Explanatory variable	Total	Total	Total	Manufacturing	Services
PCM (-1)	-1.676	-6.132	-21.47	-22.91	-7.697
	(-0.17)	(-0.19)	(-1.19)	(-0.86)	(-0.57)
PCM (-1) squared		12.40	31.63	65.15	7.362
		(0.22)	(1.22)	(1.04)	(0.47)
Distance to frontier (-1)			-0.0329	0.112	-0.177
			(-0.10)	(0.27)	(-0.60)
Cooperation (-1)			-0.227	-2.066	0.623
			(-0.13)	(-1.00)	(0.34)
Efficiency difference (-1)			-1.361	-40.22**	12.26*
			(-0.07)	(-2.22)	(1.72)
Funding (-1)			-0.145	0.275	-0.00618
			(-0.13)	(0.22)	(-0.00)
Hansen's J	0.7750	0.7823	0.6698	0.5877	0.9860
GMM C statistic	0.7219	0.7499	0.1307	0.1326	0.5343
Observations	1201	1201	820	558	262

Note: Robust z-statistics in parentheses: *** p<0.01, ** p<0.05, * p<0.1. The values reported for the Hansen's J test are the p-values for the null hypothesis of instrument validity. The values reported for GMM C (difference-in-Sargan test) statistics are the p-values for the null hypothesis whether variables are exogenous.

significant at the ten percent significance level. Concerning innovation in table 8, the coefficients for PCM are not statistically significant either.

What do these findings mean? If only industry aggregate data are available, researchers can only use (industry) PCM as measure for competition since the estimation of PE needs firm level data.[49] But, our results show that PCM is not a significant explanatory variable for either labor productivity or innovation intensity at the aggregate level, whereas PE is. This is even the case when we divide industries into high concentrated industries and low concentrated industries based on the median of the H. It can be argued that in relatively low concentrated industries

[49]The PCM measure can be derived from aggregate industry data on revenue and variable costs.

PCM should perform better as proxy for competition than in high concentrated industries since the reallocation effects will be smaller, and hence the potential bias in PCM will be less (see Boone et al. (2007)). The regression results (not reported) do not support this statement since PCM is in both cases not a significantly explanatory variable for innovation.

6. Concluding remarks

This paper examines the relationship between competition, innovation and productivity for the Netherlands. In the theoretical and empirical literature there is no consensus on how competition affects innovation, and consequently productivity. Recent evidence suggests a non-linear relation between competition and innovation (see Aghion et al. (2005)) that might, therefore, have a negative impact on productivity when competition becomes too fierce. However, studies from Tingvall and Poldahl (2006), but also Aghion et al. (2005) itself, illustrate that the finding of an inverted-U shaped relation is sensitive to the choice of both the competition and innovation indicator.

We use industry level data for more than 150 3/4-digit SIC-industries based on aggregated Dutch firm level data covering almost the whole Dutch economy over the period 1996-2006. We employ the Profit Elasticity (PE) and innovation expenditures as indicators for competition and innovation respectively. The PE is a better measure than traditional indicators like concentration rates or price cost margins (PCM) for measuring competition (see *e.g.*, Boone et al. (2007)). Similarly, Brouwer (2007) claims that innovation expenditures are a better concept in this respect than for instance cited patents that were used in Aghion et al. (2005). Our model consists of three equations – labor productivity, innovation and competition – that are estimated using the Generalized Methods of Moments (GMM) and in that way coping with the endogeneity problem between competition and innovation.

The main findings of our analysis can be summarized as follows. First, we find strong evidence for a positive impact of competition on total factor productivity (TFP) at the industry level. Competition directly increases TFP by reducing X-inefficiencies and removing inefficient firms.

Second, this paper finds evidence that there may exist an inverted U-curve between competition and innovation for the Netherlands, at least for manufacturing industries. This corresponds with findings of Aghion et al. (2005). Apparently, competition is the most important determinant of innovation but this determinant is not always conducive to innovation expenditures. When competition becomes too fierce it may therefore have a negative effect on productivity via lower innovation expenditures. However, combining all our estimation results, it turns out that this negative effect is at levels of competition that are far beyond levels observed in general. Normally, ten percent higher competition intensity leads on average to 0.1 percent higher productivity.

Third, we find no evidence for a negative feedback mechanism from innovation back to competition for the aggregate economy. In the sense that high levels of innovation expenditures do not lead to lower competition intensity. For the manufacturing industry we do find indications for such a feedback, but this occurs at levels of innovation intensity that are hardly observed in our data set.

Lastly, as indicator for competition, we use the PE in this study. To test the robustness of this indicator, we also applied PCM as indicator. The latter turns out to be not significant in any equation concerning productivity or innovation, making the PE an interesting measure for future productivity research.

Our findings have implications for policy. Results reveal that the direct effect of more intense competition appears to increase productivity at the industry level in the Netherlands. But we also find that there may exist an inverted U-curve between competition and innovation. Consequently, there might be a trade-off between competition and innovation, and this has implications for policy makers. Yet, our combined results indicate that an indirect negative effect of competition on productivity through lower innovation expenditures arises only at very high levels of competition. Therefore, given current innovation policy intensifying competition is a promising option for policy makers to raise productivity: one of the main goals for policy in the Netherlands. Certainly, if we consider our findings for innovation policy. We do not find significant econometric evidence that our indicator for innovation subsidies positively affects innovation expenditures. The findings with respect to competition are in line with Kocsis et al. (2009) as they argue that an inverse U relationship between competition and innovation can go together with a positive effect of competition on productivity.

Summarizing the discussion, this paper provides evidence for a new look at the inverted U-curve between competition and innovation as found by Aghion et al. (2005). We claim that when it comes to productivity, more intense competition is seemingly always better in the Dutch case.

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Appendix A. Logs or no logs for innovation intensity?

On the one hand, one can assume that the stock of industry knowledge only increases with the industry's innovative effort (=I)

$$S_{jt} = \delta S_{jt-1} + I_{jt-1} \tag{A.1}$$

Assuming that depreciation of knowledge stock of capital is absent ($\delta = 1$) and using

$$\nu_0 \Delta s_{jt} = \nu_0 \frac{I_{jt-1}}{S_{jt-1}} = \mu_1 \frac{I_{jt-1}}{Y_{jt-1}} = \mu_1 \, IR_{jt-1} \tag{A.2}$$

Where $\mu_1 = \frac{\partial Y}{\partial S}$, $\nu_0 = \frac{\partial Y}{\partial S}\frac{S}{Y}$, and IR innovation intensity. Then the capital knowledge stock in equation (3) can be replaced for the innovation intensity.

On the other hand, it is also defendable to use logs (I) in equation (3) instead of the innovation intensity because IR can be part of the production function in a neoclassical framework in the same way as the other input factors K and L are. Note that then the meaning of a change in A becomes different as it does not include changes caused by innovation anymore. Innovation is treated as a separate input variable. We use the former way.

Appendix B. No steeper inverted U due to more neck-and-neckness

Table 9 shows the results for two variants based on a subsample of our data analyzing whether or not the inverted U between competition and innovation becomes steeper due to more neck-and-neckness as theoretically predicted by Aghion et al. (2005). This subsample includes industries with below median differences in average variable costs or below median distance to the frontier. It is assumed that those industries are more neck-and neck (or leveled) meaning less differences in applied technology exist between firms. Again, we find an inverted U for both variants, although not significant for the variant based on distance to the frontier (see column 3). Looking at the size of the coefficients of competition and competition squared, the theoretical prediction by Aghion et al. (2005) is, however, not supported because the inverted U relationship between competition and innovation is not steeper than that in our baseline results for the total economy (see column 1 versus column 2).

Table 9: Innovation: robustness checks

	(1)	(2)	(3)
Explanatory variables	Basic variant	Small variance	Close to frontier
Competition (-1)	0.198**	0.177*	0.224
	(2.08)	(1.70)	(1.26)
Competition (-1) squared	-0.00696**	-0.00750**	-0.0117
	(-2.31)	(-1.99)	(-1.38)
Distance to frontier (-1)	0.180	1.014	1.236
	(0.59)	(1.43)	(1.28)
Cooperation (-1)	0.978	0.535	2.039
	(0.57)	(0.24)	(0.78)
Efficiency difference (-1)	6.574	15.08	5.490
	(0.73)	(0.96)	(0.45)
Funding (-1)	-0.213	-2.631**	-1.714
	(-0.19)	(-2.56)	(-0.90)
Year dummies	Yes	Yes	Yes
Industry dummies	No	No	No
Observations	1090	399	450