Finite Sample Performance of Conduct Parameter Test in Homogenous Goods Markets

Yuri Matsumura* Suguru Otani †

October 1, 2023

Abstract

We assess the finite sample performance of the conduct parameter test in homogeneous goods markets. Statistical power rises with ~~(1)~~ an increase in the number of markets, ~~(2)~~ a larger conduct parameter, and ~~(3)~~ a stronger demand rotation instrument. However, even with a moderate number of markets ~~(e.g., 1000)~~ and five firms, regardless of instrument strength and the utilization of optimal instruments, rejecting the null hypothesis of perfect competition remains challenging. Our findings indicate that empirical results ~~failing~~ to reject perfect competition are a consequence of the limited number of markets~~,~~ rather than methodological deficiencies.

Keywords: Conduct parameters, Homogenous goods market, Monte Carlo simulation, Statistical power analysis

JEL Codes: C5, C13, L1

1 Introduction

Measuring competitiveness is ~~an~~ important ~~task~~ in the empirical industrial organization literature. A conduct parameter is considered to be a useful measure of competitiveness. However, the parameter cannot be directly measured from data because data generally lack information about marginal costs. Therefore, researchers endeavor to learn conduct parameters.

Researchers estimate and test structural models to understand firm conduct in both homogeneous and differentiated good markets (Nevo 1998, Magnolfi and Sullivan 2022, Duarte et al. 2023). We focus on homogenous good markets. The conduct parameters ~~are identified~~ for the linear model by Bresnahan (1982), and Matsumura and Otani (2023b) resolve conflicts between Bresnahan (1982) and Perloff and Shen (2012) ~~on~~ identification problems. Estimation accuracy ~~might improve~~ by adding equilibrium existence conditions in the log-linear model (Matsumura

*Department of Economics, Rice University. Email: Yuri.Matsumura@rice.edu

†Department of Economics, Rice University. Email: so19@rice.edu

and Otani 2023a). Conduct parameter testing is ~~done~~ by Genesove and Mullin (1998), who compare estimates from the sugar industry with direct measures of market power.[1] When market power is around 0.1 and the number of markets is less than 100, perfect competition cannot be rejected. ~~Also,~~ Steen and Salvanes (1999) study 48 markets in the French salmon industry and Shaffer (1993) ~~study~~ 25 markets in the Canadian banking industry. They cannot reject the null hypothesis that markets are perfectly competitive ~~as well~~. Their results raise doubts about the methodology in itself (Shaffer and Spierdijk 2017).

While popular, there is a lack of formal Monte Carlo simulations for a conduct parameter test. ~~To address this~~, we investigate the finite sample performance of the conduct parameter test in homogeneous goods markets. We analyze statistical power by varying the number of markets, firms, and ~~the~~ strength of demand rotation instruments~~,~~ under the null hypothesis of perfect competition.

Our findings indicate that statistical power increases with a larger sample size ~~(more markets), a~~ larger conduct parameter, and stronger demand rotation instruments. However, even with a moderate number of markets (e.g., 1000) and five firms, we cannot achieve an 80% rejection frequency ($1-\beta = 0.8$, where β represents the probability of a Type II error), irrespective of instrument strength and the use of optimal instruments. While optimal instruments enhance rejection probability in large samples, they do not alter the core findings. This highlights the challenge of testing perfect competition, as recognized by Genesove and Mullin (1998), Steen and Salvanes (1999), and Shaffer (1993), primarily stemming from the limited number of markets rather than methodological flaws.

Our results and code provide a valuable reference for applied researchers examining assumptions about firm conduct in homogeneous goods markets, whether ~~it's~~ perfect competition, Cournot competition, or perfect collusion.

2 Model

Consider data with T markets with homogeneous products. Assume that there are N firms in each market. Let $t = 1, \ldots, T$ be the index for markets. ~~Then~~, we obtain a supply equation ~~as follows~~:

$$P_t = -\theta \frac{\partial P_t(Q_t)}{\partial Q_t} Q_t + MC_t(Q_t), \tag{1}$$

where Q_t is the aggregate quantity, $P_t(Q_t)$ is the demand function, $TC_t(Q_t)$ is the marginal cost function, and $\theta \in [0,1]$ is the conduct parameter. The equation nests perfect competition

[1] Genesove and Mullin (1998) made mistakes on how to get predicted interaction terms of rotation demand instruments and endogenous quantity in the first~~-~~stage regression. See Section A.3, Matsumura and Otani (2023b).

($\theta = 0$), Cournot competition ($\theta = 1/N$), and perfect collusion ($\theta = 1$)~~.~~ See Bresnahan ~~(~~1982).

Consider an econometric model that integrates the above ~~model~~. Assume that the demand and marginal cost functions are written as ~~follows:~~

$$P_t = f(Q_t, Y_t, \varepsilon_t^d, \alpha), \tag{2}$$

$$MC_t = g(Q_t, W_t, \varepsilon_t^c, \gamma), \tag{3}$$

where Y_t and W_t are vectors of exogenous variables, ε_t^d and ε_t^c are error terms, and α and γ are vectors of parameters. Additionally, we have demand- and supply-side instruments, Z_t^d and Z_t^c, and assume that the error terms satisfy the mean independence conditions, $E[\varepsilon_t^d \mid Y_t, Z_t^d] = E[\varepsilon_t^c \mid W_t, Z_t^c] = 0$.

2.1 Linear demand and cost

Assume that linear demand and marginal cost functions are specified as ~~follows:~~

$$P_t = \alpha_0 - (\alpha_1 + \alpha_2 Z_t^R) Q_t + \alpha_3 Y_t + \varepsilon_t^d, \tag{4}$$

$$MC_t = \gamma_0 + \gamma_1 Q_t + \gamma_2 W_t + \gamma_3 R_t + \varepsilon_t^c, \tag{5}$$

where W_t and R_t are excluded cost shifters and Z_t^R is Bresnahan's demand rotation instrument. The supply equation is written as ~~follows:~~

$$P_t = \gamma_0 + \theta(\alpha_1 + \alpha_2 Z_t^R) Q_t + \gamma_1 Q_t + \gamma_2 W_t + \gamma_3 R_t + \varepsilon_t^c. \tag{6}$$

By substituting Equation (4) with Equation (6) and solving it for P_t, we obtain the aggregate quantity Q_t based on the parameters and exogenous variables as follows:

$$Q_t = \frac{\alpha_0 + \alpha_3 Y_t - \gamma_0 - \gamma_2 W_t - \gamma_3 R_t + \varepsilon_t^d - \varepsilon_t^c}{(1+\theta)(\alpha_1 + \alpha_2 Z_t^R) + \gamma_1}. \tag{7}$$

3 Simulation results

3.1 Simulation and estimation procedure

We set true parameters and distributions as shown in Table 1. We vary the true value of θ from 0.05 (20-firm~~s~~ symmetric Cournot) to 1 (perfect collusion) and the strength of demand rotation instrument, α_2, from 0.1 (weak) to 20.0 (extremely strong), which is unrealistically larger than the price coefficient level, $\alpha_1 = 1.0$. For simulation, we generate 100 data~~-~~sets. We separately estimate the demand and supply equations ~~by using~~ two-stage least squares (2SLS) estimation. The instrumental variables for demand estimation are $Z_t^d = (1, Z_t^R, Y_t, H_t, K_t)$ and ~~the instru-~~

~~mental variables~~ for supply estimation are $Z_t^c = (1, Z_t^R, W_t, R_t, Y_t)$ for a benchmark model. To achieve theoretical efficiency bounds, we add optimal instruments of Chamberlain (1987), ~~which is~~ used in demand estimation (Reynaert and Verboven 2014). Optimal instruments ~~give rise~~ to asymptotically efficient estimators, ~~in the sense that~~ their asymptotic variance cannot be reduced ~~by using~~ additional orthogonality conditions. See Appendix A.2 for construction details. The null hypothesis is that markets are under perfect competition, that is, $\theta = 0$. We compute the rejection frequency as the power by using t-statistics at a significance level of 0.05 over 100 datasets.

Table 1: True parameters and distributions

(a) Parameters

α_0	10.0
α_1	1.0
α_2	$\{0.1, 0.5, 1.0, 5.0, 20.0\}$
α_3	1.0
γ_0	1.0
γ_1	1.0
γ_2	1.0
γ_3	1.0
θ	$\{0.05, 0.1, 0.2, 0.33, 0.5, 1.0\}$

(b) Distributions

Demand shifter	
Y_t	$N(0,1)$
Demand rotation instrument	
Z_t^R	$N(10,1)$
Cost shifter	
W_t	$N(3,1)$
R_t	$N(0,1)$
H_t	$W_t + N(0,1)$
K_t	$R_t + N(0,1)$
Error	
ε_t^d	$N(0,\sigma)$
ε_t^c	$N(0,\sigma)$

Note: $\sigma = 1.0$. N : Normal distribution. U : Uniform distribution.

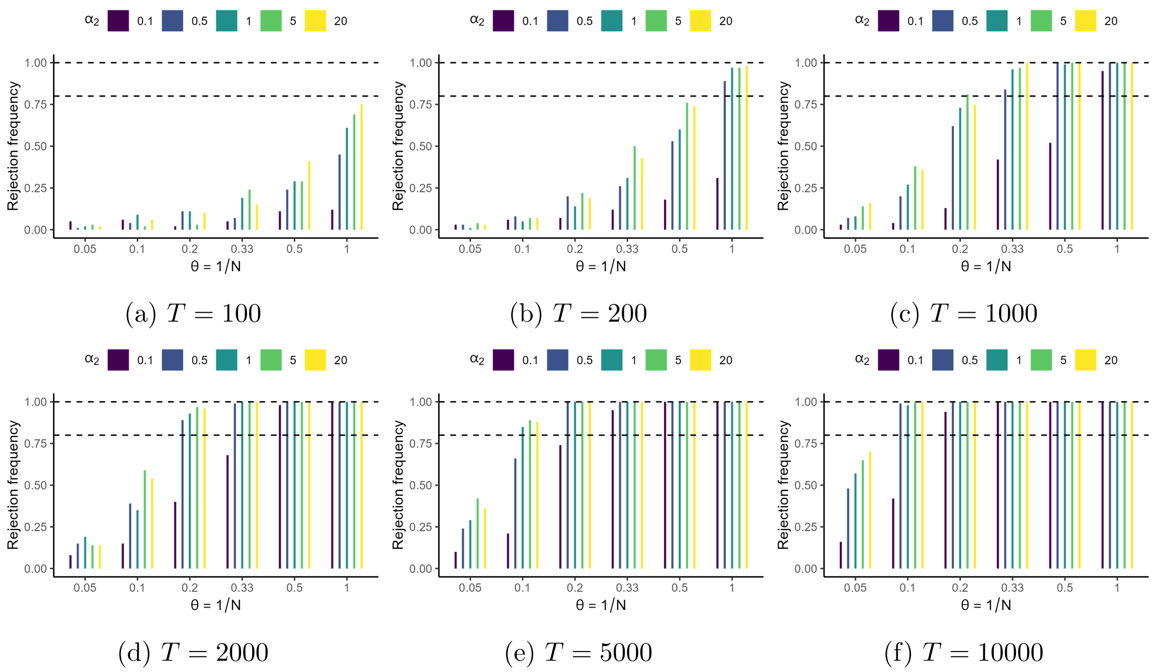
Figure 1 displays the finite sample performance results for the conduct parameter θ.[2] Rejection frequency increases under the following conditions: ~~(1) a~~ large sample size (number of markets), ~~(2) a~~ larger θ (fewer firms), and ~~(3) a~~ larger α_2 (stronger demand rotation instrument). Panel (f) indicates that with ~~twenty~~ symmetric firms ($\theta = 0.05$) and a sufficiently large number of markets, we achieve an approximately 70% power to reject the null hypothesis of markets operating under perfect competition. However, we cannot reject the null hypothesis with an acceptable sample size and power when markets follow ~~twenty~~-firm symmetric Cournot competition.

A remarkable finding is that even with a moderate number of markets (e.g., 1000 in Panel (c)) and five firms, the rejection frequency cannot achieve 80% (~~that is~~, $1 - \beta = 0.8$ where β is the probability of making a Type II error), regardless of ~~the~~ strength ~~of instruments~~. This implies that Genesove and Mullin (1998) using 97 markets~~,~~ Shaffer (1993) using 25 markets~~,~~ and Steen and Salvanes (1999) using 48 markets, fail in rejecting perfect competition due to the small sample problem.

[2]Simulation details and additional results for all other parameters are available in the online appendix.

Figure 2 ~~reports~~ the efficiency gain of optimal instruments relative to the ~~above~~ benchmark model. We find that if the number of markets ~~is more than~~ 1,000, optimal instruments increase the rejection probability. However, the gain does not change our benchmark results.

Why is it statistically challenging to differentiate between perfect~~ competition~~ and Cournot competition? In differential product markets, as demonstrated by Berry and Haile (2014), the variation in instrumental variables can aid in discerning firm behavior. Various factors such as changes in the number of products, prices in other markets, alterations in product characteristics~~, and more,~~ can be utilized~~,~~ without requiring a specific functional form. In contrast, homogeneous product markets exhibit limited variation only on demand rotation instruments. Therefore, even when the number of firms is substantial, firm conduct tests may lack the necessary power to differentiate between perfect~~ competition~~ and Cournot competition.



(a) $T = 100$ (b) $T = 200$ (c) $T = 1000$

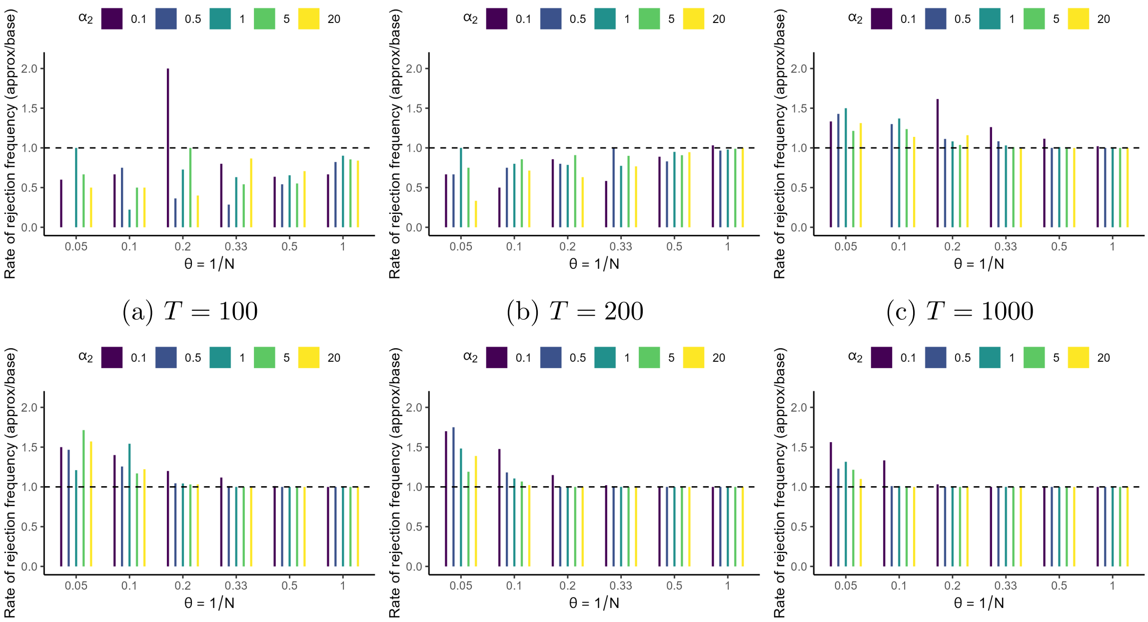
(d) $T = 2000$ (e) $T = 5000$ (f) $T = 10000$

Figure 1: Statistical power of conduct parameter θ

Note: Dotted lines are 80% and 100% rejection frequencies out of 100 simulation data.

4 Conclusion

We ~~conduct~~ a statistical power analysis for conduct parameter estimation. Power increases with ~~(1) ~~a large sample size (i.e., a high number of markets), ~~(2) a ~~large conduct parameter, and ~~(3) a ~~stronger demand rotation instrument. Nevertheless, rejecting the null hypothesis of markets operating under perfect competition remains challenging, even with a moderate number of markets (e.g., 1000) and five firms, regardless of ~~the ~~instrument~~'s~~ strength and the use of optimal instruments. This reaffirms that the difficulty in testing perfect competition, as observed



(a) $T = 100$ (b) $T = 200$ (c) $T = 1000$

(d) $T = 2000$ (e) $T = 5000$ (f) $T = 10000$

Figure 2: Relative efficiency gain of optimal instruments

by Genesove and Mullin (1998), Steen and Salvanes (1999), and Shaffer (1993), is primarily attributed to the limited number of markets~~,~~ rather than methodological shortcomings.

Acknowledgments We thank Jeremy Fox, Isabelle Perrigne, and Yuya Shimizu for their valuable advice. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.