# A note on the estimation of competition-productivity nexus: A panel quantile approach

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## Abstract

We study the impact of product market competition on productivity in 462 US manufacturing sectors for the period 1958-2009 through the lens of a panel quantile regression analysis. We confirm that there is a nonmonotonic inverse-U relationship between competition and total factor productivity. We argue that the turning point increases substantially as we move to the higher quantiles of the productivity distribution function. Our findings survive robustness checks under alternative competition measure and quantile estimator.

**Keywords:** Quantile regression; Competition; Nonlinearities; Manufacturing; US

**JEL Codes**: L11; C23; C21

## 1. Introduction

The effect of product market competition (PMC) on productivity dates back in the pioneering work of Sir John Hicks (1935) arguing that "*the best of all monopoly profits is a quiet life*". Since then several theories have brought to light different arguments. Schumpeter, (1943) claims that there is a positive linear relationship between market power and productivity appraising the ability of the monopolies to stimulate productivity and growth, while Arrow (1962) suggests that there is a nonmonotonic convex relationship between PMC and productivity.

With theory providing mixed results, researchers relied on empirical analysis (pooled OLS, IV/GMM) to uncover that the effect of competition on productivity and innovation has an inverse U-shape (Aghion et al, 2005; Van Reenen, 2011; Marshall and Parra, 2019). These studies apply several techniques which estimate the parameters of interest at the mean of the conditional distribution of the dependent variable. However, this is a strong simplification, since explanatory variables may not only affect the mean but other parameters as well such as the median or other quantiles. Another limitation of the existing studies is to pool potentially heterogeneous industries/firms as if their data were generated according to the same process (Distante et al., 2018).

To overcome these problems, we employ the Method of Moments Quantile Regression (MM-QR) analysis developed in Machado and Silva (2019). By using this nonparametric approach, we are able to study the effect of competition at different quantiles of the productivity distribution function, while we also account for the presence of fixed effects.

The rest of this note proceeds as follows. Section 2 describes the data and the empirical methodology applied. Section 3 discusses the empirical results along with the necessary robustness checks, while Section 4 concludes this study.

## 2. Data and empirical framework

The sample consists of an annual balanced data set of 462 US manufacturing sectors broken down at the six-digit NAICS level over the period 1958-2009. All variables are taken from the National Bureau of Economic Research and the U.S. Census Bureau (see Table 1 for description and statistics).

**Table 1:** Descriptive statistics

| Variables | Description | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| TFP | Five-factor TFP (*annual growth rate*) | 0.938 | 0.257 | 0.0120 | 13.15 |
| CR4 | Sum of market shares of the four largest firms | 28.26 | 6.378 | 7.890 | 98.00 |
| HHI50 | Squared sum of market shares of the fifty largest firms | 935.4 | 233.9 | 12 | 9,406 |
| SHIP | Total value of shipments (*million USD*) | 6,291 | 17,650 | 3.041 | 898,019 |
| INV | Total capital expenditure (*million USD*) | 200.4 | 500.9 | 0.184 | 15,555 |
| MAT | Total cost of materials (*million USD*) | 3,252 | 8,348 | 10.37 | 296,857 |
| ENER | Electricity and fuels cost (*million USD*) | 128 | 394.6 | 0.149 | 8,052 |

The quantile fixed effects approach is given by the following equation:

$$Q_{TFP_{it}}\left(\tau_j \left| CR4_{it}, Z_{it}\right.\right) = \alpha_1(\tau_j)\times CR4_{it} + a_2(\tau_j)\times\left(CR4_{it}\right)^2 + Z'_{it}\beta(\tau_j) + \varphi_i(\tau_j) + \mu_t(\tau_j), \tau_j \in (0,1) \quad (1)$$

where subscript $i = 1, \ldots, N$ represents the industry and t = 1, . . . , T indexes the time. $TFP_{it}$ is the growth rate of total factor productivity, $CR4_{it}$ denotes the market concentration. $Z'$ denotes the vector of covariates, including market size (SHIP), capital (INV), intermediate inputs (MAT) and energy cost (ENER) expressed in real terms, while $\varphi_i$ and $\mu_t$ are unobserved industry and year fixed effects to address potential endogeneity (Baryshnikova and Pham, 2019). We use TFP as a proxy for productivity since it is the most important driver of economic growth (Prescott, 1998; Mastromarco and Simar, 2018).

The reason for employing MM-QR analysis is twofold. First, although it is being applicable to non-linear or polynomial form models as other estimators (see Canay 2011;

Chernozhukov and Hansen, 2008), it is computationally much simpler (Machado and Silva, 2019). Second, it allows for fixed effects as in this case.

We notice though that we have a large N = 462 and small T = 52, which results in too many dummies and renders the MM-QR inconsistent. To deal with this problem, we use the simple split-panel jackknife bias correction described in Dhaene and Jochmans (2015).[1] Moreover, we supplement our analysis with the panel quantile estimator proposed by Canay (2011).

A possible threat to identification strategy is that our basic variable (CR4) could be endogenous due to reverse causality since the level of productivity in an industry could determine its market structure and the subsequent level of competition according to Structure-Conduct-Performance paradigm (Bain, 1956). Similarly to other studies (Polemis and Stengos, 2015; Altunbaş and Thornton, 2019), we address possible endogeneity by using lagged values of the competition variable.

## 3. Results and discussion

### 3.1. Main findings

Table 2 displays the estimated parameters in the location and scale functions drawn from the OLS model (see column 1) and the regression estimates obtained with the MM-QR model (see columns 2-6).

It is shown that CR4 has effects with opposite signs on the location and scale suggesting that increasing the level of concentration increases the average productivity (location shift), but also decreases the dispersion of observed productivity (scale shift). The rest of the covariates when significant are properly signed.

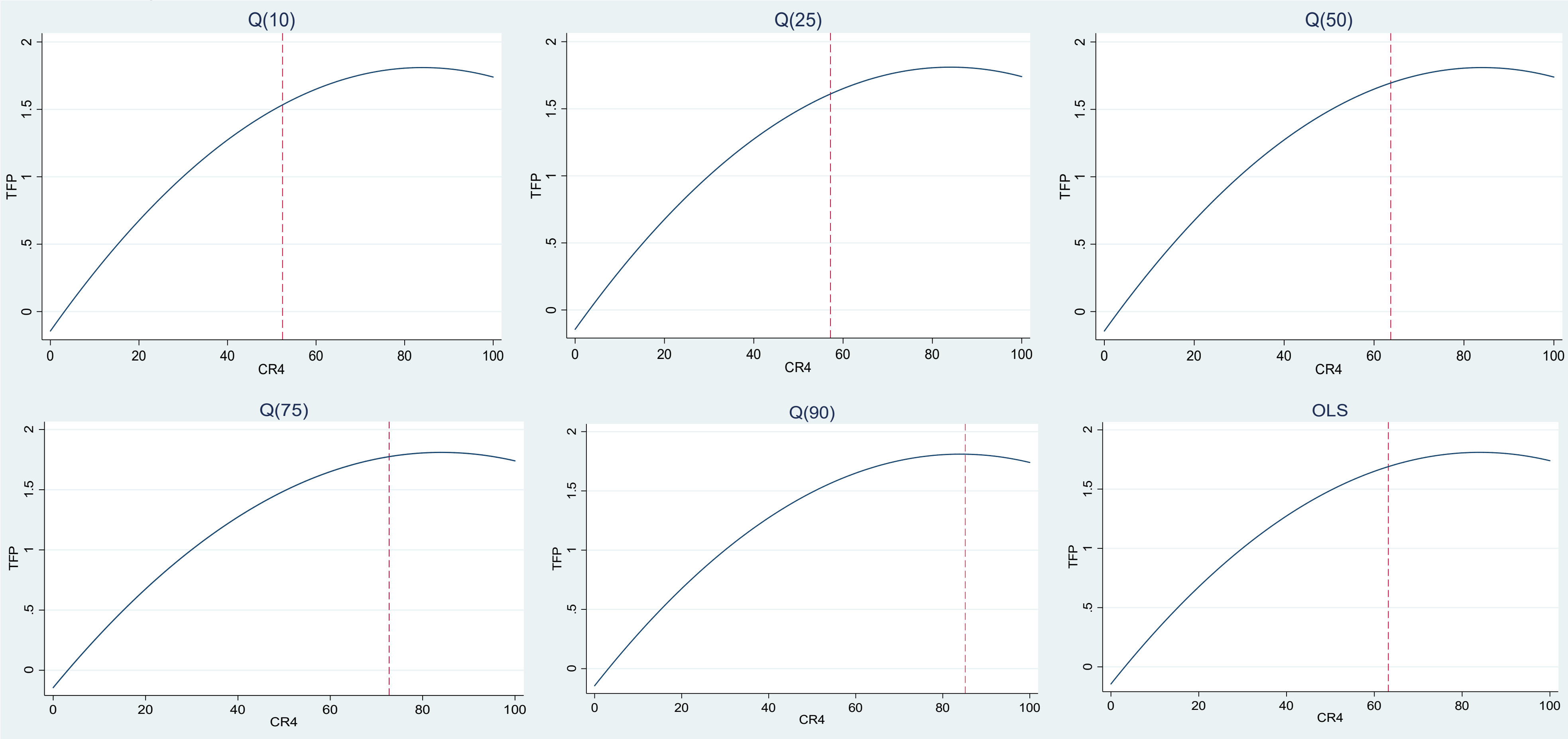
[1] As argued in Machado and Silva, (2019), the confidence intervals obtained by MM-QR have poor coverage when n/T is large (approximately 9 in our case).

**Table 2:** OLS and quantile regression results

| | (1) OLS Mean | | (2) Q(0.10) | (3) Q(0.25) | (4) Q(0.50) | (5) Q(0.75) | (6) Q(0.90) |
|---|---|---|---|---|---|---|---|
| **Variables** | **Location** | **Scale** | | | | | |
| *Competition* | 0.0456*** (0.00423) | -0.00267 (0.0026) | 0.0481*** [0.00503] | 0.0464*** [0.0035] | 0.0447*** [0.003] | 0.0429*** [0.004] | 0.0412*** [0.005] |
| *Competition (squared)* | 0.00036*** (0.000082) | 0.000072* (0.000047) | -0.000459*** [0.00008] | -0.000406*** [0.00006] | -0.00036*** [0.00004] | -0.000295*** [0.00006] | -0.000242*** (0.00009] |
| *Market size* | 0.000012*** (0.0000019) | 0.0000013*** (0.00000019) | 0.0000104*** [0.0000019] | 0.0000113*** [0.0000013] | 0.000012*** [0.000001] | 0.000013*** (0.0000014] | 0.000014*** (0.000002] |
| *Intermediate inputs* | -0.000011*** (0.0000024) | -0.0000016* (0.0000009) | -0.000008*** [0.0000031] | -0.000009*** [0.000002] | -0.000011*** [0.000001] | -0.000012*** [0.000003] | -0.000012*** [0.000003] |
| *Energy cost* | -0.000037 (0.000024) | -0.0000064 (0.0000064) | 0.0000022 [0.000028] | -0.000015 [0.00002] | -0.000033** [0.000016] | -0.00005** [0.00002] | -0.000068** [0.00003] |
| *Capital* | -0.000049* (0.00003) | 0.000019*** (0.0000073) | -0.000079* [0.000043] | -0.000066** [0.00003] | -0.000052** [0.00003] | -0.000037 [0.00003] | -0.000024 [0.00004] |
| Observations | 24,023 | 24,023 | 24,023 | 24,023 | 24,023 | 24,023 | 24,023 |
| Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | No | No | No | No | No |
| Turning point (CR4) | 63 | | 52 | 57 | 63 | 73 | 85 |

**Notes**: The dependent variable is the growth rate of TFP. Column 1 presents the OLS regression estimates. Columns 2-6 report the MM-QR regression estimates. Time dummies when included are not reported. Robust standard errors are in parenthesis and clustered standard errors from 1,000 bootstrapping repetitions to obtain heteroskedasticity robust estimates are in square brackets. Significant at ***1%, **5% and *10% respectively.

**Figure 1:** Effect of PMC on TFP.




**Notes**: The dotted dashed line indicates the turning point.

Concerning the quantile results, we observe that in all of the specifications the linear term is positive ($\hat{a}_1 > 0$), while the quadratic term ($\hat{a}_2 < 0$) is always negative indicating an inverse U-shaped curve. We notice though that the magnitude of the linear estimate is essentially the same across the five quantilies. However, the turning point varies in its magnitude across the conditional distribution function (CDF), reaching its peak (CR4 = 95) at the 90$^{th}$ quantile (see Figure 1).

### 3.2. Robustness cheeks

To check for robustness, we re-estimate the MM-QR model by using an alternative measure of PMC namely the Hirschman-Herfindahl index of the 50 largest firms in the industry (HHI50).[2] The latter, is widely used in the literature as a proxy for competition (see for example Dai et al, 2014; Polemis and Tzeremes, 2019). We also apply the panel quantile regression estimator obtained by Canay (2011).

Indeed, the results obtained with the Canay and MM-QR estimators (see Table 3; Panel B and C) suggest that an increase in competition is associated with greater productivity in concentrated industries (HHI is high) but with less productivity in competitive markets (HHI is low), justifying an inverse-U relationship across the CDF.[3] We observe though, that the magnitude of Canay estimates differs substantially across the quantiles (especially at the extreme ones) compared to MM-QR estimates, which seem to be relatively stable.

[2] The relevant indicator is calculated as: $HHI50 = \sum_{i=1}^{50} s_{it}^2 \times 10,000$ where s denotes the market share of each firm in industry i at time t.

[3] To preserve space we do not present the estimated results of the rest covariates.

**Table 3:** Robustness checks results

| Panel A: OLS | Location | Scale | | | |
|---|---|---|---|---|---|
| *Competition* | 0.256*** (0.04) | -0.0303* (0.0209) | | | |
| *Competition (squared)* | -0.0234*** (0.003) | 0.0026* (0.0017) | | | |
| **Panel B: MM-QR** | **Q(0.10)** | **Q(0.25)** | **Q(0.50)** | **Q(0.75)** | **Q(0.90)** |
| *Competition* | 0.304*** [0.056] | 0.279*** [0.04] | 0.255*** [0.03] | 0.232*** [0.04] | 0.208*** [0.053)] |
| *Competition (squared)* | -0.0276*** [0.004] | -0.0255*** [0.003] | -0.0234*** [0.002] | -0.021*** [0.003] | -0.0193*** [0.004] |
| **Panel C: Canay (2011)** | **Q(0.10)** | **Q(0.25)** | **Q(0.50)** | **Q(0.75)** | **Q(0.90)** |
| *Competition* | 0.516*** [0.132] | 0.333*** [4.97] | 0.257*** [0.026] | 0.2003*** [0.023] | 0.533*** [0.07] |
| *Competition (squared)* | -0.044*** [0.0103] | -0.030*** [-5.61] | -0.024*** [0.002] | -0.019*** [0.002] | -0.0087*** [0.005] |

**Notes:** Industry and year dummies are included but not reported. Significant at ***1%, and *10% respectively.

## 4. Conclusion

This note studies the impact of PMC on productivity growth in 462 US manufacturing sectors for the period 1958-2009 using panel quantile regression. The empirical findings justify a "*hump-shaped*" nonlinear effect of competition on productivity lending support to Aghion et al., (2005). On one hand, competition may stimulate the incremental profit from innovating ("*escape-competition effect*"), while on the other hand, it may diminish innovative activity for smaller firms ("*Schumpeterian effect*"). The turning point increases substantially for higher quantiles of the productivity distribution function. The findings survive robustness checks under alternative competition measure and quantile estimator. Future studies could use our results to shed light on the impact of competition on consumer welfare.

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