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Publication date:
2007

Citation for published version (APA):
Boone, J., van Ours, J. C., & van der Wiel, H. P. (2007). *How (Not) to Measure Competition*. (TILEC Discussion Paper; Vol. 2007-014). TILEC.

TILEC Discussion Paper

How (not) to measure competition[*]

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April 13, 2007

Abstract

We introduce a new measure of competition: the elasticity of a firm's profits with respect to its cost level. A higher value of this profit elasticity (PE) signals more intense competition. Using firm-level data we compare PE with the most popular competition measures such as the price cost margin (PCM). We show that PE and PCM are highly correlated on average. However, PCM tends to misrepresent the development of competition over time in markets with few firms and high concentration, *i.e.* in markets with high policy relevance. So, just when it is needed the most PCM fails whereas PE does not. From this we conclude that PE is a more reliable measure of competition.

Keywords: competition, profit elasticity, measures of competition, concentration, price cost margin, profits

JEL classification: D43, L13

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1. Introduction

In the empirical IO literature several measures of competition are used. It seems fair to say that concentration measures, like the Herfindahl index (H), and price cost margins (PCM) are among the most popular ones.[1] However, from a theoretical point of view both measures have severe drawbacks (see below and, for instance, Tirole (1988)). Our paper introduces a new measure of competition that is more robust both from a theoretical and an empirical point of view. We call this measure the profits elasticity (PE).[2] PE is measured for a market and is defined as the percentage fall in profits due to a percentage increase in (marginal) costs. In all markets, an increase in costs reduces a firm's profits. However, in a more competitive market, the same percentage increase in costs will lead to a bigger fall in profits. The underlying intuition is that in a more competitive market, firms are punished more harshly (in terms of profits) for being inefficient.

Our paper argues that PE is a better competition measure than PCM and H. To make this point clear, we distinguish two ways in which competition can be intensified in a market: more firms in a market due to a fall in entry barriers and more aggressive conduct by incumbents. More firms entering a market tends to lower concentration in this market. Hence, more intense competition due to more entry is correctly picked up by a concentration measure like H. The problem with concentration measures as indicators of competition is that a switch to more aggressive behavior by firms (*e.g.* because a competition authority detects and abolishes a cartel that manages to raise price and divide the market between participants) forces inefficient firms out of the market (*i.e.* selection effect). This raises concentration, but should (clearly) not be interpreted as a fall in competition. Also an increase in competition tends to raise the market shares of efficient firms at the expense of inefficient firms. Such a reallocation (of market share) effect raises H as well. We show that in our data set this reallocation effect can dominate, leading to a (seemingly inconsistent) positive correlation between H and PE.

When PCM is used as a market measure of competition, it is usually calculated as market aggregate (variable) profits over market aggregate revenues. This can also be written as the weighted average of firms' PCM's where the weights are given by firms' market shares (see,

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[1]In antitrust, concentration measures are important both in merger cases and in abuse cases (see, for instance, Bishop and Walker (2002)). In the empirical IO literature, PCM is used as a measure of competition in papers like Aghion, Bloom, Blundell, Griffith and Howitt (2005), Nevo (2001) and Nickell (1996).

[2]The measure is based on theoretical research in Boone (2000)

for instance, Nickell (1996)).[3] An increase in competition tends to reduce firms' PCM's.[4] If competition is intensified due to a fall in entry barriers, PCM falls; correctly indicating more intense competition. However, if competition is intensified due to more aggressive conduct, the reallocation effect described above can counteract this effect. In particular, an increase in competition raises the market share (and therefore the weight in the calculation of the market average PCM) of efficient firms with high PCM's.[5] Hence the weight of efficient firms (with high PCM) goes up which can raise the market PCM. This is the main problem with the market PCM as a measure of competition that we focus on: an increase in competition due to more aggressive conduct can actually raise the market PCM due to the reallocation effect. We identify this effect in the data.

We also find evidence suggesting another problem with PCM can play a role as well. If a firm's costs fall over time, its PCM tends to go up. Such an increase in PCM should not be interpreted as a fall in competition. Indeed, conditional on a firm's costs, a high PCM indicates market power. But, conditional on price, high PCM reflects efficiency.

Using Dutch firm level data for about 250 markets over the period 1993-2002, we show that PE picks up the effects of competition in an intuitive way and, in fact, in a way similar to PCM. We consider the correlation between PE and market characteristics like labor income share, import penetration, average efficiency level of the firms etc. These correlations are comparable to the results found for PCM. But the results for H differ considerably from the correlations found for PE and PCM. From this we conclude that H is less suitable as competition measure than PE and PCM.

Although PCM and PE look similar, they are not identical. When considering the change in

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[3]When firm-level data is not available this is the only market PCM one can calculate. This is an advantage of the market PCM compared to PE which does need firm level data to be estimated. However, firm level data is becoming more widely available nowadays. Moreover, by comparing PE and PCM in our firm level dataset, we indicate in which markets it is (relatively) safe to use PCM as a competition measure.

[4]This is actually not always the case as shown in papers by Amir and Lambson (2000), Bulow and Klemperer (2002) and Stiglitz (1987). There an increase in competition (through an increase in the number of firms in the market) can actually raise some firms' PCM's (for given cost function). We do not address this problem in this paper.

[5]This effect can be partly eliminated by using the unweighted PCM as measure of competition (as in Aghion et al. (2005)). This reduces the problem caused by the reallocation effect to a certain extent (as shown in Boone, Griffith and Harrison (2005)) but does not remove it completely: an increase in competition tends to remove inefficient firms from the market with low PCM which raises the average PCM in the market.

competition, we find the following. In situations where the reallocation effect is strong, PCM and PE may differ in the direction of the development of competition (one suggesting that competition went up from one year to the next, the other that it went down). This happens where our measure of the reallocation effect is high, *i.e.* in concentrated markets with high H and few firms. Theory then suggests that in these cases PCM fails while PE still is a consistent measure of competition. Note that the effect of concentration implies that PCM and PE deviate in markets that are particularly interesting for a competition authority: in highly concentrated markets an increase in PCM can be caused by more intense competition. This strengthens the point made by Fisher (1987) that PCM is not a good measure of monopoly power.

The next section discusses the related literature. In section 3, we use simulations to illustrate the features of the PE measure. Further, we show circumstances under which PE and PCM deviate. Section 4 describes the data on competition measures and shows some keys statistics. Section 5 analyses the measures PE, PCM and H in more detail. It shows that PE and PCM are correlated in a similar way with market characteristics like labor income share, import penetration etc. Then we show that an increase in competition intensity tends to increase PCM (incorrectly suggesting softer competition) if H is high and the reallocation effect is large. Section 6 concludes. Appendix A and B respectively give details on the simulations and on how we constructed our data set. In appendix C we report a number of robustness checks on how PE is estimated.

2. Related literature

In the empirical IO literature there are numerous papers using measures of competition. The use of concentration as a measure of competition goes back to the structure-conduct-performance framework. High concentration is then seen as a signal of weak competition which leads to high prices and high price cost margins. See, for instance, Scherer and Ross (1990) for an overview. Although, H as representative of the concentration rate indicators is easy to calculate if firm-level data is available, its relation with competition is, however, not always straightforward as the discussion above showed.

The PCM also has a long tradition as a measure of competition. Some papers (like Aghion et al. (2005) and Nickell (1996)) calculate it directly as the profits-sales ratio. Others, first

estimate demand and cost functions and then calculate the optimal PCM for each firm under an assumption on the relevant competitive model for the firms in the sector. Examples here include Berry, Levinsohn and Pakes (1995), Hausman, Leonard and Zona (1994) and Nevo (2001). By comparing a direct estimate of the PCM (like the profits-sales ratio) with the PCM predicted under different competitive regimes, one can identify which competitive regime applies in a sector. This method has been criticized by Corts (1999) who shows how the transitory nature of demand shocks leads to overestimation of competition intensity. We do not take a stand on the issue of how the PCM should be estimated. However, because we want to give an overview of how the competition measures vary over markets, the direct way of calculating the PCM has obvious advantages. To illustrate, with the direct method we do not need to gather additional information for all the markets in our sample, like cost instruments, product characteristics and instruments for consumers' taste parameters (such as demographic variables).[6]

Hall (1988) developed a method to test for a positive PCM without actually calculating it directly. The idea is that under constant returns to scale and perfect competition, the Solow residual is not affected by instrumental variables like military spending and the oil price (Klette (1999) generalized this method by allowing for increasing returns to scale). We do not use this method for two reasons. First, the Hall-method tests whether there is either perfect competition or market power. In the markets where there is market power (most of the markets in his sample), the method does not provide a degree of market power. Second, for this method convincing instrumental variables are needed which we do not have for all the markets in our sample. Roeger (1995) adapts Hall's method by combining primal and dual estimates of the Solow residual. This allows him to estimate mark ups without the use of instrumental variables. However, for Roeger's method data is needed on the capital stock and the rental rate of capital. Constructing a capital stock is rather complicated with firm-level data, therefore we do not use this method to estimate PCM. Moreover, we are particularly interested in changes in the competition measures over time. Roeger's method only provides an average PCM over time.

The PCM is often interpreted in a normative way: lower PCM is "better" in the sense

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[6]In the estimation of the PE measure, similar issues arise. In particular, one can chose a structural method to derive the demand and cost curves and then from these curves calculate the profit elasticity. For the reasons mentioned, we do not use such a structural model in this paper.

that it is associated with higher welfare. Although this is true in a very simple model, in general there is no clear relation between PCM and welfare.[7] Further, as pointed out by Fisher (1987) the profits-sales ratio is not a good measure of monopoly power because the user cost of capital is hard to measure.[8] The PE measure avoids this problem for two reasons. First, admittedly a bit trivial, there is no simple benchmark for PE (like the –supposedly optimal– zero benchmark for PCM). As shown by Boone (2003) the welfare maximizing value of PE depends on the characteristics of a market, like the cost structure in the market and consumers' tastes. Second, it is not so much the levels of profits and costs that are important for PE. The crucial issue is how a change in (marginal) costs causes a change in profits. To the extent that capital costs are fixed costs, we actually do not need to take them into account (although we will show that high capital costs are associated with less intense competition). A related point here is that empirical evidence is mounting which shows that more intense competition leads to more innovation and higher efficiency (see, among others, Aghion et al. (2005), Klette (1999), Nickell (1996) and Porter (1990)). If less intense competition leads to higher (marginal) costs due to X-inefficiency or lack of innovations to reduce costs, PCM is reduced. This could cause an overestimation of competition using PCM. Again because PE does not focus on profits and costs *levels*, it avoids this pitfall.

The PE introduced here is reminiscent of the measure based on factor price elasticities used by Panzar and Rosse (1987). In particular, they show that the sum of the factor price elasticities of a monopolist's revenue, denoted by ψ, must be nonpositive: $\psi \leq 0$. Hence, if $\psi > 0$ for a firm, it is not a monopolist. If $\psi = 1$, the firms in the sector are in a long-run competitive equilibrium. In a monopolistic competition outcome one finds $\psi \leq 1$. The statistic ψ is derived as a test for monopoly. However, using ψ as a measure of competition has two main drawbacks. First, if $\psi \leq 0$, we actually do not learn anything, except that the sector is not in a long run competitive equilibrium. A negative sum of elasticities is consistent with both monopoly and oligopoly. In the oligopoly model used, one is the upperbound on ψ. There is no sense in which ψ closer to one implies a more competitive sector. Second, to calculate ψ one needs information on factor prices. This is usually harder to come by than information on revenue and costs. Moreover, we have no information on factor prices in our data set.

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[7]See, for instance, Mankiw and Whinston (1986) and Amir (2002) for examples where lower PCM does not imply higher welfare.

[8]Fisher and McGowan (1983) give a related criticism on the use of accounting rates of return to infer market power.

Finally, whereas we are mainly interested in competition in terms of aggressiveness of conduct, Bresnahan and Reiss (1990) and Bresnahan and Reiss (1991) focus on competition in terms of entry. They focus on geographically isolated markets (in the same market) to establish the relation between the size of the market and the number of firms in the market. This indirectly gives information on firms' conduct. As we are interested in the developments of competition measures economy-wide over time, we do not use this relative time-consuming method to derive information on market power.

3. Model

We use the following notion of competition. In a more competitive market, firms are punished more harshly in terms of profits for being inefficient. In fact, PE estimates a relation between firms' profits and (marginal) costs in a market. This section presents the theory underlying this measure. The starting point is that there are two ways in which competition can be intensified. First, competition becomes more intense as the number of firms in a market increases (for given conduct) due to a fall in entry costs. Second, competition becomes more intense as firms' conduct becomes more aggressive due to *e.g.* changes in consumer preferences. Using simulations we show that the competition measures PCM and H work well in the former case but not in the latter, this particularly involves H. We argue that PE picks up both forms of changes in competition correctly.

3.1. Introduction of profit elasticity

In any IO model, the relation between firm i's profit π_i and marginal cost level c_i is downward sloping. Higher marginal costs c_i imply –for given price p_i– a lower margin per unit of output sold. Further, higher marginal costs tend to lead to higher prices, which reduces the amount of output x_i sold. Roughly speaking, we use the following specification of this relationship

$$\ln(\pi_i) = \alpha - \beta \ln(c_i). \tag{1}$$

With this linear specification between $\ln(\pi_i)$ and $\ln(c_i)$, which can be viewed as a first order Taylor approximation, the slope β can be interpreted as an elasticity. It indicates the percentage

fall in profits due to a one percent increase in marginal costs. We call β the profit elasticity, PE.

To interpret PE, first consider a simple monopoly model where the firm faces a constant elasticity demand function $x = p^{-\varepsilon}$ where x denotes output and p the price charged. We assume $\varepsilon > 1$ and constant marginal costs $c > 0$. This monopolist chooses output level x to solve

$$\max_{x}\{x^{\frac{\varepsilon-1}{\varepsilon}} - cx\}$$

It is routine to verify that output is given by $x = \left(\frac{\varepsilon-1}{\varepsilon c}\right)^{\varepsilon}$ and profits by $\pi = \frac{(\varepsilon-1)^{\varepsilon-1}}{\varepsilon^{\varepsilon}}c^{-(\varepsilon-1)}$. Hence we find $\ln(\pi) = \alpha - \beta \ln(c)$ with $\alpha = \ln\left(\frac{(\varepsilon-1)^{\varepsilon-1}}{\varepsilon^{\varepsilon}}\right)$ and $\beta = \varepsilon - 1 > 0$. Hence in this case the linear relation between $\ln(\pi)$ and $\ln(c)$ fits the model perfectly. Higher β here implies that the monopolist faces a more elastic demand curve, which indeed limits the monopolist's market power. In general the fit will not be perfect and equation (1) is then interpreted as a linear approximation. Further, if the firm is not a monopolist but faces competitors, then ε is interpreted as the firm's own price elasticity or the elasticity of its residual demand curve (which exceeds (in absolute value) the market demand elasticity).

To get intuition for the case with more than one firm, consider the following standard Cournot model. There is a market where each firm i produces only one symmetrically differentiated product, faces a demand curve of the form

$$p(x_i, x_{-i}) = a - bx_i - d\sum_{j \neq i} x_j,$$

and has constant marginal costs c_i. This linear demand curve implies that the elasticity is not constant and hence equation (1) is not a perfect fit. The parameter a captures the size of the market, the parameter b captures the market elasticity of demand and the parameter d captures the extent to which consumers see the different products in a market as close substitutes for each other. Firm i chooses output x_i to solve

$$\max_{x \geq 0}\{(a - bx - d\sum_{j \neq i} x_j)x - c_i x\},$$

where we assume that $a > c_i > 0$ and $0 < d \leq b$. The first order condition for a Cournot Nash equilibrium can be written as

$$a - 2bx_i - d\sum_{j \neq i} x_j - c_i = 0. \tag{2}$$

Assuming N firms produce positive output levels, one can solve the N first order conditions (2). This yields

$$x\left(c_i\right) = \frac{\left(\frac{2b}{d} - 1\right) a - \left(\frac{2b}{d} + N - 1\right) c_i + \sum_{j=1}^{N} c_j}{(2b + d(N-1))\left(\frac{2b}{d} - 1\right)}. \tag{3}$$

We define a firm's variable profits as $\pi\left(c_i\right) = (a - bx\left(c_i\right) - d\sum_{j\neq i} x\left(c_j\right))x\left(c_i\right) - c_i x\left(c_i\right)$. These are variable profits in the sense that they do not include the fixed cost f.

A firm with marginal costs c_i enters the market if and only if $\pi\left(c_i\right) \geq f$ in equilibrium. This fixes the number of firms N that enter in equilibrium where we assume that more efficient firms enter first.

Since we cannot directly observe c_i in the data, we approximate marginal costs with average variable costs defined as $\frac{c_i x_i}{p_i x_i}$. Hence, the relation we are interested in is between $\ln(\pi_i)$ and $\ln\left(\frac{c_i}{p_i}\right)$.

To compare the behavior of the three competition measures, we use as starting point the standard Cournot model for the case with $a = 40, b = 30, d = 20, f = 0.004$. Further, we draw randomly cost levels c_i for 110 firms out of a lognormal distribution with mean 0.7 and standard deviation 0.08.[9] Now, we change competition in two ways: (i) we change the entry cost and (ii) we consider the effects of more aggressive interaction between firms. We begin with the first way.

[Figure 1 about here.]

Figure 1 presents a simulation with a change in the entry cost. The comparison presented in the figure is between a situation with high entry cost ($f = 0.02$) and low entry costs ($f = 0.004$). The relationship is steeper, PE is higher and competition more intense with low entry costs than with high entry costs, as one would expect. In this case, PCM and H are lower with the lower entry cost, where we define PCM as

$$PCM = \frac{\sum_{i=1}^{n}\left(p_i x_i - c_i x_i\right)}{\sum_{i=1}^{n} p_i x_i} = \sum_{i=1}^{n} \frac{p_i x_i}{\sum_j p_j x_j} pcm_i.$$

and H as

$$H = \sum_{i=1}^{n}\left(\frac{p_i x_i}{\sum_{j=1}^{n} p_j x_j}\right)^2,$$

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[9]More precisely, $\ln(c_i)$ is normally distributed with $\mu = 0.7$ and $\sigma = 0.08$.

In particular, PCM falls from 0.32 to 0.22 and H falls from 0.016 to 0.010. Hence, all three measures clearly indicate that lower entry barriers lead to more intense competition. This is true more generally: reductions in entry barriers leading to more firms in the market and therefore more intense competition are correctly picked up by all three measures.

Note that with the higher entry cost, firms' profits tend to be higher to cover this entry cost. Hence the observations with $f = 0.02$ feature higher values on the vertical $(\ln(\pi_i))$ axis. Second, prices will be higher with higher entry cost (fewer firms in the market). For given draws of c_i, the values of c_i/p_i shift to the left.

The second way to intensify competition is by more aggressive interaction between firms. In this case, we increase competition by making goods closer substitutes: raising d from 20 to 30.[10] We calculate the Cournot equilibrium. The small dots in Figure 2 give the relation between $\ln(\pi_i)$ and $\ln\left(\frac{c_i}{p_i}\right)$ before the increase in competition and the large dots the relation after competition has become more intense. After the increase in competition, the relation becomes steeper. Doing a simple OLS-estimation of PE with the data in this graph yields PE= 6.78 before and PE= 7.50 after competition is intensified. The number of active firms before and after equals 101 and 74 resp. Hence under the more competitive regime, inefficient firms can no longer enter and concentration increases. H incorrectly suggests that competition has become less intense, since the value increases from 0.010 to 0.014. The PCM falls here from 0.22 to 0.21. Hence PE and PCM correctly indicate that competition has increased after d goes up.

The reason why H incorrectly suggests a fall in competition when the interaction between firms has become more aggressive is the *reallocation effect*. As competition becomes more intense, market share is reallocated from inefficient firms (with low initial market shares) to efficient firms (with relatively high initial market shares). Some inefficient firms may even go bankrupt due to the intensified competition and leave the market. This raises concentration in the market incorrectly suggesting a fall in competition.

Because here the three measures can diverge, the simulations below entirely focus on changes in conduct leading to more intense competition. Since concentration always increases in re-

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[10]This is a fairly standard way in which competition is parameterized in the literature. See, for instance, Aghion et al. (2005), Blanchard and Giavazzi (2003) and Vives (2004). The intuition is that product differentiation gives firms some market power. Since products are different, there is no head-to-head competition between firms. Making goods closer substitutes, reduces this market power and intensifies competition.

sponse to more aggressive conduct, we no longer discuss H and focus on PCM and PE as measures of competition.

[Figure 2 about here.]

3.2. Simulations of competition measures

The previous subsection suggests that PE and PCM coincide in predicting the change in competition in both ways of intensifying competition. However, this is not always true. We use simulations to show that PE and PCM can point in opposite directions after an increase in competition in the case of changes in conduct. In such cases, PE usually points in the correct direction. Further, we show that two variables (*i.e.* H and reallocation effect) have some power in predicting when PCM incorrectly points to less intense competition. The simulations are based on the Cournot model with linear demand described above,[11] where $a = 40, b = 30$ and d equals (in the original situation) either 15 or 20. As above, competition is made more intense by increasing d with 10 (to 25 and 30, resp.). Firm i produces with constant marginal costs equal to c_i and faces a fixed cost that varies from $f = 0.004$ to 0.012. We assume that c_i is drawn from a lognormal distribution with mean 0.7 and standard deviation *stdev* which varies from 0.08 to 0.32. See table 6 in the appendix for the details of the parameter values in the simulations.

For each combination of parameters we draw 110 values for c_i, as above. We calculate which of these 110 firms can profitably enter (pay the fixed cost f) under Cournot competition, where firms are assumed to enter in order of efficiency (most efficient firms first). Then we increase d with 10. This makes goods closer substitutes and is seen as an increase in competition. We derive the new Cournot outcome, again calculate H, PE and PCM. This we do 100 times for each parameter constellation (with each iteration we draw 110 new values from the cost distribution). We count the fraction of times that a measure gets it right. That is, after the increase in d competition has increased and PCM should decrease and PE should increase to signal this.

An aggregate change in PCM for a particular market is made up from changes at the firm level, but also from the consequences of the interaction between firms in this market. Looking

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[11]These results do not only hold for the Cournot model, but also across other models as shown in Boone (2000).

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at the productivity literature, several methods have been developed to decompose an aggregate change (see Balk (2001) for an overview). We opt for a Laspeyres-type of decomposition. Therefore, we decompose the change in the PCM for a market in four different effects. In particular, we write

$$PCM_1 - PCM_0 = \sum_{i \in I_1} ms_{i1}pcm_{i1} - \sum_{i \in I_0} ms_{i0}pcm_{i0} =$$

$$\sum_{i \in I} \{ \underbrace{ms_{i0}(pcm_{i1} - pcm_{i0})}_{\text{within effect}} + \underbrace{pcm_{i0}(ms_{i1} - ms_{i0})}_{\text{reallocation effect}} + \underbrace{(pcm_{i1} - pcm_{i0})(ms_{i1} - ms_{i0})}_{\text{interaction effect}} \}$$

$$+ \underbrace{\sum_{i \in I_1 \setminus I} ms_{i1}pcm_{i1} - \sum_{i \in I_0 \setminus I} ms_{i0}pcm_{i0}}_{\text{change in active firms effect}} \qquad (4)$$

where $I_0(I_1)$ is the set of active firms before (after) the change in competition, $I = I_0 \bigcap I_1$ and $i \in I_1 \setminus I$ if both $i \in I_1$ and $i \notin I$. In words, the set I contains all firms that are active both before and after the increase in competition. Working with a balanced panel implies limiting the data to this set I. The set $I_0 \setminus I$ ($I_1 \setminus I$) contains firms that are active before the increase in competition but which are forced to exit after competition intensifies (firms that are active after the increase in competition but were not present before; in the simulations that we do below, this set is empty; in the real data, however, this set is not empty).

In the simulations it turns out that PE and the within effect are strongly correlated. Since the within effect (by construction) is not affected by the reallocation effect, in theory it is a better measure of competition. In practice, however, there are two problems with the within effect as a measure of competition. First, it has to be based on a balanced panel (set I in equation (4)). That is, if one wants to measure competition using the within effect consistently over a period of, say, 10 years one can only use data on the firms that are in the panel for all 10 periods. This may limit the number of observations considerably if a data set is based on a (rotating) sample such as ours. Alternatively, one can calculate the within effect for consecutive years from t to $t+1$ and then with a new sample from $t+1$ to $t+2$ etc. In this way, fewer observations are lost. The disadvantage of this approach is that the reallocation effect plays a role again in the comparison of competition between t and $t+2$ as the base changes between those years. In this way, the within effect is not a consistent measure over the whole period. Second, in our data the within effect is a magnitude 10 smaller than the change in active firms effect (due to the fact that we use an unbalanced panel).[12] Hence due to the noise in the other

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[12] As shown in Table 2, in our data the average (standard deviation) of the within effect equals 0.02 (0.46),

effects, we cannot use the within effect in the data and do not report it here.

[Figure 3 about here.]

We use figure 3 to summarize the findings of the simulations.[13] Each point in these graphs is the result of 100 iterations for one particular choice of parameters. The top graph shows the fraction of these 100 cases in which PE and PCM correctly indicate an increase in competition (the parameter d is raised by 10) as a function of the average (over the 100 iterations) H before competition is intensified. A number of points follow from this figure. First, PE performs very well with scores above 90% but it is not a perfect measure of competition. The estimated PE may fall in response to a rise in competition if the relation between "Log" profits and "Log" costs is non-linear. Then the first order Taylor approximation is no longer accurate. Entry or exit by firms relatively far removed from the other firms in the sample can then have a disproportionate effect. Second, the PE score is not affected by the level of H. Third, PCM can point in the wrong direction, for some parameter values with scores of below even 10%. Moreover, the higher H initially is, the more likely it is that PCM increases after an increase in competition. The reason is that high concentration is a necessary condition for a big reallocation effect. Intuitively, if there are 1000 small firms in a market, an increase in competition will not create much of a reallocation effect. The bottom graph in figure 3 relates the PCM and PE scores directly to the reallocation effect as defined in equation (4). The PE score is not correlated with the reallocation effect, but the PCM score clearly decreases with the reallocation effect. A higher reallocation effect increases the probability that PCM goes up after an increase in competition. The reallocation effect can be identified in the data, as we show below.

4. Data on competition measures

In this section we take a first look at the three measures PE, PCM and H based on Dutch firm level data from about 250 markets over the period 1993-2002. We define a market to be a 3-digit SIC-code divided into small and medium sized firms (SMEs) and large firms (BEs) operating

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of the reallocation effect 0.02 (0.18), interaction effect 0.01 (0.12), the entry part of the change in active firms effect 0.27 (0.32) and the exit part 0.26 (0.20) where all effects are normalized by PCM.

[13]Details can be found in table 6 in appendix A.

in the Netherlands.[14] The calculation of PCM and H in the data is straightforward and has already been discussed in section 3. In our data set we do not have information on either quantity or price separately. Hence we cannot calculate (marginal) cost per unit of output. Therefore we divide variable costs by revenue assuming that marginal costs are constant. The theoretical model discussed in section 3 suggests that PE can indeed be estimated with this approximation of marginal costs. Moreover, as suggested by figures 1 and 2, to estimate the relation between profits and costs, we need not have the data on all firms in the market. Clearly, more data is always better, but we can still estimate the relationship reliably when we only have a sample of firms in the market. This is not the case for measures like concentration and PCM which only make sense if the whole population can be observed.

Table 1 gives the summary statistics for the variables that we use in the analysis hereafter (see appendix B for their definitions). Here, we work with the full sample of markets.[15] We find that on average (over all markets and years) PE equals 7: a one percent increase in costs leads to a seven percent reduction in profits. However, there is substantial variation in PE. In one market, a one percent increase in a firm's costs leads to a 39% fall in its profits. The average values for PCM and H equal 0.18 and 0.12, respectively. Moreover, the standard deviations of both PCM and H are much smaller than the one for PE.

The variables ΔPE and ΔPCM denote first differences in PE and PCM. It is interesting to note that both variables are on average nearly zero. The following variables are used to disentangle differences between the competition measures. Labor income share is defined as total wage costs over gross value added. In other words, it is the share of labor in the surplus created by labor and capital. We interpret a high labor income share as a property of the market that there are low capital requirements to enter the market. In this sense, we view a high labor income share as indicating low entry costs. The import share denotes the fraction of output sold on the domestic market by foreign firms.[16] Variance of average variable costs (AVC) is the variance (over firms in a market) in our estimate of firms' marginal costs.

[Table 1 about here.]

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[14]In appendix B, we explain how we estimate PE.

[15]Van der Wiel (2007) also considers the subsample where PE is estimated with 10% significance, subsample where PE is positive etc. Similar results to the ones reported here are found.

[16]Note that H is calculated on the basis of domestic revenues of domestic firms. This may introduce a spurious – positive – correlation between import share and H. Such a positive correlation is indeed what we find below.

Figure 4 summarizes the PE's that we find in the data with histograms. We give separate histograms for manufacturing and services. Further, for each SIC code we split the sample into the two sub-markets of small and medium sized enterprizes (SMEs) which have less than 50 employees and big enterprizes (BEs) which have 50 employees and more. This subdivision of each market is data-driven. As one can see in figure 4 comparing top to bottom histograms, BEs have substantially higher values for PE than SMEs. This is in contrast to the idea in policy circles that entrepreneurship and SMEs are key to economic performance. These firms supposedly increase productivity and competitiveness. Moreover, with respect to innovative change, they play an important dynamic role. In other words, these firms are claimed to face very intense competition and therefore have a big incentive to reduce costs and innovate. We find exactly the opposite. It is the big firms that face the higher values for PE. If their costs go up by 1% the percentage fall in profits is bigger. Note that this is not just a trivial size effect as we consider the percentage change in profits.[17] Further, comparing the histograms on the left with the ones on the right suggests that firms in manufacturing tend to face more competition than firms in services. This finding is in line with Creusen, Minne and van der Wiel (2006).

[Table 2 about here.]

[Figure 4 about here.]

Figure 5 gives the histograms for PCM. Those histograms show a similar picture as for PE. PCM is lower in manufacturing than it is in services confirming that manufacturing tends to be more competitive. Further, PCM tends to be lower for BEs than for SMEs, again showing that BEs are active on a more competitive market. Our interpretation is that in many markets BEs compete on a national market while SMEs compete on local markets. Instead of looking at the cross section variation in PCM, table 2 considers the time variation of PCM and the decomposition of ΔPE using equation (4).

[Figure 5 about here.]

The histograms for H in figure 6 do not confirm the results seen for PE and PCM. Manu-facturing is more concentrated than services, suggesting that it is less competitive. Similarly,

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[17]It is obviously the case that the absolute change in profits due to an increase in marginal costs is bigger for a firm with a higher output level.

the market for BEs tends to be more concentrated than the market for SMEs. Given that H is based on market shares, it is not surprising that BEs tend to be active on highly concentrated sub-markets.[18] However, section 3 and the histograms above for PE and PCM clearly indicate that higher concentration should not be associated with less intense competition.

[Figure 6 about here.]

5. Comparing measures of competition

This section first considers the cross section correlations between the three measures. As in the simulations and as suggested by figures 4, 5 and 6, we find that PCM and PE are closely (negatively) correlated while H seems the "odd one out". Although this might suggest that PE and PCM always point in the same direction, this is not the case. We analyze the changes in PCM and PE over time and find that PCM tends to make mistakes in concentrated markets.

5.1. Properties of competition measures

It turns out that the (direct) correlation between PE and PCM is negative and significant. However, this could be a spurious correlation in the following sense. It could be that in some types of markets one measure is low and the other is high while in other types of markets the reverse is the case. If so, a negative correlation between the two measures may have to do with differences in market characteristics rather than with agreement in the underlying intensity of competition. To deal with spuriously correlation we compare all three measures of competition in two steps. First, we relate them to market characteristics. Then, we investigate the partial correlation between various measures conditional on the market characteristics.

Thus, in the first step, we perform a number of regressions in which PE (and other endogenous variables; see below) in market k at time t is explained through a number of market characteristics that are assumed to be exogenous to competition.

$$PE_{kt} = \gamma_0 + \gamma_t + x'_{kt}\gamma + \epsilon_{kt} \tag{5}$$

[18]Remember that market shares –and thus concentration– are calculated for submarkets consisting of a 3 digit SIC code and size class.

where x is a vector of market characteristics, the $\gamma's$ are parameters – with γ_t being calendar year fixed effects[19] – and ϵ is an error term. As market characteristics we use the labor share in value added, the import share, the type of industry (dummy variable for manufacturing) and the average firm size (dummy variable for large firms).

[Table 3 about here.]

We view these market characteristics as exogenous. Nonetheless, we acknowledge that the first two characteristics are not completely exogenous to the intensity of competition. To illustrate, intensity of competition in the product market can affect labor unions' bargaining power, thereby affecting the wage rate and the labor income share. Further, domestic markets where firms hardly compete are particularly attractive for foreign firms to enter, leading to a high import share. These caveats should be kept in mind. However, we believe that both variables are also driven by exogenous variation. The market's technology determines how much capital is needed to produce thereby affecting the capital income share and its complement the labor income share. Also, some products are easier to import than others which affects the import share. Markets where foreign products are close substitutes of domestic firms' products will face a tougher competitive regime. It is this effect that we try to capture.

We estimate equation (5) for PE, PCM and H. In addition to the referred market characteristics we estimate this relation for variables that we believe are rather closely driven by the intensity of competition: labor productivity, variance in average variable costs and the total number of (domestic) firms in the market. One would expect that in a competitive market, labor productivity is high while the variance in costs and the number of firms are small as inefficient firms cannot survive under intense competition.

[Table 4 about here.]

Table 3 shows the estimation results.[20] The labor income share has a positive effect on PE. A high labor income share indicates low capital costs and hence it is easier to enter the market. The import share has a positive but insignificant effect on PE. The dummy variable for manufacturing industries also has a positive and significant effect on PE. Conditional on the other market characteristics there is more competition in manufacturing industries than in

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[19]The calendar year fixed effects are included to take cyclical effects into account.

[20]Note that PE is divided by 10 in these regressions.

service industries, confirming what we see in figure 4. Also in markets where large firms operate there is more competition. The second column of Table 3 shows the parameter estimates when PCM is the dependent variable. By and large the parameter estimates are very similar – though of course with opposite signs. The third column of Table 3 presents how H is affected by the market characteristics. As expected the labor income share has a negative effect on H. As less capital is required, it is easier to enter and concentration is lower. The import share has a positive effect on H. This is due to the fact that the imports itself are not taken into account when calculating H. More imports on a market lead *ceteris paribus* the size of the market to less "space" for domestic firms. This tends to increase the domestic concentration. H is also large for markets with big enterprizes. Since PE and PCM suggest that markets with big enterprizes are more competitive, this suggests that more intense competition can go together with high concentration. More intense competition removes inefficient firms from the market thereby increasing H. We come back to this point below.

The fourth column of Table 3 shows that the average labor productivity is low in markets with a high labor income share. This may be due to the fact that such industries are labor intensive and therefore labor productivity is low. Labor productivity is high in markets with big firms and higher in manufacturing than in services. Import share does not have a significant effect on the average labor productivity. The fifth column shows that the variance of the AVC is influenced in the same way by market characteristics as the PCM. Finally, the last column in Table 3 shows that the number of firms in the market is positively correlated with labor income share. This also suggests that a higher labor income share is associated with lower entry costs and hence more firms enter the market. The number of (domestic) firms is negatively correlated with import share, manufacturing and the market segment with big enterprizes. Since each of these variables are correlated with more intense competition (see columns for PE and PCM) this again indicates that more intense competition due to more aggressive conduct leads to fewer firms in the market.

Table 4 shows the partial correlation coefficients between the three competition measures and other variables closely related to competition. As shown PE and PCM are not only negatively correlated through market characteristics but also when keeping the market characteristics constant, there is a significant negative correlation between PE and PCM. This is mutually consistent, *i.e.* if one measure indicates more (less) competition so does the other. However, between PE and H there is a significant positive correlation. At first sight this seems incon-

sistent. After all, higher PE means more competition and a higher H means less competition. Yet, this confirms the idea introduced above: in a more competitive market, inefficient firms cannot survive and concentration goes up. Table 4 also shows that average labor productivity is positively correlated with PE. More intense competition weeds out inefficient firms and hence average productivity goes up. Furthermore, PE is negatively correlated with the variance of the average variable costs and with the number of firms in the market. This also suggests that more intense competition weeds out inefficient firms thereby reducing the variance in costs.

PCM and H are negatively correlated, also suggesting that more intense competition in terms of lower PCM can go together with higher concentration. The partial correlations of PCM with variance AVC and number of firms are in line with the correlations of PE (with opposite sign). An interesting result is the positive correlation between PCM and labor productivity. This suggests that more efficient firms (higher productivity) have higher PCM for given mode of competition. Although PCM suggests that competition is less intense in more efficient markets, PE points to more intense competition in such markets. Analyzing this point in depth is beyond the scope of this paper. We leave it for future research to establish whether PCM can give the wrong impression in markets where firms can affect their cost levels.

The partial correlations of H with labor productivity and number of firms are consistent with the idea above that more intense competition removes inefficient firms from the market, thereby raising concentration and labor productivity while reducing the number of firms in the market.

As the average labor producity is higher, ceteris paribus, the wider the range of AVC-levels that can be supported by a market. More firms on the market is correlated with lower average labor productivity. Finally, more firms on the market goes together with a higher variance in AVC.

5.2. How to measure changes in competition

[Figure 7 about here.]

In the empirical analysis above we find that PE and PCM are affected by the same market characteristics and conditional on these market characteristics they are significantly negatively correlated. Nevertheless, in section 3 we have shown that there may be circumstances in which changes in PCM indicate, say, a fall in competition whereas PE shows an increase in competition

intensity.

As shown in Table 1, the average changes in both PE and PCM are close to zero. However, in particular markets there may be (big) changes which are not always mutually consistent in terms of changes over time in competition. It turns out that this happens in roughly one third of the cases. To investigate this in more detail we first localize the markets in which there is an inconsistency between the two measures, *i.e.* markets where they are positively correlated from one period to the next. In these cases one measure indicates an increase in competition while the other measure indicates a decrease in competition intensity. We refer to these cases as being *strictly* inconsistent. However, if the changes in the measures are close to zero, the fact that they have similar signs does not matter that much. Such differences can be caused by observational errors and not by underlying changes in competition intensity. Only if both changes in the measures are substantially different from zero and with the same sign there is clearly something wrong. We focus on these cases in the following way.

We define a dummy variable I_z which indicates whether ($I_z = 1$) or not ($I_z = 0$) ΔPE and ΔPCM are inconsistent, *i.e.* they have the same sign and are of sufficient magnitude. More specific we define $I_z = 1$, if

$$\Delta PE < \mu_{1,z} \text{ and } \Delta PCM < \mu_{2,z} \tag{6}$$

or

$$\Delta PE > \mu_{1,100-z} \text{ and } \Delta PCM > \mu_{2,100-z} \tag{7}$$

and $I_z = 0$ otherwise. Here $\mu_{1,z}$ is the value of the zth-percentile of the distribution of ΔPE and $\mu_{2,z}$ is the value of the zth-percentile of the distribution of ΔPCM. Hence $I_z = 1$ if both ΔPE and ΔPCM are either "strongly" negative or "strongly" positive. In these cases the two measures clearly contradict each other. This is illustrated by the shaded areas in figure 7. In addition, to investigate the importance of the reallocation effect in the change in PCM we define a new dummy variable "Big reallocation effect" which has a value of 1 if the reallocation effect (relative to PCM) is below the 25th-percentile or above the 75th- percentile of the distribution of reallocation effects.[21]

Now it is possible to investigate the determinants of the probability that the changes in the two measures are inconsistent, for various values of z. Figure 8 shows how the probability of

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[21]As argued in footnote 12 the within effect is too small to use here to identify the reallocation effect. Since the reallocation effect is also quite noisy, we turn it into a dummy variable.

inconsistency increases with H. This is hardly perceptible for cases with strict inconsistency ($z = 50$), but the increase is clear for low z values, *i.e.* when there is a big inconsistency. Similarly, Figure 9 shows that this probability of inconsistency is decreasing in the number of firms.

We investigate the determinants of inconsistency in more detail using a logit model to estimate the probability of inconsistency and relate this to the H, number of firms and the reallocation dummy. Table 5 presents the parameter estimates. Even if we consider the situation in which the ΔPE and ΔPCM have the same sign – the changes are strictly inconsistent – H has a positive and significant effect (although this is not visible in figure 8). The number of firms in the market has a negative and significant effect on the probability of inconsistency for values of z below 45. Intuitively, with many small firms in the market, the reallocation effect will not be big enough to push PCM in the "wrong" direction. Further, the effects of the reallocation dummy are significant for low values of z.[22] In markets with a high H, a low number of firms and a big reallocation effect we find that the probability of inconsistency between PCM and PE is large.

We conclude that the reallocation effect is responsible for the inconsistency between the changes in PE and PCM. There is direct evidence because the probability of inconsistency increases with the size of the reallocation effect. There is also indirect evidence because the probability of inconsistency increases with H and falls with the number of firms. For this effect to be significant, we need to focus more on the tails of the distributions of ΔPE and ΔPCM ($z = 40$ and $z = 35$).

[Table 5 about here.]

[Figure 8 about here.]

[Figure 9 about here.]

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[22]We also investigated whether other variables used in tables 3 and 4 are important but none of them differed significantly from zero in any of the estimates.

6. Conclusions

In this paper we introduce a new measure of competition: the profit elasticity PE – the percentage increase in profits due to a 1% increase in (marginal) costs. An increase of this elasticity indicates an increase in competition because firms are punished for losing efficiency more harshly in terms of profits.

In general, PE and PCM are consistent, whereas changes in firms' conduct are not correctly picked up by H due to a reallocation effect of markets shares between firms. However, we argue that PE and PCM can be inconsistent as well if firms' conduct changes. To analyze this, we have compared their evolution over time within an market. It turns out that PCM and PE point in different directions (one suggesting that competition went up while the other suggests that competition went down) in concentrated markets where the reallocation effect is important, *i.e.* when H is high the number of firms is low. Simulations suggest that in such markets PCM can increase in response to more intense competition. Hence in highly concentrated markets *i.e.* in markets that are most relevant for competition policy and regulation, one should be careful using PCM as a measure of competition intensity

Finally, we have found empirical support for the idea that more intense competition (due to more aggressive conduct by firms) removes inefficient firms from the market thereby increasing concentration. Such an increase in concentration should not be interpreted as a fall in intensity of competition. Further, more intense competition also tends to increase the average productivity of the remaining firms in the market (either due to a selection effect or because remaining firms are forced to invest more to reduce costs). This can also raise PCM while it is not a sign of weakened competition.

All in all, our results suggest that policy makers should be careful in relying only on standard competition measures like H and PCM. Just when they are needed the most they fail. PE is an informative and more reliable measure of competition.

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Appendix A. Simulations

Table 6 gives the details of the simulations presented in the main text.

[Table 6 about here.]

Appendix B. Data and measurement issues

Initial uncleaned data set

The estimates for PE, PCM and H are based on firm-level data for the Netherlands. These data are derived from the annual survey for the Production Statistics (PS) by Statistics Netherlands. The survey gives complete coverage of firms with at least 20 employees, while firms with fewer than 20 employees are sampled. This paper focuses on the period 1993-2001 (and 2002 for service industries). The data set has been constructed after matching the detailed accounting data over time. We have no data at our disposal on the agriculture and fishing industry, banking and insurance, public utilities and health care industries but otherwise we cover all industries in the Netherlands.

It turns out that the matched data set was not complete for all industries in manufacturing and wholesale trade. For some industries at the 3 digit SIC code, observations for certain years were missing for firms with size less than 100 employees. Therefore, we excluded all observations of these industries. Furthermore, for the analysis of the competition measures, we leave out firms without employees.

From uncleaned to cleaned data set

Unprocessed firm-level data may contain errors for various reasons. In order to obtain reliable firm-level data we performed several 'cleaning' activities. We removed: 1) observations of firms with no turnover and employment; 2) the second observation of the same firm in one year; 3) observation of year t+1 if a firm has identical output and employment data (or value added) in two consecutive years; 4) observation of firms with negative variable profits; 5) observations of firms with negative intermediate inputs; 6) observations of firms with huge changes in key

variables as output and employment; in particular, firms with more than 500% increase in turnover or employment or decrease by more than 80% in these variables. Finally, due to confidentiality requirements of Statistics Netherlands, we had to remove 3-digit SIC industries if less than 5 firms per year were available. Table 7 shows that the consequences of all those cleaning steps are limited. All in all, approximately 52 000 firms (i.e approximately 18 percent) have been removed from the matched data set to obtain a clean data set for further analysis. This cleaned data set contains almost 240,000 observations over the period 1993-2002 based on information of about 90,000 different firms in the Netherlands from 139 industries at the 3-digit SIC-level.

[Table 7 about here.]

Basic variables

To measure and to analyze the three competition measures, we use a number of variables. Table 8 provides a brief overview of their derivation and sources. Except for the import share, which is derived from the National Accounts of Statistics Netherlands, all indicators are based on the PS. Gross output denotes the output of firms including other activities (*e.g.* industrial services such as installation costs). Labor costs are defined as the salary of employees including social security charges and extra allowances. Intermediate inputs consist of costs like materials, energy and marketing. The variable costs are calculated as the sum of the labor costs and the intermediate inputs. Because data on marginal costs are absent, we use the variable costs over gross output (average variable costs, AVC) as an approximation. Profits (π) are defined as firm's revenue (or gross output) minus variable costs. The definitions of PCM and H are discussed in the main text. Labor productivity is defined as the (un-weighted) average labor productivity of the firms in an industry, where labor productivity is defined as gross value added per worker. Labor income share is defined as total wage costs over gross value added – gross output minus intermediate inputs. Finally, the import share denotes the fraction of output sold on the domestic market of products from outside the Netherlands.

[Table 8 about here.]

Measuring PE

Theory suggests that an increase in competition (say, firms switch to more aggressive conduct or an additional firm enters the market) increases the profits of a firm relative to the profits of

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a less efficient firm. In particular, it is not necessarily the case that an increase in competition reduces every firm's profits. Some efficient firms may gain from more intense competition as it allows them to exploit their cost advantage more aggressively. As shown in Boone (2000), an increase in competition increases profits of a firm relative to a less efficient firm. We denote the profits and marginal costs at time t of this benchmark firm by resp. $\bar{\pi}_t, \bar{c}_t$. The benchmark firm could be the median firm or the least efficient firm in the market. The exact identity of this firm does not matter as it will end up in the time fixed effects, as explained below. A further advantage of normalizing profits and costs in this way, is that it automatically corrects for inflation which affects numerator and denominator (π_{it} and $\bar{\pi}_t$ and resp. c_{it} and $\bar{c}_t$) in the same way.

In our analysis, we allow for the fact that we cannot perfectly observe the relevant values for firms' profits and marginal costs. For instance, a firm may produce other products than the products for the market under consideration. The statistical office (or other agency gathering the data) may decide to classify these sales and costs of other products under the same heading (industry classification). We denote the observed profit level for firm i at time t by $\pi_{it}u_i$. Hence the observation error equals $(u_i - 1)\pi_{it}$. Similarly, the observed marginal costs are denoted by $c_{it}v_i$. The assumption that we make is that these observation errors may differ between firms but are constant over time (or, if the observational errors do change over time, they change in the same way for all firms in a sector such that they are picked up by the time fixed effect).

Hence the equation we estimate is

$$\ln\left(\frac{\pi_{it}u_i}{\bar{\pi}_t}\right) = \alpha - \beta_t \ln\left(\frac{c_{it}v_i}{\bar{c}_t}\right) + \varepsilon_{it}$$

or equivalently[23]

$$\ln(\pi_{it}) = \alpha_i + \alpha_t - \beta_t \ln(c_{it}) + \varepsilon_{it} \tag{B.1}$$

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[23]The firm fixed effect is given by

$$\alpha_i \approx \alpha - \ln(u_i) + \beta_t \ln(v_i)$$

Note that the firm fixed effects are really fixed if $\beta_t = \beta$. We use an approximation which holds if the variation in v_i is much bigger than the variation in β_t. The time fixed effect is given by

$$\alpha_t = \ln(\bar{\pi}_t) + \beta_t(\bar{c}_t).$$

For each market, defined by a 3 digit SIC industry divided into SMEs and BEs we estimate equation (B.1).[24]

Equation (B.1) contains constructed variables based on the same information on both the left and the right hand side. In particular, the profit variable on the left hand side is calculated as the difference between revenues and costs, the costs variable on the right hand side is calculated as the ratio of costs and revenues (to get a cost per unit variable). Measurement errors in firms' revenues or costs will tend to overemphasize the effects of costs on profits and hence PE will be overestimated. Nevertheless, as long as the errors are uncorrelated with a change in competition the change in PE will be measured correctly. Furthermore, to the extent that the measurement errors are time invariant they will be picked up by the firm fixed effects.[25] This also includes unobserved explanatory variables that are constant over time but may have an impact on profits. Although it is possible that the parameter estimates of PE are a mixture of "signal" and "noise", it is clear that the signal dominates as shown in the main text. Finally, Appendix C reports four robustness checks in the estimation of PE and shows that the main results are unchanged.

Table 1 gives an overview of the three competition measures and some market characteristics. Ideally, the number of observations should be 139*2*10=2780 (*i.e.* 139 3-digit SIC-industries divided into SMEs and BEs for the period 1993-2002). However, the full sample contains less observations: 2104 observations. This smaller set is due to that (i) for manufacturing industries data only runs to 2001; (ii) not for every SIC-code SMEs or BEs are available; (iii) some SIC-codes are absent in particular years.

Appendix C. Robustness checks

To investigate the robustness of our estimation results we run four alternative equations compared to our basic equation (B.1).[26]

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[24]To control for changes of firms over time with respect to their SIC-code and their size class, firms are classified according to their SIC-code most reported and to their lowest size class level in the period observed.

[25]Note that the potential bias introduced by the measurement errors may be corrected by the use of instrumental variables. Unfortunately, we do not have firm characteristics that could be used as instrumental variables.

[26]More details can be found in Van der Wiel (2007), which examines a number of ways to estimate PE and analyzes the estimation results for a number of subsamples. Results turn out to be robust.

The first alternative way to estimate PE is that we change the dependent variable and the explanatory variable from places. In fact, this is one way to test the impact of measurement problems

$$\ln(c_{it}) = \alpha_i + \alpha_t - \tilde{\beta}_t \ln(\pi_{it}) + \varepsilon_{it} \tag{C.1}$$

In this case, PE is defined as $PE_t = 1/\tilde{\beta}_t$

The second alternative allows for a non-linear relationship between $\ln(\pi_i)$ and $\ln(c_i)$:

$$\ln(\pi_{it}) = \alpha_i + \alpha_t - \beta_{1t} \ln(c_{it}) + \beta_{2t}(\ln(c_{it}))^2 + \varepsilon_{it} \tag{C.2}$$

Due to this non-linearity, the results for the β's cannot be directly interpreted as a measure of market competition. Taking the first derivative of (C.2) with respect to c, we get

$$\frac{\partial \ln(\pi_{it})}{\partial \ln(c_{it})} = -\beta_{1t} + 2\beta_{2t} \ln(c_{it}) \tag{C.3}$$

which is different for different firms in the market. A market value for PE can now be derived by using the market average of the marginal cost ($\bar{c}_{it}$) as follows: $PE_t = -\beta_{1t} + 2\beta_{2t} \ln(\bar{c}_{it})$.

The third alternative measure for PE is that we use a balanced panel instead of an unbalanced panel to make sure that our results are not driven by panel attrition. To be left with sufficient observations, we use a balanced panel for two subperiods: 1993-1997 and 1998-onwards respectively.

The fourth alternative is that we adjust the marginal cost concept accounting only for the labor costs and neglecting the costs for materials and other intermediate inputs. This relaxes the problem of using the same variables to construct the left hand side and right hand side of equation (B.1). Table 9 checks whether our main result is robust to these alternative specifications of PE. Indeed we find for all four alternatives that the probability of inconsistency is higher in more concentrated markets (higher H and lower number of firms). For alternatives 1, 3 and 4 it is also the case that a big reallocation effect raises the probability of inconsistency. In this sense, the main result in section 5.2 is robust to different ways in which PE can be estimated.

[Table 9 about here.]
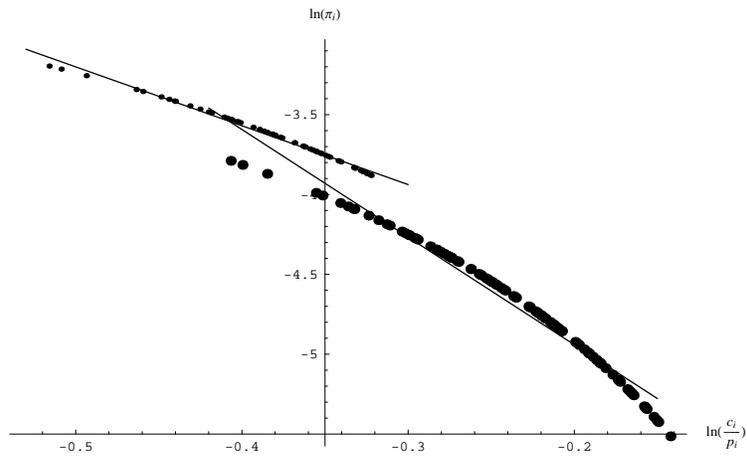
Figures

Figure 1: *Relation between* $\ln(\pi_i)$ *and* $\ln\left(\frac{c_i}{p_i}\right)$ *with* $f = 0.02$ *(small dots) and* $f = 0.004$ *(large dots) with estimated linear relations (PE= 3.69 in the former case and PE= 6.78 in the latter).*
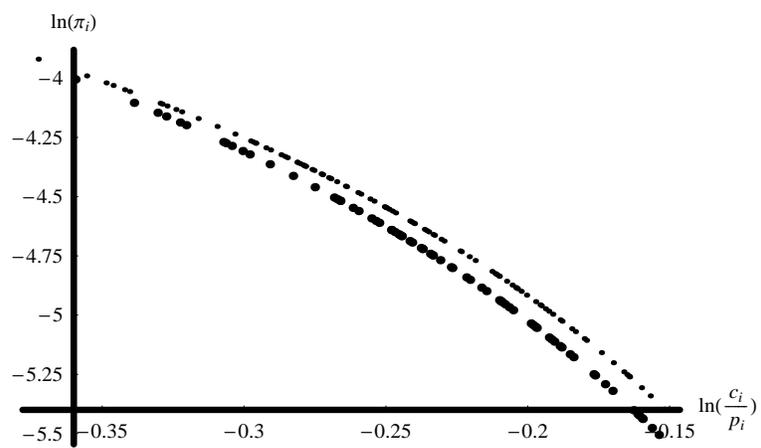
Figure 2: *Relation between* $\ln(\pi_i)$ *and* $\ln\left(\frac{c_i}{p_i}\right)$ *with* $d = 20$ *(small dots) and* $d = 30$ *(large dots).*
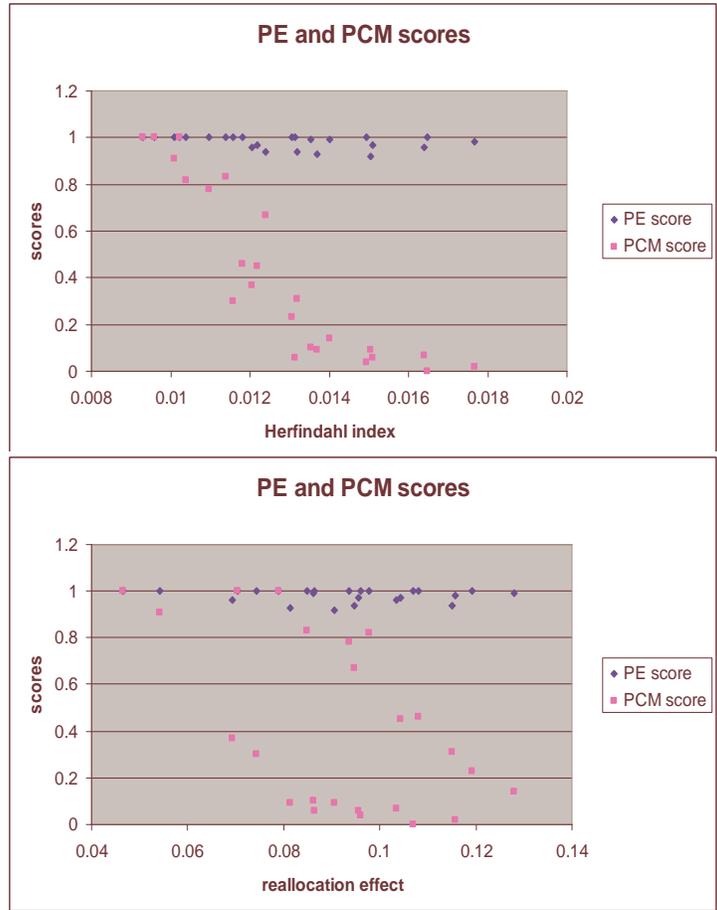
Figure 3: *Fraction of cases in which PE and PCM correctly indicate an increase in competition as a function of the average H and the value of the reallocation effect, respectively.*

Figure 4: *Distribution of PE (shown for PE < 30) in Dutch economy. Left: services, right: manufacturing; top: SME, bottom: BE.*

Figure 5: *Distribution of PCM in Dutch economy. Left: services, right: manufacturing; top: SME, bottom: BE.*
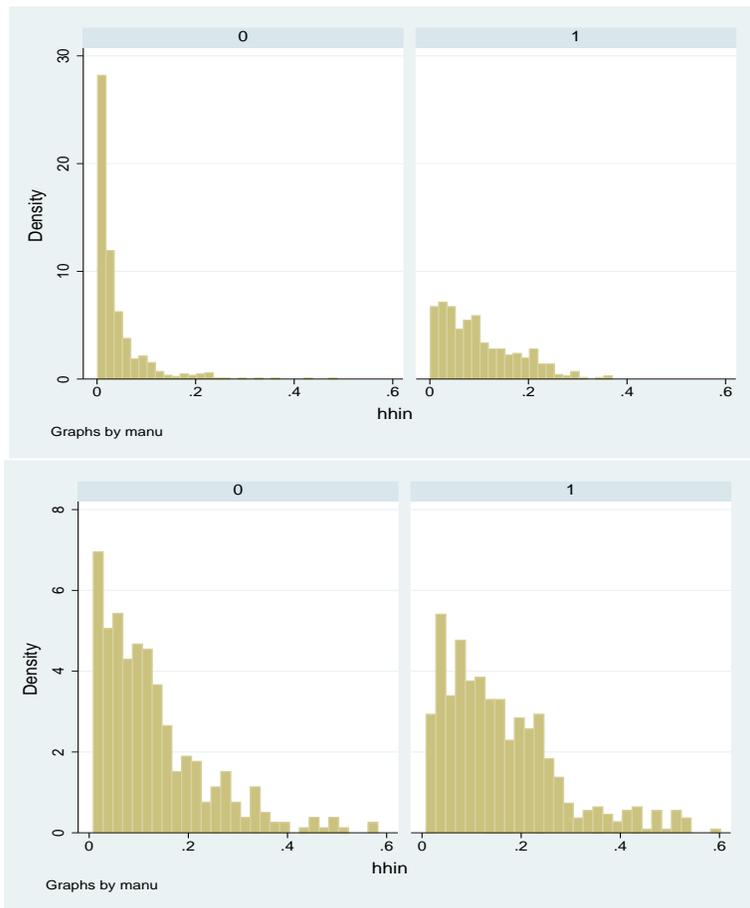
Figure 6: *Distribution of H in Dutch economy. Left: services, right: manufacturing; top: SME, bottom: BE.*
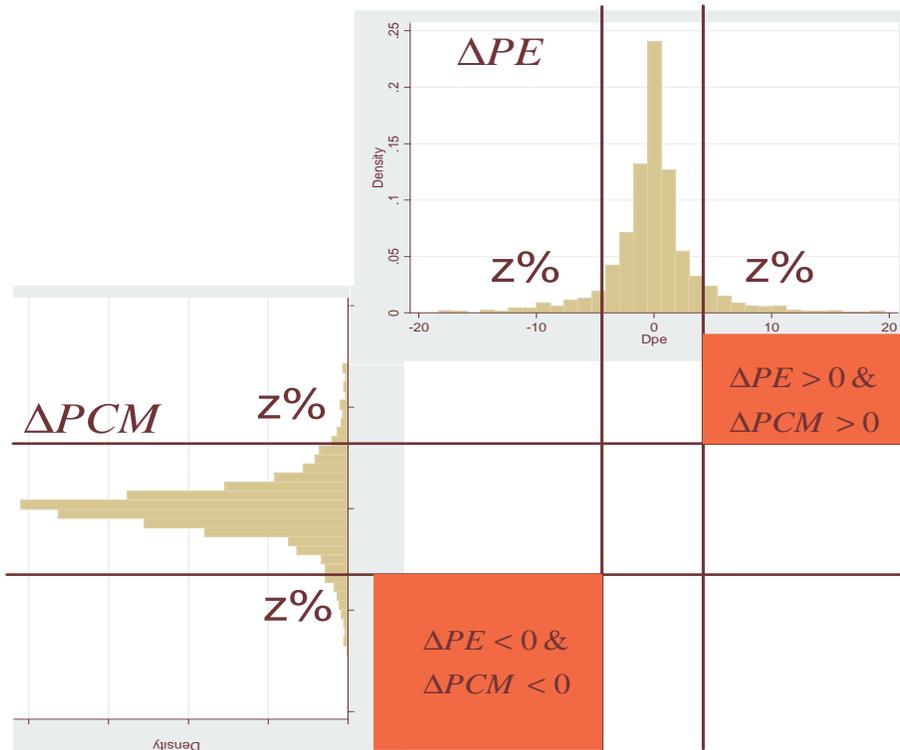
Figure 7: ΔPE and ΔPCM are "very" inconsistent for market-year combinations in the red areas.

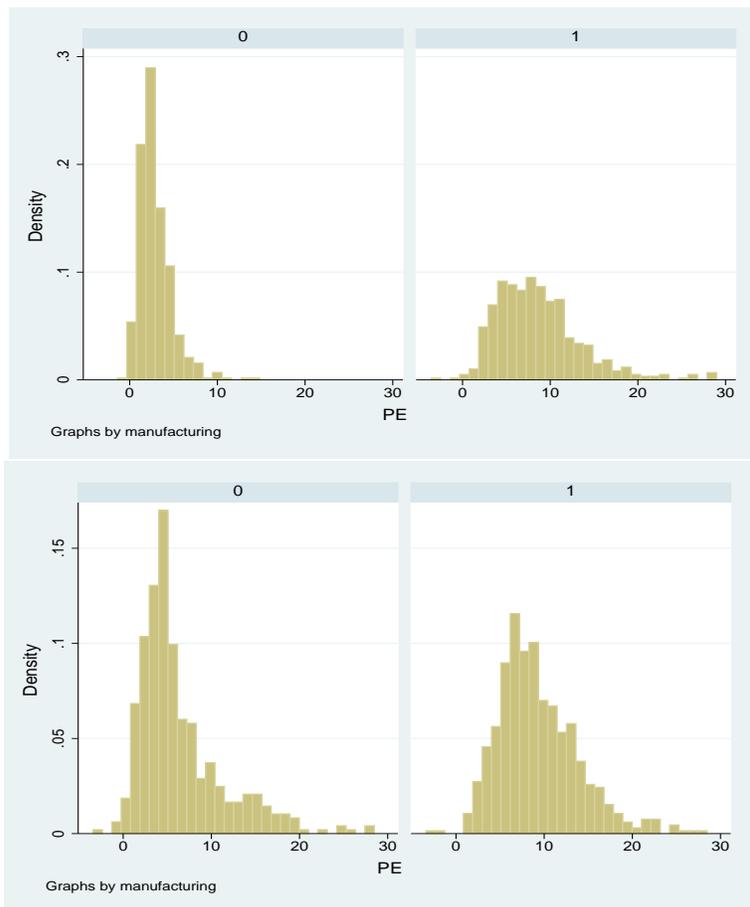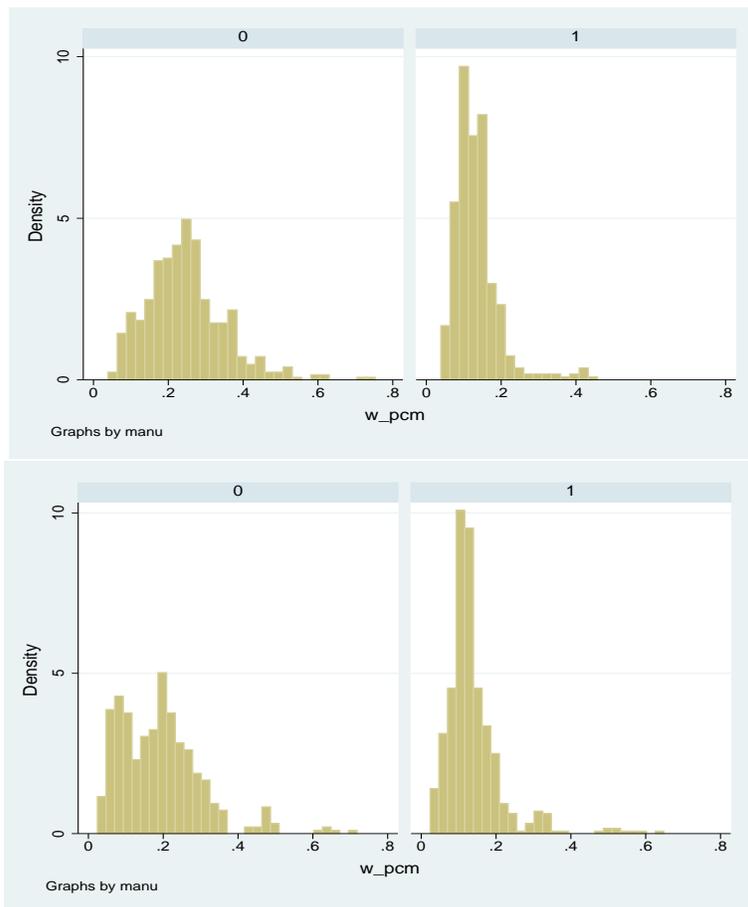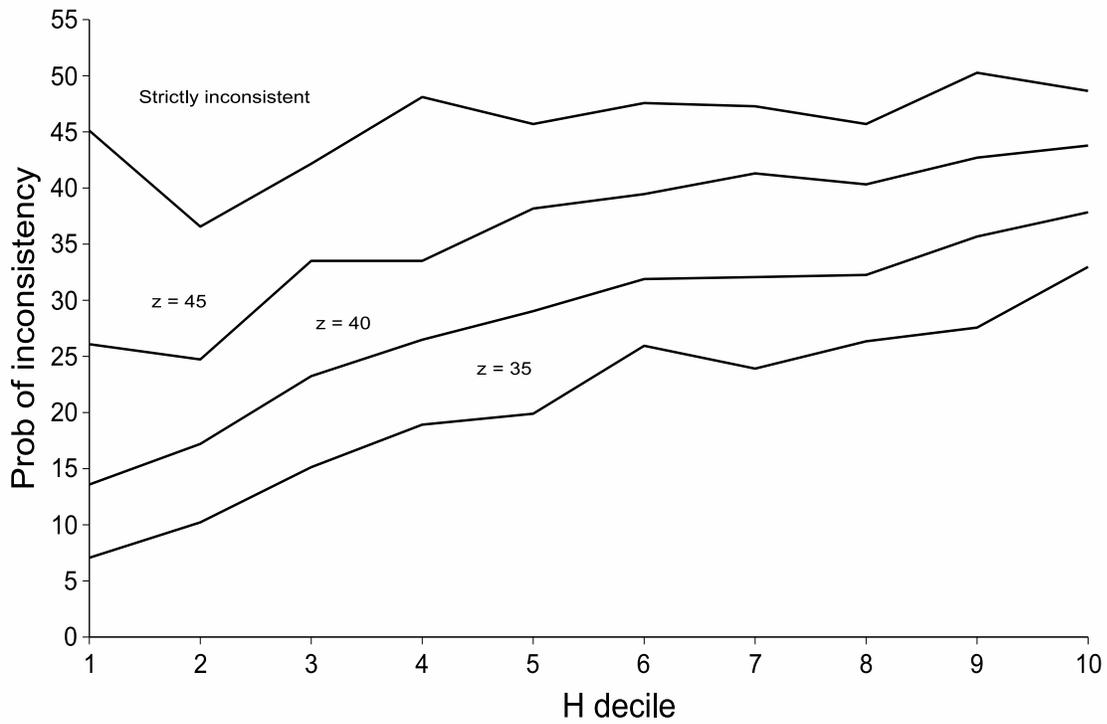Figure 8: Probability of inconsistency as a function of deciles of the H-index
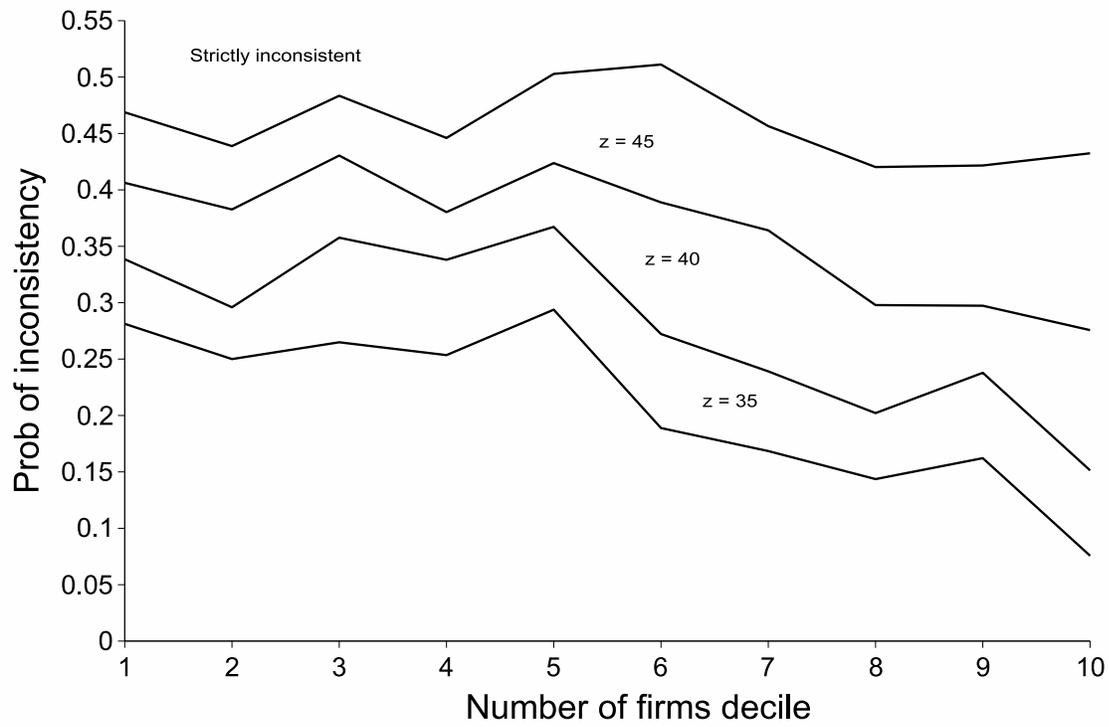
Figure 9: Probability of inconsistency as a function of deciles of the Number of firms in the market

Tables

Table 1: Overview of variables

variable	mean	standard dev.	Minimum	Maximum	Oberservations
PE	7.03	5.21	-5.47	39.07	2104
Δ PE	-0.13	4.41	-32.81	34.45	1851
PCM	0.18	0.10	0.02	0.85	2104
Δ PCM	0.00	0.05	-0.50	0.61	1851
H	0.12	0.12	0.00	0.97	2104
Labor productivity	0.59	0.62	0.08	13.36	2104
Variance AVC	0.05	0.14	0.00	4.29	2104
ln (number of firms)	3.97	1.90	1.44	10.20	2104
Import share	0.30	0.27	0	0.91	2104
Labor income share	0.61	0.14	0.04	0.93	2104

Table 2: Decomposition ΔPCM using equation (4)

variable	Mean	Standard dev.	Minimum	Maximum	Observations
ΔPCM	0.06	0.64	-0.83	20.82	1638
within-effect	0.02	0.46	-0.72	16.71	1638
reallocation effect	0.02	0.18	-0.96	1.80	1638
interaction-effect	0.01	0.12	-0.62	3.01	1638
entry-effect	0.27	0.32	0.00	6.08	1638
exit-effect	0.26	0.20	0.00	0.95	1638

Table 3: Properties of competition measures

	PE	PCM	H	Labor product.	Variance AVC	Numb. Firms
Lab. inc. share	1.39 (10.6)**	-0.49 (14.3)**	-0.17 (3.7)**	-2.63 (5.6)**	-0.29 (5.8)*	1.46 (3.2)**
Import share	0.07 (0.7)	-0.02 (0.9)	0.11 (3.1)**	-0.09 (0.5)	0.02 (1.6)	-1.60 (4.1)**
Manufacturing	0.40 (8.4)**	-0.07 (5.5)**	-0.01 (0.6)	0.12 (1.2)	-0.08 (7.1)**	-1.34 (5.8)**
Big enterprizes	0.19 (5.7)**	-0.02 (2.4)**	0.08 (6.4)**	0.15 (3.4)**	-0.04 (5.2)**	-1.47 (8.8)**
R^2	0.385	0.642	0.189	0.376	0.185	0.503

Note: Based on 2104 observations (253 markets); all estimates contain fixed effects for calender years; absolute t-statistics in parentheses – corrected for clustering of observations across markets; a ** (*) indicates a parameter estimate significantly different from zero at a 5% (10%) level.

Table 4: Partial correlation coefficients

	PE	PCM	H	Labor prod.	Var. AVC	Numb. firms
PE	–	-0.147**	0.175**	0.091**	-0.026	-0.207**
PCM		–	-0.007	0.154**	0.178**	0.096**
H			–	0.177**	0.008	-0.571**
Lab. prod.				–	0.101**	-0.109**
Var. AVC					–	0.017
Numb. firms						–

Note: The partial correlation coefficients are calculated holding the exogenous variables and the calendar year effects constant.

Table 5: Probability of inconsistency between ΔPE and ΔPCM; parameter estimates logit model

	H-index	Big reallocation effect	Numb. of firms	% inconsistent
Strictly inconsistent	0.60 (1.7)*	–	–	
	0.59 (1.6)	0.06 (0.8)	–	
	0.33 (0.7)	0.06 (0.7)	-0.03 (0.9)	45.7
$z = 45$	1.52 (3.7)**	–	–	
	1.48 (3.6)**	0.16 (1.6)	–	
	0.70 (1.4)	0.15 (1.5)	-0.08 (2.2)**	36.4
$z = 40$	2.17 (5.0)**	–	–	
	2.12 (5.0)**	0.25 (2.4)**	–	
	0.91 (1.8)*	0.23 (2.3)**	-0.14 (3.3)**	27.9
$z = 35$	2.85 (6.3)**	–	–	
	2.79 (6.5)**	0.44 (3.9)**	–	
	1.53 (2.9)**	0.42 (3.7)**	-0.15 (4.3)**	20.8

Note: based on 1851 observations (250 markets); absolute t-statistics corrected for clustering of observations across markets; a ** (*) indicates a parameter estimate significantly different from zero at a 5% (10%) level.

Table 6: Simulations with $a = 40, b = 30$ and c_i drawn from log normal distribution with mean 0.7 and standard deviation $st.dev.$ Competition becomes more intense by raising d with 10.

d	f	$st.dev.$	PCM score[a]	PE score[b]	H[c]	Reallocation[d]	PCM[e]	PE[f]
15	0.004	0.08	1.00	1.00	0.0093	0.047	0.26	-7.37
15	0.004	0.16	1.00	1.00	0.0102	0.070	0.28	-6.87
15	0.004	0.24	0.83	1.00	0.0114	0.085	0.32	-6.16
15	0.004	0.32	0.67	0.94	0.0124	0.095	0.36	-5.63
15	0.008	0.08	1.00	1.00	0.0096	0.079	0.26	-6.89
15	0.008	0.16	0.78	1.00	0.0110	0.094	0.30	-6.02
15	0.008	0.24	0.45	0.97	0.0122	0.104	0.34	-5.40
15	0.008	0.32	0.31	0.94	0.0132	0.115	0.37	-4.95
15	0.012	0.08	0.82	1.00	0.0104	0.098	0.28	-6.26
15	0.012	0.16	0.46	1.00	0.0118	0.108	0.32	-5.47
15	0.012	0.24	0.23	1.00	0.0131	0.119	0.35	-4.92
15	0.012	0.32	0.14	0.99	0.0140	0.128	0.39	-4.53
20	0.004	0.08	0.91	1.00	0.0101	0.054	0.22	-8.68
20	0.004	0.16	0.37	0.96	0.0121	0.069	0.27	-7.34
20	0.004	0.24	0.09	0.93	0.0137	0.081	0.31	-6.48
20	0.004	0.32	0.09	0.92	0.0150	0.091	0.35	-5.87
20	0.008	0.08	0.30	1.00	0.0116	0.074	0.25	-7.36
20	0.008	0.16	0.10	0.99	0.0135	0.086	0.29	-6.28
20	0.008	0.24	0.06	0.97	0.0151	0.096	0.33	-5.61
20	0.008	0.32	0.07	0.96	0.0164	0.103	0.37	-5.11
20	0.012	0.08	0.06	1.00	0.0131	0.086	0.28	-6.53
20	0.012	0.16	0.04	1.00	0.0150	0.096	0.32	-5.67
20	0.012	0.24	0.00	1.00	0.0165	0.107	0.36	-5.06
20	0.012	0.32	0.02	0.98	0.0177	0.116	0.39	-4.64

[a]Fraction of cases in which PCM decreases (correctly pointing at increase in competition)
[b]Fraction of cases in which PE increases (correctly pointing at increase in competition)
[c]Average value of Herfindahl index before increase in competition
[d]Average value of reallocation effect
[e]Average value of PCM before increase in competition
[f]Average value of PE before increase in competition

Table 7: Comparison of uncleaned and cleaned data set, 1993-2002.

Variable	Uncleaned dataset	Cleaned dataset
Number of firms	288660	236346
Average firm size sample	71	74
Number of workers (x1000)	27559	23718
Labor productivity	0.45	0.47
AVC	0.85	0.82
PCM	0.16	0.18

Table 8: Overview of main variables and sources.

Variable	Method	Source
Gross output	directly available	PS
Labor costs	directly available	PS
Intermediate inputs	directly available	PS
Variable costs	derived	PS
Average variable costs	derived	PS
Profits	derived	PS
PE	regression	PS
PCM	derived	PS
H	derived	PS
Labor productivity	derived	PS
Labor income share	derived	PS
Import share	derived	National Accounts

Table 9: Comparing alternative Profit elasticities – Probability of inconsistency between ΔPE and ΔPCM; parameter estimates logit model – full sample – $z = 35$

		H-index	Big reallocation effect	Numb. of firms	% inconsistent
Baseline		2.85 (6.3)**	–	–	
Alternative	1	3.49 (6.2)**	–	–	
Alternative	2	3.52 (6.8)**	–	–	
Alternative	3	2.56 (5.4)**	–	–	
Alternative	4	2.95 (6.3)**	–	–	
Baseline		2.79 (6.5)**	0.44 (3.9)**	–	
Alternative	1	3.45 (6.3)**	0.26 (2.2)**	–	
Alternative	2	3.49 (6.8)**	0.16 (1.4)	–	
Alternative	3	2.51 (5.4)**	0.28 (2.6)**	–	
Alternative	4	2.90 (6.3)**	0.26 (2.3)**	–	
Baseline		1.53 (2.9)**	0.42 (3.7)**	-0.15 (3.4)**	20.8
Alternative	1	2.38 (2.8)**	0.24 (2.1)**	-0.13 (2.6)**	20.4
Alternative	2	0.26 (0.5)	0.11 (1.0)	-0.39 (8.3)**	25.2
Alternative	3	1.04 (1.7)*	0.25 (2.5)**	-0.17 (3.5)**	19.7
Alternative	4	1.07 (2.0)**	0.23 (2.1)**	-0.21 (4.5)**	23.8

Note: based on 1851 observations (250 markets); absolute t-statistics corrected for clustering of observations across markets; a ** (*) indicates a parameter estimate significantly different from zero at a 5% (10%) level.