Relaxing Competition through Product Innovation*

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Abstract

Preliminary and incomplete

We study the relation between competition and innovation. Using firm level data for the period 1993-2006 from the Statistics Netherlands, we first estimate the elasticity of each firm's profits with respect to its costs to measure the degree of competition each firm faces, as proposed by Boone(2008). We then use the estimated profit elasticity to explain firms innovation activity. Our results provide empirical evidence for the claim that more competition leads to more innovation but that firms innovate to release competitive pressure.

Keywords: competition, innovation, product differentiation

JEL classification:D21,D22, D43, L13

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1. Introduction

Firms innovate to raise their profits. This can happen in a number of ways. The innovation can reduce the firm's production costs (this is usually called a process innovation) and hence may increase the firm's profits relative to its competitors that do not innovate. A firm's profit can also increase due to a product innovation (*i.e.* new good or services). In this case, the innovation differentiates a firm's product from its competitors' products. This differentiation can be horizontal (preferred by some consumers but not by all) or vertical (preferred by all consumers if sold at the same price).[1] With such product innovation, the firm is able to raise its product margin for two reasons. One is that consumers like the product better and hence are willing to pay more. The other reason is that by moving away from its competitors the firm gains market power (competitive pressure is reduced) which allows it to raise its price.

In this paper we are interested in the effect of product differentiation related to making products less close substitutes, and hence less competitive. This effect is relevant for two reasons. The first is policy related. There is a debate whether there is a trade off between static and dynamic efficiency. The former relates to welfare with given technology (in the short term) and the latter relates to welfare due to innovations (in the long term). Traditionally, the answer depends on whether an increase in competition intensity leads to a fall or rise in innovation. Inspired by Schumpeters work (see *e.g.* Schumpeter (1934) and Schumpeter (1942)), positive as well as negative effects from competition on innovation can be found in theory and empirics, while recent literature points to an inverse U relation between competition and innovation: the positive effect dominates at low levels of competition and the negative effect at higher levels of competition (see Aghion, Bloom, Blundell, Griffith and Howitt (2005)). The effect we are interested in is where firms innovate in order to reduce the intensity of competition. So again there is a trade off between competition and innovation but with the causality going from innovation to competition intensity (instead of the other way around). The second reason why we are interested in this relation is research related. It follows from our analysis that competition becomes endogenous when firms innovate. Hence it needs to be instrumented when considering the relation between competition and innovation, especially in case of product innovation.

[1] To illustrate, everyone prefers a faster computer if sold at the same price (*i.e.* vertical product differentiation). However, some consumers prefer an Apple computer, others a Dell even when sold at exactly the same price (*i.e.* horizontal differentiation).

The way we identify the effect of product innovation reducing competition intensity is as follows. We use Dutch firm level data covering large parts of the Dutch economy over the period 1993-2006. Two data sources from Statistics Netherlands are merged containing figures to measure competition indicators and innovation indicators at the firm level. When we look at the association between competition and innovation, we find a positive correlation across all firms and industries. We find this positive correlation for two types of innovation indicators related to product innovation. The first type of innovation indicator captures whether a firm has applied for a patent. Since usually quite some time elapses between applying for a patent and introducing new products based on that patent, we conjecture that this variable is not affected by the endogeneity problem just described. That is, a firm that has applied for a patent is not (yet) able to use the patent to differentiate its products from its competitors, and hence affect the level of competition. The other type of indicator that we use is whether the firm has recently introduced new products in the market. If product differentiation plays a role, we expect to see an effect for innovation variables of this type on competition.

Indeed, once we look inside industries (by using industry or firm fixed effects), the correlation between competition and innovation remains positive for the variable based on patent applications but turns negative for variables capturing new products introduced in the market. That is, within a market (or industry) the firms that introduce new products are the ones that face relatively little competition. We interpret this as innovating firms differentiating themselves from competitors and in this way reducing the competitive pressure that they face in the market.

Summarizing we find that more intense competition stimulates an industry to innovate more, but within the industry the firms that have successfully introduced new products are the ones that face less intense competition.

This paper is organized as follows. The next section discusses the (empirical) literature. Data and variables for the empirical analysis are discussed in section 3. Section 4 explains our empirical strategy and shows some descriptive statistics. Section 5 presents our main results on the relationship between competition and product innovation and checks the robustness of these results. Section 6 introduces a model that captures that more intense competition leads to more innovation in an industry. But within the industry, the firms that introduce new products are the ones that move away from competitors and in this way reduce the intensity of competition that they face. Section 7 summarizes and concludes.

2. Empirical literature

Firms are seeking profits (or rents) and innovation can give firms a (temporarily) monopoly position or a cost advantage over competitors. This allows them to have a higher mark up. A rise in competition may enhance a firm's incentives to improve efficiency or to innovate with the aim to protect or enlarge its market share. But, competition may also discourage innovation as the rewards to innovation are reduced (see *e.g.* , Griffith, Harrison and Simpson (2006)). In fact, there are two general views on the relationship between competition and innovation.

First, the view of a positive effect of competition on innovation can be found in Schumpeter (1934) and Scherer (1980). The idea is that competition stimulates incumbents to innovate otherwise the firm is forced to leave the market. Aghion and Howitt (1999) formalize this mechanism in a theoretical model. More intense competition raises innovation activities by increasing the difference between post-innovation and pre-innovation rents.

Second, the view of a negative effect of competition on innovation originally stems from Schumpeter (1942). Fiercer competition generates less R&D, reducing the rate of innovation and hence economic growth. This is often called the 'Schumpeterian effect' of competition on innovation. The intuition is that because the expectation of high profits drives innovation, an increase in competition reduces innovation if it results in lower profits. Firms need (some) market power to limit access to their innovation and to provide the incentive to innovate. 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)).

Recent work by Aghion et al. (2005) comes up with an inverted U relationship between competition and innovation. At a low level of competition, competition has a positive effect on innovation, whereas at a high level of competition, it reduces innovation.

Papers such as 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 relation between competition and innovation, imply that there is no trade off between static and dynamic efficiency at all. But papers such as Aghion et al. (2005) that find a negative effect of competition on innovation imply an (ex ante) trade off. More competition leads to lower prices and hence enhances static efficiency. However, if more competition leads to less innovation, it reduces dynamic efficiency.

We document that there is a trade off between static and dynamic efficiency, but this one is ex post. Our results are consistent with the view that more competition makes industries more innovative. However, firms that have innovated manage (ex post) to reduce the competition intensity that they face (reverse causality). Thus we find ex post a trade off between dynamic and static efficiency. This finding has implications for policy makers as the message is different from an ex ante trade off: an increase in competition is always good for innovation.

We are not the first to point to the possibility of endogeneity of competition when firms innovate. Aghion et al. (2005) use policy instruments related to product market interventions that differ over industries and time to cope with this endogeneity problem.[2] In their paper, however, the estimated coefficients with and without instruments hardly differ. This can be seen as suggesting that endogeneity is not a problem. We show that when focusing on creating niches by product innovation, the endogeneity problem is present and actually quite severe.

3. Data

Here we outline the procedure followed to construct the panel data that we use. This panel data is obtained from matching two data sources from Statistics Netherlands – Production Surveys (PS) and CIS. Both sources are surveys from Statistics Netherlands and based on firm level data with the same unique identifier and a similar unit of observation (*i.e.* firm or enterprize). This unique identifier enables us to merge the two data sources at the firm level. The competition measure employed in this paper is derived from PS, whereas the innovation measures stem from CIS.

[2]Note that Aghion et al. (2005) discuss another endogeneity mechanism based on innovation as entry barrier.

3.1. Two sources: PS and CIS

The PS provide data on, amongst others, total sales, employment, value added and profitability on a yearly basis. Data from the PS is available for the years 1993 to 2006.[3] The PS is a sampled survey; only larger firms (*i.e.* 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.

In order to obtain reliable firm level data we performed several 'cleansing' activities. For instance, we removed: (i) observations of firms with no turnover and employment, (ii) the second observation of the same firm in one year, (iii) observation of year t+1 if a firm has identical output and employment data (or value added) in two consecutive years.

Data on innovation activities for our study has been gathered from the Dutch section of the CIS. The CIS is a European harmonized questionnaire, held every two years, containing questions about innovative activities in enterprises.[4] This questionnaire follows the guidelines of the Oslo Manual for collecting innovation data (see OECD and Eurostat (1997) and OECD (2005)). CIS provides figures for the input, throughput and output of innovation activities. It focuses, amongst others, on innovation expenditures and (the effect) on process and product innovations.

Our innovation data covers the period 1996-2006. In fact, we use six consecutive waves of CIS for analyzing the dynamics of innovation in connection with competition: *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 CIS4,5 for 2004-2006.[5] CIS only includes firms with at least ten or more employees, and samples firms with less than 50 employees.

The structure of all these CIS questionnaires is the same, but the (definition of the) variables

[3]Except for transport and telecom, data for these industries covers the period 2000-2006.

[4]The CIS was launched by a number of countries as a result of the OECD initiative for setting up guidelines for innovation surveys. Those surveys emerged from a growing concern about the weaknesses of the traditional R&D surveys (see van Leeuwen (2009)).

[5]We cannot use CIS1, covering the period 1992-1994, due to the use of different sampling frames. In contrast to other (Eurostat) countries, Statistics Netherlands has carried out two intervening surveys (*i.e.* CIS2,5 and CIS3,5).

included are not always identical. For example, both the definition of the indicator 'sales new to the market' and the indicator 'sales new to the firm' in 1996 are not completely the same as the definition of those indicators in 2006. In cooperation with Statistics Netherlands, we matched earlier variables as much as possible to the equivalent definition used in the last CIS.[6] Given our panel approach we only select variables from questions that are identical over time or are identical after some modification. Because of this we did not lose observations building our panel data set.

A main advantage of CIS is that after merging with PS one can directly relate firms' innovation activities to their performance in the product market.

CIS has several shortcomings that limit the options for research, particularly in terms of panel data (see also van der Wiel (2001)). 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. This narrows the matching with the PS, considerably reducing the number of observations in our panel data. And small firms are therefore less represented in CIS than in PS, while those firms might be considered as important sources of innovativeness. Moreover, linking firm level data from CIS over time creates a loss of data as most firms are not surveyed in consecutive waves. Hence, we miss the complete innovation history for many firms complicating our analysis. Additionally, CIS contains firms belonging to 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 than PS and the responses can be selective as it is likely that innovative firms are more inclined to respond than firms that do not innovate. Third, the use of consecutive surveys of CIS may lead to double counting of some innovation activities, and consequently lead to overreporting innovation. Take for instance CIS3,5 and CIS4. The former covers the period 2000-2002, the latter covers the period 2002-2004. Hence, the year 2002 is twice present, that is, as end year of CIS3,5 and as starting year of CIS4. Consequently, firms that are innovative in 2002 may have reported that twice (*i.e.* both in CIS3,5 and CIS4). This can lead to double counting of innovation activities and hence measurement errors for variables that are based on this three year reference period. Since there is no further information

[6] We are very grateful to Statistics Netherlands for their time consuming efforts to make the data of our CIS panel as much as possible comparable from 1996 to 2006. Given our knowledge of CIS, (one of the authors of this paper was one of the founders of the CIS in the Netherlands) we were able to make this CIS panel richer by making more variables comparable over time.

available, we cannot say anything about the size of this measurement error. Finally, CIS does not capture all relevant issues of innovation. For example, new firms entering the market are initially not included in the sample, while these firms may enter the market because they are innovative. The absence or low coverage of these starting firms may underestimate the importance of innovation. In our analysis we ignore these issues, but they should be kept in mind as caveats.

3.2. Variables

In order to analyze the relation between competition and innovation, we need appropriate measures for competition and innovation. This subsection explains which variables we use.

Profit elasticity

As competition measure, we use the profit elasticity (PE), which was introduced by Boone (2008) and Boone, van Ours and van der Wiel (2009). As argued in these papers, the PE is a robust way to measure competition. Other well known competition measures like the Herfindahl (H) index and the price cost margin (PCM) are less robust in the sense that they sometimes increase and sometimes decrease with the intensity of competition. Further, in order to use firm fixed effects in our analysis, we need a competition measure that varies between firms and correctly indicates competition. This is problematic with the PCM at the firm level. Firms that are less efficient will partly compensate their higher (marginal) costs by charging a higher price. However, it is unlikely that they can fully pass through their higher cost. Hence within an industry, firms with higher costs also have lower price cost margins. However, the standard interpretation is that lower PCM (here due to inefficiency) signals more intense competition. Industry average PCM is easier to interpret in terms of competition intensity,[7] but does not allow us to use firm fixed effects. Similarly, H also does not allow for firm fixed effects either. Hence, we do not use PCM and H in this paper.

The idea of the PE is to measure the slope of the relation between profits and efficiency. More intense competition makes the relation between profits and efficiency steeper. We use $PE_i = |d \ln \pi_i / d \ln c_i| > 0$ as a measure of competition, where π_i denotes firm i's profits and c_i its costs. Section 4 explains how we exactly implement PE in the data.

[7] Although as shown by Boone, van Ours and van der Wiel (2009) this is not a perfect competition measure either, especially in concentrated industries.

As discussed above, we are interested in whether or not firms differentiate their products in reaction to more intense competition. To identify this effect, we have chosen the following four innovation indicators from CIS that are closely related to product innovation.

Dummy applied for patent

This dummy indicates whether or not a firm applied for a patent during the relevant three year period. A patent in CIS is defined as a set of exclusive rights granted by a state (national government) to an inventor or their assignee for a limited period of time in exchange for a public disclosure of an invention.

This is the indicator that should not suffer (much) from endogeneity problems since there is quite some time between applying for a patent and implementing the patent in a successful product launch. This step between patent and product sold in the market usually takes on average 8 years, but with a lot of variation.[8] Since firms have only applied for patents, it is presumably too early for these innovations to affect revenues and hence PE as our indicator for competition.

With the following three innovation indicators we do expect an effect of product innovation on competition intensity.[9]

Dummy product innovation

A product innovation is defined as the market introduction of a new good or service or a significantly improved good or service with respect to its capabilities, components or subsystem during the relevant three years period. The innovation needs to be new to at least the firm, but it does not need to be new to its industry or market. In other words, it does not matter if the innovation was originally developed by the enterprize itself or by other enterprizes (*i.e.* imitation).

Dummy sales new to firm

This dummy variable takes value 1 for sales during the relevant three years period related to the introduction of a new or significantly improved product by a firm that was already supplied by some competitors on its market.

[8] Moreover, patent data are indicators of inventions, not necessarily leading to innovations.

[9] Note that the second and third indicator are a further distinction of the first one (dummy product innovation).

Dummy sales new to market

This dummy variable takes value 1 for sales during the relevant three years period related to the introduction of a new or significantly improved product by a firm that was new on its market.

We prefer to use dummy variables instead of, for example, the percentage of total turnover related to goods or services innovations new to the firm (or new to the market) for the following reasons. First, firms probably do not exactly know what the percentage is, but presumably they do know whether or not they have introduced new products. Second, the percentage sales of new products is itself affected by competition (if more competition leads to lower prices, it tends to raise sales), making the variable harder to interpret. Further, we prefer using the 'dummy product innovation' over the 'dummy process innovation' since our story is about product differentiation that may have an effect on the intensity of competition. Process innovation does not necessarily lead to reductions in competition.

Finally, we are aware that our indicators have weaknesses as well. With regard to patents, not every innovative firm applies for a patent due to, amongst others, high costs of application and a preference to keep the innovation secret. A disadvantage of this variable is also that firms have only applied for patents; they have not been granted (yet). Hence we do not know for sure whether the firms actually "invented" something new. Next, patents focus on new innovation activities ignoring the possibility of imitation that can also enhance firm's performance (see, inter alia, Griffith, Redding and van Reenen (2004) for the so called second face of R&D expenditures).

We do not employ R&D expenditures (or its broader concept: innovation expenditure) because this indicator is not useful for the question we are interested in. The main problem with R&D expenditures is that the relation with output in terms of innovation is not clear. Moreover, it can be affected by competition in a way that is not relevant for us. When competition is low, there can be generous R&D budgets which are wasted on less relevant things. As competition intensity goes up, the budget may go down but R&D workers may work harder as they worry about their firm's survival. Hence as competition intensity goes up, R&D output increases (the effect we are interested in) while R&D inputs may fall. In contrast, our output indicators (except applied for patents) directly measure innovation in the form of market introduction of a new good or service.

4. Empirical strategy and descriptive statistics

4.1. Empirical strategy

The empirical analysis proceeds in two-steps. First, yearly PEs are estimated for each firm in the sample. Then the correlations between the estimated PEs and different innovation measures are estimated.

In order to estimate PE the first step specifies the following functional form

$$\ln \pi_{it} = \alpha_i + \alpha_t + \beta_{st} \ln c_{it} + \gamma_{st} \left(\ln c_{it}\right)^2 + \epsilon_{it}$$

where $\pi_{it}$is the profit of firm i in year t, c_{it} captures its efficiency in year t , β_{st}, γ_{st} are industry-year specific parameters to be estimated and α_i and $\alpha_t$are respectively firm and year fixed effects.

In our application below we measure c_{it} as the firm's ratio between total variable costs and total revenues. Given the functional form chosen above, the PE for firm i at time t is then calculated as:

$$PE_{it} = \beta_{st} + 2\gamma_{st} \ln c_{it}$$

so that across industries and years the variation in the estimated PE is due to both the estimates β_{st} and γ_{st} and to the variation in the marginal cost c_{it} while within industries and years variation in PE is given only by variation in the marginal cost c_{it}. We do not constrain estimation in such a way as to guarantee that the estimated PE_{it} are negative (meaning a higher costs implies lower profits, as theory predicts). Rather, as 3% of PE_{it} are estimated to be positive, we replace them with missing values before using them in the second step of the analysis.

In the second step the absolute value of the estimated PE is then used as explanatory variable in a linear regression where the dependent variable is a dummy variable measuring innovation, I_{it}. In fact the variable I_{it} takes the form of the four different dummy variables discussed above, respectively measuring whether a firm "applied for a patent", "sold products new to the firm", "sold products new to the market" or "introduced a product innovation".

To estimate such correlations a simple OLS specification is first estimated

$$I_{it} = \alpha + \beta PE_{it} + \epsilon_{it}$$

which is likely to suffer from endogeneity as on the one hand PE is a determinant of the decision of whether to innovate or not but on the other hand innovation itself might reduce competitive pressure on the innovating firms. Moreover, it is conceivable that industries differ in their level of innovation activity without a direct causal relationship with competition. This correlation then simply reflects other institutional features of the industry. One way to take up this problem is by using fixed effects that remove any spurious correlation or endogeneity. Therefore, we also estimate specifications with different fixed effects:

- year fixed effects: $I_{it} = \alpha_t + \beta PE_{it} + \epsilon_{it}$
- industry fixed effects: $I_{it} = \alpha_s + \beta PE_{it} + \epsilon_{it}$
- industry and year fixed effects: $I_{it} = \alpha_s + \alpha_t + \beta PE_{it} + \epsilon_{it}$
- industry-year fixed effects: $I_{it} = \alpha_s + \alpha_t + \beta PE_{it} + \epsilon_{it}$
- firm fixed effects: $I_{it} = \alpha_i + \beta PE_{it} + \epsilon_{it}$
- firm and year fixed effects: $I_{it} = \alpha_i + \alpha_t + \beta PE_{it} + \epsilon_{it}$

The objective is to learn something about the structure of correlations in the data and the type of endogeneity affecting them. In all specifications, except those with firm fixed effects, the error term ϵ_{it} is clustered by firm in order to account for persistence in innovating behavior by firms.

In addition, the same specifications are estimated using the previous year PE_{it-2} rather than the contemporaneous PE_{it} as an explanatory variable. The aim is once again to understand more about the presence and, in case, the causes of endogeneity. The reason using PE_{it-2} instead of PE_{it-1} is the observation that the CIS survey is bi-annual and the variables measuring innovation refer to the year of the survey and the previous year. Using PE_{it-2} therefore ensures that the explanatory variable is not contemporaneous to the dependent variable and therefore more able to correct for endogeneity.

Finally, to further investigate and check the robustness of the results we also use a logit specification[10].

We use logit for the following reason: the outcome (response) variables of our product innovation measures are binary: 0 (no innovation) or 1 (innovation); as these indicators are binary the use of OLS-regression might be problematic because OLS ignores the discreteness of the dependent variable and does not constrain predicted probabilities to be between zero and one. A more appropriate model that handles binary variables better is the logit model with a cumulative logistic distribution function.[11] Using maximum likelihood estimation this model avoids events that occur with probability greater than one or less than zero. The probability of I_{it}=1 (or I_{it}=0) is P_{it} (or $1 - P_{it}$) and will vary across individual firms and years as a function of the PE_{it}

$$P_{it} = F(y_{it}) = \frac{e^{y_i t}}{1 + e^{y_{ti}}}$$

with

$$y_{it} = log(\frac{P_{it}}{1 - P_{it}}) = \alpha + \beta PE_{it} + \mu_{it}$$

where μ_{it} is the error term

In terms of size, the coefficients of this estimation do not have a direct intuitive interpretation as, for instance, the marginal effect of a change in competition should be calculated. And this marginal effect is not constant because it depends on the value of X (in our case the intensity of competition). However, in this study, we are mainly interested in the sign and significance of the coefficients of the explanatory variable, and this sign is the same as the sign of the marginal effect in all cases.

Again we also estimate specifications with different fixed effects: year, industry, both industry and year, industry-year, firm and both firm and year

As before, the same specifications are estimated using the previous year PE_{it-2}rather than the contemporaneous PE_{it} as an explanatory variable to correct for endogeneity.

[10]We also tried a probit specification. Results on the sign and size of the coefficients are exactly those obtained with logit. We therefore limit our discussion here to the logit specification.

[11]Another option here is a probit model. The choice between both models depends on the assumptions made about the error term. In case of the logit model, the cumulative distribution of μ_{it} is logistics, whereas μ_{it} is normal distributed in case of the probit model. As already mentioned, the results of both models are similar.

Table 1: Summary statistics: step 1

Variable	observations	mean	standard deviation
Profits	287971	1160.242	14888.74
Variable costs/revenues	287971	0.6538517	0.2968564
PE (absolute value)			4.337289

4.2. Descriptive statistics

For estimating PE we have approximately 288 000 observations at our disposal for approximately 160 SIC 3-digit industries over the period 1993-2006. After matching the two data sources CIS and PS, we obtained around 18 000 to 26 000 observations (depending on the type of innovation indicator) for estimations of the relationship between innovation and competition.

Table 1 reports summary statistics on profits (π_{it}) and our proxy for capturing efficiency (ratio variable costs/revenues (c_{it})) – the variables used in the estimation of the PE_{it} – and the result of the estimate of PE_{it} itself. There is wide variation in both profits and the level of competition as indicated by PE_{it} across industries.

Table 2 reports summary statistics for the different innovation measures I_{it} and our estimates for PE_{it}. These variables are used in the second step where we estimate the relationship between innovation and competition. Note that the number of observations of PE_{it} is much smaller here than in table 1 as innovation measures are available only for even years and therefore almost half of the estimates PE_{it} are used in each regression.Since the panel is unbalanced, the number of observations for PE_{it-2} is approxmately 60% smaller than that for PE_{it}.

With regard to our product innovation indicators, the distribution of innovative activities are highly skewed, with the majority of firms reporting no activities in any year.[12] Looking more precisely, firms reported having introduced a product innovation the most, whereas the dummy applied for patent is reported the least on average across industries and time.[13] The latter is not that surprising as patents are not used by every firm or in every industry.

[12]Not reported, but there are also significant differences between industries.

[13]The sum of the means of products ‘new to market’ and ‘new to the firm’ is not exactly equal to the mean of ‘introduced a product innovation’, as the number of observations differ partly due to the absence of observations for product innovation in CIS4,5.

Table 2: Summary statistics: step 2

Variable	observations	mean	standard deviation
PE (absolute value)	130721	5.314547	4.239405
PE-2 (absolute value)	80691	5.622764	4.660099
Applied for a patent	21184	0.0971488	0.2961673
Sold products new to the firm	26515	0.2360173	0.424641
Sold products new to the market	26515	0.1574203	0.3642035
Introduced a product innovation	18421	0.3486239	0.4765476

Table 3: Summary statistics: correlation matrix

	Newfrmd	Newmktd	Paap	Prodinn	PE
Sold products new to the firm	1.0000				
Sold products new to the market	0.4795	1.0000			
Applied for a patent	0.2815	0.3351	1.0000		
Introduced a product innovation	0.8920	0.6422	0.3250	1.0000	
PE	0.0857	0.0477	0.0519	0.0815	1.0000

Table 3 reports the correlation (coefficient) between our innovation indicators and competition. PE correlates positively with each measure of innovation, suggesting that more competition and more innovation goes together. The indicator ‘applied for a patent’ exhibits the least coherence with the other innovation indicators, suggesting that it picks up other innovative efforts as well.

5. Empirical results

5.1. Impact of competition on innovation

The OLS regressions reported in table 4 show a positive and significant correlation between PE and all the product innovation measures, meaning that higher competition is associated with higher innovative activities related to new or significantly improved products.

As explained above, the OLS estimates might be affected by endogeneity. If the endogeneity

Table 4: OLS regressions: Innovation and competition

	(1)	(2)	(3)	(4)
VARIABLES	paap	newfrmd	newmktd	prodinn
pe	0.00209***	0.0150***	0.00930***	0.0111***
	(0.000512)	(0.000672)	(0.000581)	(0.000845)
Constant	0.0840***	0.140***	0.0977***	0.271***
	(0.00380)	(0.00462)	(0.00397)	(0.00678)
Observations	20928	26205	26205	18252
R-squared	0.001	0.025	0.013	0.011

Robust standard errors in parentheses

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

is due to the fact that innovation reduces competitive pressure on innovative firms, then the estimated coefficients in table 4 are upward biased estimates of the effect of competitive pressure of innovation on productivity. The reason is as follows. For a given increase in innovation, the observed increase in competition is smaller than the underlying increase in competition (which is partly undone by firms differentiating themselves from competitors).

Surprisingly, at least at first sight, when we introduce industry or firm fixed effects, and irrespective of whether we also add year fixed effects or not, the findings are mostly reversed. Indeed, as reported in tables 5 and 6 (both without year fixed effects), a negative and significant correlation is found between PE and three out of four innovation measures: "sold a product new to the firm", "sold a product new to the market", "introduced a product innovation". Instead a positive correlation is still found between PE and the variable "applied for a patent".

Apparently, only across industries, higher competition seems to be associated with higher innovation, while within industries higher competition is associated with lower innovation. Yet the finding of a negative correlation between PE_{it} and I_{it} within industries can also be seen as evidence that in fact product innovation releases competitive pressure on the innovating firm.

Table 5: Sector fixed effects regressions: Innovation and competition

	(1)	(2)	(3)	(4)
VARIABLES	paap	newfrmd	newmktd	prodinn
pe	0.00124	-0.00459***	-0.00180*	-0.00300**
	(0.000926)	(0.00110)	(0.00100)	(0.00136)
Constant	-0.000954	-0.120	0.116	0.00231**
	(0.000714)	(2,675)		(0.00105)
Observations	20928	26205	26205	18252
R-squared	0.086	0.205	0.155	0.198

Robust standard errors in parentheses

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

Table 6: Firm fixed effects regressions: Innovation and competition

VARIABLES	paap	newfrmd	newmktd	prodinn
pe	0.00328**	-0.00643***	-0.00177	-0.00485***
	(0.00129)	(0.00144)	(0.00128)	(0.00171)
Constant	0.0761***	0.278***	0.169***	0.383***
	(0.00866)	(0.00952)	(0.00850)	(0.0122)
Observations	20928	26205	26205	18252
R-squared	0.7089	0.7228	0.7439	0.8158
Number of id	13739	16096	16096	12257

Robust standard errors in parentheses

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

Indeed negative correlations are found when the dependent variable is a variable measuring innovation introduced into the market, whereas a positive correlation is still found when the dependent variable is one that measures innovation not yet introduced into the market. One can argue that "applying for a patent" does not release competitive pressure on a firm as it has no effect on the output market yet, whereas "selling a product which is new to the firm" or "selling a product which is new to the market" or "introducing a product innovation" do directly affect competition in the market. The release in competitive pressure is therefore due to the innovating firm differentiating its product from those of its competitors in a market.

One could put forward an alternative story for innovating firms having lower PE levels due to better products. Assume that particularly efficient firms that innovate increase the quality of their products, and higher quality lead to higher marginal costs. Hence we get firms with high costs and relatively high profits (as they sell higher quality goods). This, however, does not lead to a flatter relation between costs and profits, but leads to a steeper slope and hence higher PE. In contrast, we find a negative effect of product innovation on PE.

In order to investigate these findings further,as explained in the previous section, we estimate again the equations above replacing PE_{it} with its first lag PE_{it-2}. The resuts from OLS regressions are reported in Table 7 Again a positive and significant correlation between PE and all the innovation measures is estimated, and again these finding is robust to the introduction of year fixed effects.

However, when we introduce sector or firm fixed effects, irrespective of whether we also add year fixed effects or not, the findings are not reversed anymore.Rather, as shown in Tables 8 and 9 below, most of the coefficients appear to be insignificant, but the few ones that are significant are now positive (as also the insignificant ones). As innovation at time t cannot release competitive pressure on the inovating firm at time $t-2$, the finding of positive coefficients seems to suggest that indeed not only across sectors higher competition is associated with higher innovation but also that within sector and within firm higher competitive pressure leads to higher innovation, which is however used by innovating firms to release competitive pressure.

5.2. Robustness

This section checks the robustness of the previous results to draw more reliable conclusions. We use the logit specification explained in section 4 to take into account that we use dummies that cannot be negative or larger than one.

Table 7: OLS regressions with PE lagged two periods: Innovation and competition

	(1)	(2)	(3)	(4)
VARIABLES	paap	newfrmd	newmktd	prodinn
pelag	0.00234***	0.0162***	0.00914***	0.0129***
	(0.000522)	(0.00102)	(0.000711)	(0.00124)
Constant	0.0875***	0.130***	0.0984***	0.259***
	(0.00417)	(0.00705)	(0.00502)	(0.00968)
Observations	17300	21879	21879	15150
R-squared	0.002	0.037	0.016	0.020

Robust standard errors in parentheses

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

Table 8: Sector fixed effects regressions with PE lagged two periods: Innovation and competition

VARIABLES	paap	newfrmd	newmktd	prodinn
pelag	0.000800	0.00118	-0.00129	0.00364***
	(0.000973)	(0.00113)	(0.00110)	(0.00131)
Constant	0.151	0.983***	0.0183	0.949***
		(0.0159)	(0.0155)	(0.0185)
Observations	17300	21879	21879	15150
R-squared	0.088	0.215	0.161	0.207

Robust standard errors in parentheses

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

Table 9: Firm fixed effects regressions with Pe lagged two periods: Innovation and competition

	(1)	(2)	(3)	(4)
VARIABLES	paap	newfrmd	newmktd	prodinn
pelag	0.00312**	0.00407***	0.00274**	0.00809***
	(0.00141)	(0.00150)	(0.00134)	(0.00177)
Constant	0.0820***	0.211***	0.142***	0.294***
	(0.0102)	(0.0104)	(0.00930)	(0.0132)
Observations	17300	21879	21879	15150
R-squared	0.7100	0.7177	0.7388	0.8146
Number of id	11166	13218	13218	10093

Robust standard errors in parentheses

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

Table 10: Firm and time fixed effects regressions with Pe lagged two periods: Innovation and competition

	(1)	(2)	(3)	(4)
VARIABLES	paap	newfrmd	newmktd	prodinn
pelag	0.00335**	0.00585***	0.00379***	0.00378**
	(0.00144)	(0.00152)	(0.00138)	(0.00179)
Constant	0.0705***	0.205***	0.102***	0.428***
	(0.0127)	(0.0137)	(0.0124)	(0.0195)
Observations	17300	21879	21879	15150
R-squared	0.7107	0.7204	0.7470	0.8236
Number of id	11166	13218	13218	10093

Standard errors in parentheses

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

Table 11: Logit regressions: Innovation and competition

	(1)	(2)	(3)	(4)
	paap	newfrmd	newmktd	prodinn
Without fixed effects				
PE	0.00455***	0.0158***	0.00970***	0.0184***
	(0.000535)	(0.000899)	(0.000749)	(0.00134)
Observations	18316	23191	23191	16425
Sector fixed effects				
PE	0.00123***	-0.00432***	-0.00147***	-0.00448***
	(0.000460)	(0.000856)	(0.000501)	(0.00114)
Observations	17753	23106	23088	16354
Firm fixed effects				
PE	0.0319**	-0.0283***	-0.0199**	-0.0304***
	(0.0139)	(0.00813)	(0.00866)	(0.0101)
Observations	1992	4738	3742	2815
Number of firms	715	1560	1207	1064

Standard errors in parentheses

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

Table 11 presents the results for using this logit specification estimation. The results are similar with respect to the signs to the previous ones and underlines our story that product innovation reduces the competitive pressure within industries. The coefficient for PE is positive for applied for patents whatever specific specification, whereas the sign of the coefficient of PE changes from positive to negative for the other innovation indicators when including industry or firm fixed effects in the logit estimation.[14]

We further test the robustness of the results estimating logit specifications with PE_{it-2} *rather than* $PE_{it.}$ *The results are reported in Table 12 Again a positive and significant correlation between the second lag of PE and most innovation measures is estimated and when using* PE_{it-2}*,these finding is robust to the introduction of not only year fixed effects but also sector and firm fixed effects (and irrespective of whether also year fixed effects are used). Again this suggests that not only across sectors higher competition is associated with higher innovation but also that within sector and within firm higher competitive pressure leads to higher innovation, which is however used by innovating firms to release competitive pressure.*

6. Model

We use the following framework to analyze the relationship between competition intensity and innovation. Firms can produce either a standard version of the product or a new version. We assume that standard products are closer substitutes than new goods. But creating a differentiated version of a standard product requires R&D investments.

We want the model to capture the following results that we found above. First, more intense competition in the standard products market leads to more innovation. Second, firms that have innovated and sell newly invented, differentiated goods today, face less intense competition today. If we do not control for firms' opportunities to innovate and we assume that intense competition in the standard products is negatively correlated with opportunity to innovate we find an inverse U relation between competition and innovation. Intuitively, if there are very competitive sectors in which innovation is close to impossible, then we find an inverse U between competition and innovation. If we control for firm's opportunities for innovation (by using firm fixed effects) the inverse U disappears.

[14]Again, not reported but findings are similar when time fixed effects are included.

Table 12: Logit regressions with Pe lagged two periods: Innovation and competition

	(1) paap	(2) newfrmd	(3) newmktd	(4) prodinn
Without fixed effects				
PE	0.00452***	0.0222***	0.0117***	0.0247***
	(0.000525)	(0.00106)	(0.000744)	(0.00138)
Observations	11614	14784	14784	11060
Sector fixed effects				
PE	0.0000691	0.00404***	0.00153**	0.00532***
	(0.000549)	(0.000880)	(0.000598)	(0.00132)
Observations	11218	14698	14666	10990
Firm fixed effects				
PE	0.00215**	0.00841***	0.00255	0.00887***
	(0.00322)	(0.00235)	(0.00233)	(0.00293)
Observations	1329	3321	2701	2016
Number of firms	493	1125	902	769

Standard errors in parentheses

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

Consider a utility function of the form

$$u = \left(\left(\int_S x_i^\alpha di \right)^{\frac{\beta}{\alpha}} + \int_N x_k^\beta dk \right)^{\frac{1}{\beta}} \tag{1}$$

where x_i denotes the output level of firm i and S denotes the set of firms producing standard goods and N is the set of firms producing new goods. We assume that new goods are shielded from competition from standard goods: $1 > \alpha > \beta > 0$. Intuitively, a new good is differentiated (one way or another) from existing goods (otherwise it would not be new). Hence consumers view this as being differentiated both from standard goods and from other new goods.

With this utility function, demand functions take the form

$$p_i^s(x_i) = \beta \left(\int_S x_i^\alpha di \right)^{\frac{\beta-\alpha}{\alpha}} x_i^{\alpha-1} \tag{2}$$

$$p_k^n(x_k) = \beta x_k^{\beta-1} \tag{3}$$

We assume that each firm i produces with constant marginal cost c_i which (to save on notation) is the same whether it produces a standard or new product. Firm i chooses x_i to maximize profits $p_i(x_i)x_i - c_i x_i$. Following the literature on monopolistic competition, we assume that firm $i \in S$ ignores the effect of x_i on $\int_S x_i^\alpha di$. It is routine to verify that this leads to the following output levels for producers of standard and new products resp.

$$x_i^s = (\alpha\beta)^{\frac{1}{1-\beta}} c_i^{\frac{-1}{1-\alpha}} \left(\int_S \left(\frac{1}{c_j} dj \right)^{\frac{\alpha}{1-\alpha}} \right)^{\frac{\beta-\alpha}{\alpha(1-\beta)}} \tag{4}$$

$$x_i^n = c_i^{\frac{-1}{1-\beta}} \beta^{\frac{2}{1-\beta}} \tag{5}$$

Substituting these expressions into the demand functions (2) and (5), we find the equilibrium profit functions:

$$\ln(\pi_i^s) = \text{constant} - \frac{\alpha}{1-\alpha} \ln(c_i) \tag{6}$$

$$\ln(\pi_k^n) = \text{constant} - \frac{\beta}{1-\beta} \ln(c_k) \tag{7}$$

In our empirical analysis, we use the profit elasticity $PE = \left| \frac{d \ln \pi_i}{d \ln c_i} \right|$ to measure competition. It follows from these equations that PE is lower for firms that have innovated than for firms selling standard goods because of the assumption that $\alpha > \beta$. Hence, ex post innovation relaxes competitive pressure on the firm.

To see the ex ante effect, let $\gamma(z, \omega_i)$ denote the cost function of inventing a new product with probability z. We assume that $\gamma(0, \omega_i) = 0, \gamma_z, \gamma_{zz} > 0$: R&D costs are zero if the firm does not try to innovate ($z = 0$), costs are increasing in the probability of finding a new product, z. Finally, we assume that costs are convex in the success probability z.

We allow for the fact that some firms may have more opportunities to innovate than others. This difference can happen on the sectoral level or at the firm level within a sector. On the sectoral level: in some sectors there may not be much scope to introduce new products. Bulk goods, like coal; container shipping; fruit, like apples etc. have been more or less the same over the past decades. In such sectors there is not much opportunity for product innovation. Within a sector, if there is scope for innovation, firms can choose different strategies. One strategy is to become the cheapest producer of the standard product. Firms following this strategy will not invest in an R&D lab and will try to hire low cost workers. A firm focusing on innovation, will invest in R&D facilities and hire high skilled workers to do R&D. Clearly, the firms focusing on a low cost strategy for standard goods and firms in sectors where there is no scope for innovation, will not react by innovating as competitive pressure changes (at least not in the short run).

The parameter ω_i captures this idea whether firm i has opportunity to innovate or not. Higher ω implies less opportunity: $\gamma_\omega, \gamma_{z\omega} > 0$ for $z > 0$. Hence as ω increases both the costs of R&D (if undertaken) and the marginal costs of R&D increase.

Firm i solves the following optimization problem

$$\max_z \{z\pi_i^n + (1 - z)\pi_i^s - \gamma(z, \omega_i)\}$$

With probability z the firm finds a new product and earns π_i^n with probability $(1 - z)$ it does not find a new product and earns π_i^s. If there is an interior solution, $z_i > 0$ solves

$$\gamma_z(z_i, \omega_i) = \pi_i^n - \pi_i^s \tag{8}$$

As long as there are enough firms producing standard products in the industry,[15] we find that

$$\frac{d(\pi_i^n - \pi_i^s)}{d\alpha} > 0 \tag{9}$$

[15] Note that equation (1) implies that producing a standard good becomes actually quite attractive when the set S is small. However, we know from the data that most firms produce standard goods and did not innovate. Hence the assumption that the set S is big enough is satisfied in our data.

Hence equation (8) together with the assumption that $\gamma_{zz} > 0$ implies that $dz_i/d\alpha > 0$. Firms that face more intense competitive pressure have a higher incentive to innovate. By introducing new products on the market, they manage to relax competitive pressure. Relaxing competitive pressure is more attractive, the more competitive the standard goods market is.

Finally, if α and ω are positively correlated we can explain why we find an inverse U relation between competition and innovation if we do not use firm fixed effects (not yet reported in the paper). Without fixed effects, there is a positive relation between competition and innovation which follows from equation (9). However, if α and ω are positively correlated, there will be firms with high PE (as α is high) who have close to zero innovation (because ω is high). Hence, allowing for a quadratic relation between competition and innovation, there is a tendency to pull the relation downwards for high PE: an inverse U. If we use fixed effects, we control for each firm's opportunity (ω_i) to do R&D. Then we only have the effect in equation (9) and we do not find an inverse U but a positive (ex ante) effect of competition on innovation.

7. Summary and conclusions

This paper focuses on the effect of product differentiation related to making products less close substitutes, and hence less competitive. More intense competition leads industries to innovate more. However, firms innovate to reduce competition. Hence within an industry, successful innovators of new products are the ones that face less intense competition after the innovation. We identify these effects of product innovation reducing competition intensity using Dutch firm level data covering large parts of the Dutch economy over the period 1993-2006. We exploit two types of innovation indicators to cope with reverse causality from innovation to the intensity of competition. One that measures whether or not an innovation is introduced into the market. The other type measures innovation not yet introduced into the market. We conjecture that this second type is not affected by the endogeneity problem. One can argue that the latter does not release competitive pressure on a firm as it has no effect on the output market yet, whereas the first type of innovation does directly affect competition in the market. The release in competitive pressure is therefore due to the innovating firm differentiating its product from those of its competitors in a market.

Our main findings are as follows. We come up with an alternative explanation for the negative correlation between competition and innovation, and hence for the trade off between static and dynamic efficiency. We claim, however, that the policy implication is the opposite: more competition is always better for (product) innovation in industries! However, firms that have innovated manage (ex post) to reduce the competition intensity that they face. Thus we find ex post a trade off between dynamic and static efficiency. Indeed, once we look inside industries (by using industry or firm fixed effects), the correlation between competition and innovation remains positive for the variable based on patent applications but turns negative for variables capturing new products introduced in the market. That is, within a market (or industry) the firms that introduce new products are the ones that face relatively little competition. We interpret this as innovating firms differentiating themselves from competitors and in this way reducing the competitive pressure that they face in the market.

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