On the effectiveness of Recidivism on Productivity Growth: Evidence from anti-cartel enforcement in the US

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ABSTRACT

Explicit collusion, or cartel behavior, involves coordinated efforts among firms within a market to restrict competition for their mutual benefit. Recidivism in this context occurs when cartel members, previously fined for such activities, establish a new cartel in the future. This paper examines 111 cartel cases from various markets and periods in the US to assess the impact of recidivism on productivity growth. We define a recidivist as a repeat offender with at least two fines. Investigating the causality between cartel recidivism and total factor productivity (TFP) growth is crucial for several reasons. First, understanding this relationship helps policymakers and regulators design more effective anti-cartel enforcement strategies. Second, examining the causality between cartel recidivism and TFP growth provides insights into the broader economic impacts of anti-competitive practices. Ultimately, such investigations help in creating a more efficient and equitable economy, where market forces drive productivity improvements and sustainable economic growth. Our econometric findings drawn from OLS and quantile regression analysis indicate a negative relationship between recidivism and productivity growth. The rationale is that recidivism undermines the effectiveness of anti-cartel enforcement, which consequently hampers productivity growth in the affected markets.

Keywords: Cartels; Recidivism; Competition Policy; Anti-Cartel Enforcement; TFP

JEL Classification: K21; L41; D24

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1. Introduction

Firms form a cartel with their competitors due to higher profits that may be gained from the implemented collusion practices. Cartel allows its members to exercise market power that they would not otherwise have and restricts investments in innovative assets and R&D that would be required in more competitive markets. Therefore, a cartel is coordinated conduct among firms in the market with an incentive to restrict competition for their mutual benefit (see, among others, Harrington, 2023).

The purpose of the Sherman Act in the US is to protect consumers from the failure of the market and not to protect firms from the working of the market[1]. It prohibits unfair monopolies, that is, anticompetitive agreements and unilateral conduct that monopolizes or attempts to monopolize the market. The Clayton Act passed in 1914, enhances the scope of the Sherman Act by proscribing certain anti-competitive practices.

In the US the total cartel fines imposed by the Antitrust Division of the Department of Justice (DoJ) increased by almost 17,5% (from 1.5 million in 2022 to 264.2 million in 2023) from 2022 to 2023, indicating a continuing intent by the Antitrust Division to pursue cartels and impose severe sanctions (Shah et al. 2024). Table 1 presents the average values of anti-cartel enforcement and related issues by the DoJ from 1969 to 2016 (48 years).

In 2020 20 criminal cases were filed compared to the four-year average of 22 cases per year. The DoJ collected $67 US million in fines in 2017, $172 US million in 2018, $365 US million in 2019 and $529 US million in 2020 (Table 2).

1 See *Spectrum Sports, Inc. v. McQuillan, 506 U.S. 447 (1993)*.

Table 1. Anti-Cartel Enforcement & related issues by DoJ: 1969 - 2016

	Mean
Total Cartel cases per year	44,52
Total fines per year (2010$, '000)	264,940.62
Total jail days per year	6,101.32
Fines per cartel (2010$, '000)	7,068.64
Number of individuals fined per cartel	1.22
Number of firms fined per cartel	1.81

Source: Ghosal & Sokol (2020) (Division Operations, U.S. DoJ, *https://www.justice.gov/atr/division-operations* (last updated July 1, 2019).

Table 2. Collection of fines by DoJ: 2016 - 2020

Years	Total fines per year (*in US million*)
2017	67
2018	172
2019	365
2020	529

Source: Global Competition Review, US: Cartels (*https://globalcompetitionreview.com/review/the-antitrust-review-of-the-americas/2022/article/united-states-cartels*).

Article 101 of the Treaty on the Functioning of the European Union (TEFU) prohibits agreements between two or more independent firms, which restrict competition. The most critical example of illegal conduct infringing Article 101 of TEFU is the creation of a cartel between competitors. Major cartel practices are the limitation or control of production, markets, technical developments or investment, the sharing of markets or sources of supply (including bid-rigging), the direct or indirect fixing of prices or other trading conditions, the restriction of imports and/or exports and, under certain circumstances, the exchange of sensitive information among competitors.

Even though the European Commission (EC) imposed fines totaling 95.8 million euros in 2023, less than the corresponding figure for the year 2022 of 205.4 million euros, it issued four decisions more than in 2022 and 2020 (Shah et al. 2024). During the period from 2019 to 2023 (as of 07 December 2023), the EC has imposed fines (adjusted for Court judgments2) totaling 3.796.756.000,00 euros on firms for cartel infringements, while from 1990 to 2023 the corresponding amount totaling 29.729.236.184,50 euros (EU 2023). Table 3 shows the highest cartel fines per case imposed by the EC from 2001 to 2023.

Table 3. Highest cartel fines* per case by the EC: 2001 – 2023 (07.12.2023)

A/A	Year	Cases	Fine in €
1	2016/2017	Trucks (**T**)	**3 807 022 000**
2	2019/2019/2021	Forex**	1.329.980.000
		(*three-way Banana Split*) (**TWBS**)	**811.197.000**
		(*Essex Express*) (**EE**)	**257.682 000**
		(*Sterling Lands*) (**SL**)	**261 101 000**
3	2012	TV and Computer Monitor Tubes (TVCMT)***	1.490.615.000
		CPT CARTEL	**328.187.000**
		CDT CARTEL	**1.162.428.000**
4	2013/2016/2021****	Euro Interest Rates Derivatives (**EIRD**)	**1.308.172.000**
5	2014	Automotive Bearings (**AB**)	**953 306 000**
6	2021	Car Emissions (**CE**)	**875 189 000**
7	2007	Elevators and Escalators (**E&E**)	**992 312 000**
		BELGIUM	185.620.050
		GERMANY	617.091.750
		LUXEMBOURG	49.361.400
		THE NETHERLANDS	140.239.000
8	2010/2017	Airfreight (air cargo carriers) (**ACC**)	**1.215.215.000**
9	2001	Vitamins (**V**)	**855.230.000**
10	2013/2015	Yen Interest Rate Derivatives (**YIRD**)	**689.859.000**
		TOTAL IMPOSED FINES	**13.496.900.200**

*Amounts adjusted for changes following judgments of the Courts (General Court and European Court of Justice) and/or amendment decisions. **The Forex case consists of three Settlement cases/decisions and one ordinary cartel decision. *** The TVCMT case consists of two ordinary cartel decisions: the CPT case consists of one ordinary cartel decision in the sector of color display tubes used in computer monitors and the CDT case consists of one ordinary cartel decision in the sector of color picture tubes used for color televisions. **** The EIRD case consists of two amendment cases in 2016 and 2021. For the ordinary cartel decision see *https://ec.europa.eu/commission/presscorner/detail/en/mex_21_3283*.

Source: Cartel cases (CASE AT.39258 – AIRFREIGHT, CASE COMP/39922 – AUTOMOTIVE BEARINGS, CASE AT.40178 – CAR EMISSIONS, Case COMP/E-1/38.823 - PO/ELEVATORS AND ESCALATORS, CASE AT.39914 - EURO INTEREST RATE DERIVATIVES, CASE AT.40135 FOREX (Sterling Lads), CASE AT.40135 FOREX (Essex Express), CASE AT.40135 FOREX (Three Way Banana Split), CASE AT.39824 -TRUCKS, CASE AT.39437 – TV AND COMPUTER MONITOR TUBES, Case COMP/E-1/37.512 VITAMINS, CASE AT.39861 – YEN INTEREST RATE DERIVATIVES); Laina & Bogdanov (2019); EC (2023; 2019).

Most cartels in the European Union (EU) take place in the manufacturing sector. Particularly, from 2010 to 2023 (as of 07 December 2023), 49,56% of fines imposed by the

[2] Fines corrected for changes (incl. corrections following amendment decisions) and judgments of the Courts (General Court and Court of Justice).

Commission concerned the manufacturing sector (car parts[3] and others). 21,16% of fines (3.918.180.000,00 euros) imposed by the Commission concern the financial sector, 15,75% of fines concern the basic industry and 13,53% of fines concern the ICT sector (EC 2023).

Recidivism exists if cartel members who have been fined initiate a new cartel in the future (Levenstein et al. 2015; Werden et al. 2011). Werden et al. (2011) introduce the notion of true recidivists (10 firms), while Marvão (2016) identifies 4 and Marvão (2023) identifies 10 true recidivists. Connor (2010) defines a cartel member as a recidivist who infringes antitrust law multiple times. According to Maltz (1984), the DoJ defines a recidivist as any firm that «*after release from custody for having committed a crime, is not rehabilitated*».[4]

Cartel recidivism negatively impacts total factor productivity (TFP) growth by perpetuating anti-competitive practices that stifle innovation and efficiency. When firms engage in repeated cartel behavior, they create an environment where market dynamics are manipulated to maintain artificially high prices and restricted output. This collusive activity undermines competitive pressures that typically drive firms to innovate, improve processes, and reduce costs. As a result, resources are allocated inefficiently, and the potential for technological advancements and productivity enhancements is diminished. The lack of competition means that firms are less motivated to improve their performance, leading to a slower rate of TFP growth across the industry.

Moreover, the recurrence of cartels indicates that existing anti-cartel enforcement mechanisms are insufficiently deterrent. When firms perceive the consequences of being caught and fined as manageable or insignificant relative to the profits from collusion, they

[3] The total amount of fines by the Commission since 2013 is 2.169.466.000,00 euros.
[4] For a review of the notion of recidivism see Levenstein et al. (2015).

are more likely to re-offend. This ongoing cycle of collusion and recidivism erodes the credibility and effectiveness of regulatory frameworks designed to foster competitive markets. As enforcement becomes less effective, the overall market environment deteriorates, further inhibiting the factors that contribute to productivity growth. In such markets, the continual suppression of competitive forces leads to a persistent drag on TFP, as the incentives for firms to pursue efficiency gains and innovation are continually undermined.

The first time the EC acknowledged the serious issue of recidivism was in 2006 with the introduction of the guidelines on setting fines (EC, 2006). According to the guidelines, multiple cartel members will be fined more heavily than before, and, therefore, EC strengthened the fines for repeat offenders imposing a fine increase of up to 100%[5], instead of 50% as set in the previous guidelines (Marvão, 2023; Veljanovski, 2011). In practice, recidivism constitutes an aggravating factor since in cartel cases, the fine can be increased for a repeated offender by a one-time amount equivalent to 15% - 25% of the yearly sales (EC, 2011). In the US recidivism also constitutes an aggravating factor in the Sentencing Guidelines first issued in 1987 (Conor, 2016). Recidivism may raise the maximum cartel fine by 0% - 16%, depending on the size of the firm, which also constitutes an aggravating factor under Sentencing Guidelines.

In this paper, we use a sample of 111 cartel cases in the US that took place in various markets from different periods to show the effect of recidivism on productivity growth. For this purpose, we define a recidivist as a multiple offender with at least 2 fines (Bryant & Eckard, 1991; Conor, 2010; Wils, 2012; Le Coq & Marvão, 2021; Abraham & Marvão,

[5] According to the previous guidelines (EC, 2002), Commission strengthened the fines for repeat offenders imposing a fine increase of up to 50%.

2021).[6] The results of our paper support the idea that there is a negative relationship between recidivism and productivity growth. The intuition behind this result is that the presence of recidivism restricts the effectiveness of anti-cartel enforcement which, in turn, negatively affects productivity growth in the markets under scrutiny.

The rest of the paper is organized as follows: Section 2 reviews the literature and Section 3 presents the data and the sample variables. Section 4 discusses the conceptual framework, while Section 5 describes the empirical methodology and the main research hypothesis. Section 6 discusses the empirical results drawn from the OLS and the quantile regression analysis, whereas Section 7 concludes the paper.

2. Literature review

Many academic scholars have theoretically and empirically explored the issue of recidivism. From a theoretical point of view, Shen (2017) explores a reputation model with two firms that produce and collude on a homogeneous product. In a finite-period repeated game, the model explores the incentives of firms to apply for the Leniency Program (LP) and it suggests that a firm that may form several cartels (recidivist) finally applies for the LP to protect its reputation and deter future cartel deviations. Katsoulacos et al., (2023) provide a conceptual framework for measuring the effectiveness of the Competition Authority's anti-cartel enforcement when there is a possibility a cartel might reemerge (recidivism) after a successful prosecution by a Competition Authority (CA). The authors state, *among others*, that recidivism significantly affects CAs' performance and, therefore, the latter have to take account of it. Harding & Gibbs (2005) have also noted that recidivism appears among major firms which shows a culture of business delinquency.

[6] See also Marvão (2016; 2023) and Levenstein et al. (2016).

From an empirical standpoint, in the US, Bryant & Eckard (1991) estimate the probability that a cartel is detected. The authors use data on 1300 cartel members fined by the US DOJ between 1961 and 1988 and find that the probability of detection is between 13% to 17%. Moreover, the authors also state that 14% of the cartel members are recidivists. Levenstein & Suslow (2014) use a comprehensive sample of 524 US cartels of Sherman Act's section 1 from 1961 to 2013. Among 2589 firms of the sample, 114 of them were defined as multiple offenders, while 14 firms among the sample of multiple offenders met the criteria of DoJ (the DoJ defines a recidivist as any firm that «*after release from custody for having committed a crime, is not rehabilitated*»). Interestingly enough, none of the 14 firms were indicted by the DoJ (Levenstein et al. 2015).

Levenstein et al., (2016) expand the data from Bryant & Eckard (1991) up to 2013 by including bid-rigging cases and cases that had been appealed. The data consists of 524 cartels and 6% of the cartel members are identified as recidivists. Levenstein et al., (2016) also explore if recidivism should be analyzed at the industry or firm level, finding that it depends on the success of prior cartels, therefore the focus should be on firm-level recidivism. Contrary to the above-mentioned literature, Werden et al., (2011) explore the issue of recidivism in the post-1999 period and conclude that in the US, since 1999, recidivism has been eliminated.

From an empirical point of view, in the EU, Wils (2012) explores the issue of recidivism and reports that between 2006 and 2010, 12% of convicted cartel members participated in more than one cartel. Based on this study, a recidivist has a higher propensity to collude and, a lower probability of detection, moral condemnation, and discovery of the profitability of cartels. Marvão (2016) examines EC cartel fines between 1998 and 2014. The scope of the paper is the empirical examination of the % leniency reduction granted to each cartel member. The basic finding supports the idea that recidivism positively influences the granting and scale of EU leniency reductions. The author also states that, contrary to Werden et al., (2011), in the EU, true recidivists, that is, a firm that starts a new cartel after a cartel fine, compromise 1% of the examined sample.

From an empirical point of view, worldwide, Connor (2010) indicates a large amount of recidivism worldwide. Particularly, the author states that there exist 389 recidivists worldwide in the period between 1990 and 2009, that is, 18.4% of the total number of firms involved in 648 international cartel cases. Connor (2018) extends the work of Conor (2020) and identifies multiple offenders[7] in 86% of worldwide cartels between 1990 and 2015 and states that cartels are formed by recidivists. Therefore, the author points out that cartel legislation should directly target recidivists. Marvão & Spagnolo (2018) examine empirically the likelihood of prison sentences in the US, for individuals involved in cartels, during the period from 1990 to 2014. The analysis shows that multiple offenders are more likely to avoid a jail sentence, indicating a learning effect also in the US, which may be connected to the LP. In the EU, prison sentences are rare with a rising trend and it appears that the current level of EC sanctions has a modest effect on corporate governance and needs to be strengthened.

Abraham & Marvão (2021) examine the LP in India and identify 46 out of 197 cartel members fined between 2009 and 2017 as multiple offenders (recidivists). They indicate that recidivists obtain larger fine savings and, in addition, while the competent authority of India's fining decisions are inconsistent, lenient, and exceedingly appealed even though it can impose harsher sanctions than in jurisdictions such as the EU or the US. Marvao (2023) uses comprehensive data from 161 cartels fined by the EU from 1998 to 2020. Among the members of these cartels, the EU imposed 814 fines on 555 firms. The author identifies 103

7 The author uses the term "global serial cartels" which refers to the number of offenses by a parent firm. See also Marvão (2016).

firms as multiple offenders with at least two fines (19%), 18 firms as repeated offenders (when a firm starts a new cartel after investigation for another cartel – 3,2%) and 10 firms as true recidivists (when a firm starts new cartel after fined for another cartel).

Buccirossi et al., (2013) empirically assess the effectiveness of competition policy on TFP growth for 22 industries in 12 OECD countries over the period from 1995 to 2005. The results provide a positive and significant effect of competition policy on TFP growth. Levenstein et al. (2016) state that since many cartel members have been discovered to collude multiple times, recidivism may be perceived as the outcome of the limited efficiency of competition policy.

All the above literature explores the amount of recidivism in detected and convicted cartel offenses. However, since undetected cartels differ from detected ones in many dimensions, the empirical results on recidivism are biased. Le Coq & Marvão (2021) use a dataset of a population of cartels that were legal in Sweden up until 1993. They point out that firms colluded in many cartels (48% of the firms colluded in up to 63 cartels over 46 years) and most cartels include recidivists.

Based on the above-mentioned literature review, the motivation of this paper is to empirically explore the relationship between recidivism and productivity growth. Since the presence of recidivism restricts the efficiency of competition policy, which, in turn, negatively affects productivity growth, recidivism may also negatively affect it.

Particularly, our study contributes to the existing literature by empirically investigating the relationship between recidivism and productivity growth. It aligns with recent influential studies, both theoretical and empirical, such as those by Buccirossi et al. (2013), Levenstein et al. (2016), Katsoulacos (2023) and Harding & Gibbs (2005). The primary contribution of our research is the finding that recidivism negatively impacts TFP growth. The presence of recidivism undermines the effectiveness of competition policy, which in turn negatively influences productivity growth. By demonstrating that recidivism can hinder the efficiency of market dynamics, our paper highlights the broader economic consequences of persistent anti-competitive behavior and the importance of robust enforcement measures to promote sustained productivity improvements.

3. Data and sample collection

We use recidivism data from Conor (2020) dataset, which is part of the largest collection of price-fixing cartels (Private International Cartels - PIC). Particularly, we analyse a sample of 111 price-fixing cartels of 1044 cartel members that took place from 1966 to 2016 in the US. The sample comprised members of cartels from various product/service markets. In Appendix 1 we show the product/service markets and NAICS codes of the cartels under scrutiny (Table 1A).

Table 1B in Appendix 1 presents the duration of 111 cartels. The average duration of a cartel is 7,2 years or 86,3 months. The cartel case with the highest duration is no 93 in Table 1B in Appendix 1 (26 years or 312 months), which started in 1986 and ended in 2012. The cartel case with the lowest duration is no 28 in Table 1B in Appendix 1 (0,4 years or 5 months), which started in December 2022 and ended in May 2003.

In our sample, 62% of cartel cases of our sample compromise a multiple offender with at least 2 fines. In the rest 38% of cartel cases the engaged firms are not recidivists. Table 4 presents the duration of cartels with or without recidivists is presented in Table 4. It is evident from the said Table that cartel cases with multiple offenders last longer than cartel cases without recidivists. On average, the former lasts almost 3 years more than the latter.

Table 4. Duration of cartels with or without recidivists in the US from 1966 to 2016

	No of cases (% of cases)	Mean duration (years)
Cartels with Recidivists	69 (62%)	**8,3**
Cartels without Recidivist	42 (38%)	**5,4**

Source: Authors' elaboration of Conor's (2020) dataset

We use the NBER-CES manufacturing industry database (Becker et al., 2021) for the dependent and independent (except the independent variable *REC*) variables of eq. (3) and (4). The database spans from 1968 to 2018. Table 5 presents summary statistics for selected variables of the empirical models (eq. 3 & 4). Table 1C in Appendix 1 presents summary statistics for the remaining variables of the empirical models.

Table 5. Summary statistics for selected variables of the empirical models

Variables	Observations	Mean	Standard deviation	Min	Max
REC	111	0.396	0.491	0	1
ΔVSHIP	111	1,277	9,246	-19,877	31,910
GVSHIP	111	0.102	0.367	-0.481	1.357
MVSHIP	111	29,135	35,260	1,270	159,327
ΔLP1	111	70.78	91.14	-259.5	447.9
GLP1	111	0.391	0.540	-0.797	3.521
MLP1	111	277.4	325.8	26.56	1,404
ΔLP2	111	34.77	47.51	-140.2	244.4
GLP2	111	0.388	0.552	-0.797	3.683
MLP2	111	136.6	164.4	13.40	719.3
ΔHC	111	2.801	3.429	-19.62	13.70
GHC	111	0.237	0.413	-0.800	2.885
MHC	111	17.37	6.689	4.326	37.91
ΔEQ	111	522.8	2,962	-3,675	15,456
GEQ	111	0.640	6.235	-19.98	48.40
MEQ	111	5,125	7,219	-81.80	44,207
ΔINVEST	111	-18.34	709.9	-4,173	2,757
GINVEST	111	0.0770	0.956	-1.723	4.372
MINVEST	111	1,019	1,571	17.43	9,592
ΔINVENT	111	285.8	893.5	-1,290	3,608
GINVENT	111	0.133	0.395	-0.559	2.169
MINVENT	111	2,833	4,406	100.6	19,472
ΔTFP5	111	0.0212	0.132	-0.625	0.356
ΔTFP4	111	0.0216	0.132	-0.625	0.357
GΔTFP5	111	0.0232	0.125	-0.381	0.470
GΔTFP4	111	0.0236	0.125	-0.380	0.471
Trend	111	56	32.19	1	111

Source: Authors' elaboration of Becker et al.'s (2021) dataset

4. Conceptual framework

Katsoulacos et al. (2023) argue that despite the efforts of a Competition Authority (CA), the harm from the formation of cartels arises by comparing the flow of Consumer Surplus (CS) in markets with collusive activity with that which would have arisen under perfectly competitive markets.

$$H(d, D, p^{cartel}) = CS_{(compet)} - CS_{(cartel)} \quad (1)$$

where H is the harm generated from the formation of a cartel, $CS_{(compet)}$ is the flow of CS under perfectly competitive markets, $CS_{(cartel)}$ is the flow (average) of CS in markets with collusive activity, that is, in markets where stable cartels exist in only a fraction *1-D*, while the remaining fraction behaves competitively and generates a flow of consumer surplus $CS_{(compet)}$, $CS_{(compet)} - CS_{(cartel)}$ is the loss of CS due to cartel activity, d is the degree of disruption of collusive activity brought about by CA post-prosecution interventions, D is the degree of deterrence achieved by an active CA, p^{cartel} is the cartel price. The authors conclude that the final harm suffered from the formation of cartels is given by eq. (2):

$$H(d, D, p^{cartel}) = (1 - D)(1 - d)\left(CS_{(compet)} - CS_{(cartel)}\right) \quad (2)$$

It is obvious from eq. (2) that $H(d, D, p^{cartel})$ is smaller the larger is the degree of disruption, the larger is the degree of deterrence and the smaller is the cartel price.

Katsoulacos et al. (2023) conclude that if the long–run interventions of CAs are weak relative to their short–run interventions against cartels, then CAs falsely that their interventions stop cartels forever. However, if the long–run interventions of CAs are quite strong relative to its short–run interventions against cartels, the latter will ignore the benefits arising from all future interventions against cartels. The existence of recidivism may significantly affect CAs' performance, by decreasing the degree of deterrence by CAs to stop cartels and, consequently, their efforts to enhance the level of competition in product/service markets where cartel activity re-emerges. Therefore, CAs that fail to adequately take account of the effect of recidivism on competition should be treated with considerable caution. Conor (2016) has also reached almost the same conclusion, indicating that multiple violations of antitrust laws by the same firm constitute evidence that deterrence penalties are inadequate.

5. Empirical specifications and Research Hypothesis

We empirically explore the hypothesis that recidivism negatively affects productivity growth. For this purpose, we estimate the empirical models in eq. (3) and (4). We estimate both empirical models by using OLS and quantile methods of estimation.

$$TFP_i = a_i + \beta REC_i + \gamma LP_i + \delta \Phi_\iota + trend + \varepsilon_\iota \quad (3)$$

$$LP_i = a_i + \beta REC_i + \gamma HC + \delta \Phi_\iota + trend + \varepsilon_\iota \quad (4)$$

We use Total Factor Productivity (TFP) (eq. 3) and Labor Productivity (LP) (eq. 4) as proxies of productivity growth. Following standard notation, *i* stands for the product/service market where the cartel took place. $TFP_i = \begin{bmatrix} \Delta TFP5_i \\ GTFP5_i \\ \Delta TFP4_i \\ GTFP4_i \end{bmatrix}$ denotes the vector of the annual growth rate of TFP in the market *i* (the dependent variables of eq. (3)), where ΔTFP_i is the difference and $GTFP_i$ is the growth of 5 and 4 factors TFP in market *i*. The variable REC_i is a dummy variable that takes the value 1 if a cartel case compromises a recidivist, otherwise it takes the value 0. It denotes the main independent variable of eq. (3) and (4). $LP_i = \begin{bmatrix} \Delta LP1_i \\ GLP1_i \\ \Delta LP2_i \\ GLP2_i \end{bmatrix}$ denotes the vector of Labor Productivity of market *i*, where ΔLP_i is the difference and GLP_ia is the growth of Labor Productivity in the market *i*.

$\Phi_i = \begin{bmatrix} \Delta\Phi_i \\ G\Phi_i \end{bmatrix}$ denotes the vector of other independent variables that may affect TFP_i or/and LP_i in market i, such as the variables $\Phi_i = \begin{bmatrix} \Delta INVEST_i \\ GINVEST_i \end{bmatrix} = \begin{bmatrix} \Delta INVENT_i \\ GINVENT_i \end{bmatrix} = \begin{bmatrix} \Delta VSHIP_i \\ GVSHIP_i \end{bmatrix}$ denote the vector of Total Capital Expenditure in \$1m, End-of-year Inventories in \$1min of market *i* and Total value of Shipments in \$1m of market *i* respectively. $\Delta INVEST_i$ and $GINVEST_i$ are the difference and growth of Total Capital Expenditure in market *i*, $\Delta INVENT_i$ and $GINVENT_i$ are the difference and growth of End-of-year Inventories in market *i* and $\Delta VSHIP_i$ and $GVSHIP_i$ are the difference and growth of the Total value of Shipments in the market *i*. The variable $HC_i = \begin{bmatrix} \Delta HC_i \\ GHC_i \end{bmatrix}$ denotes the vector of Human Capital, that is, ΔHC_i and GHC_i are the differences and growth of Human Capital in the market *i*.

Based on the above considerations, the research hypothesis we test in this paper is the following:

H1: Recidivism negatively affects productivity growth.

Given *H1*, we empirically explore the relationship between recidivism and productivity growth (see eqs. 3 & 4). The intuition behind *H1* is as follows: since the presence of recidivism restricts the efficiency[8] of competition policy, which, in turn, negatively affects productivity growth, the higher the level of recidivism, the lower the level of productivity growth.

[8] By deterring anticompetitive practices, competition policy should make markets work more effectively and foster efficiency.

6. Results and discussion

6.1 OLS estimations

Table 6 presents the empirical results from OLS estimations when the dependent variable is the TFP in the market i. It is evident from Table 6 that recidivism negatively affects the level of annual rate of productivity growth. Particularly, the negative effect of recidivism on growth is a statistically significant result, either we use the difference, or we use the growth of 4 & 5 factors TFP. Therefore, the above-mentioned results confirm the testable hypothesis of this paper, that is, recidivism negatively affects productivity growth.

Table 6. Empirical results from OLS estimations*: Dependent variable TFP

Independent variables [a]	**Dependent variables**			
	$\Delta TFP5_i$	$GTFP5_i$	$\Delta TFP4_i$	$GTFP4_i$
REC_i	-0.044*	-0.044*	-0.044*	-0.044*
$\Delta LP1_i$	0.00022*, b	-	0.00023*, d	-
$\Delta LP2_i$	0.00042**, c	-	0.00049**, e	-
$GLP1_i$	-	0.044*, h	-	-0.044*, f
$GLP2_i$	-	0.044**, i	-	0.044**, g

[a] We have also estimated the effect of the vector of independent variables Φ_i on TFP_i. However, most of the estimates are statistically insignificant. The estimates are available upon request. [b] F-value (3, 107): 2,37; Obs: 111. [c] F-value (3, 107): 2,93; Obs: 111. [d] F-value (3, 107): 2,35; Obs: 111. [e] F-value (3, 107): 3,02; Obs: 111. [f] F-value (3, 107): 2,93; Obs: 111. [g] F-value (3, 107): 3,07; Obs: 111. [h] F-value (3, 107): 2,87; Obs: 111. [i] F-value (3, 107): 3,01; Obs: 111.
* Significant at ***1%, **5%, and *10% respectively.
Source: Authors' elaboration of data from Conor's (2020) and Becker et al.'s (2021) databases.

Furthermore, LP positively affects TFP either we use the difference, or we use the growth of LP. Indeed, the effect of growth LP is higher than the effect of difference LP on productivity growth.

Table 7 presents the empirical results from OLS estimations when the dependent variable is the LP in the market i. It is evident from Table 7 that recidivism affects negatively the level of annual rate of productivity growth. Particularly, the negative effect of recidivism on growth LP is a statistically significant result, but the corresponding effect on difference LP is not a statistically significant result. Therefore, the above-mentioned results confirm, at least in the case of growth LP, the testable hypothesis of this paper, that is, recidivism negatively affects productivity growth.

Table 7. Empirical results from OLS estimations*: Dependent variable LP

Independent variables[a]	**Dependent variables**			
	$\Delta LP1_i$	$GLP1_i$	$\Delta LP2_i$	$GLP2_i$
REC_i	-8.53	-0.08***	-3.78	-0.07**
ΔHC_i	15.18***, b	-	7.89***, c	-
GHC_i	-	1.24***, e	-	1.27***, d

[a] We have also estimated the effect of the vector of independent variables Φ_i on TFP_i. However, most of the estimates are statistically insignificant. The estimates are available upon request. [b] F-value (3, 107): 18,30; Obs: 111; Adj R-squared = 0.32. [c] F-value (3, 107): 18,26; Obs: 111; Adj R-squared = 0.34. [d] F-value (3, 107): 335,10; Obs: 111; Adj R-squared = 0.90. [e] F-value (3, 107): 370,19; Obs: 111; Adj R-squared = 0.91.
** Significant at ***1%, **5%, and *10% respectively.
Source: Authors' elaboration of data from Conor's (2020) and Becker et al.'s (2021) databases.

Furthermore, HC positively affects LP either we use the difference, or we use the growth of HC. Indeed, the effect of difference HC is higher than the effect of growth HC on productivity growth. In any case, both results are statistically significant at 1% of the level of significance

7.2 Quantile Regression results

The quantile methodology provides a more comprehensive and accurate description of the data by offering an in-depth analysis of the entire distribution of the dependent variable. This approach captures extreme values that other econometric methods, such as OLS, may struggle to identify. Consequently, it is more robust to outliers, as it can detect extreme values and their potential impact on regression results. Moreover, multiple quantile regression analysis is an appropriate econometric technique for correcting selection bias. By examining various points of the distribution, it allows for a nuanced understanding of how different quantiles of the dependent variable are influenced, making it a powerful tool in addressing biases that might affect the regression outcomes (Bos et al., 2018).

In Tables 8 and 9 we present the empirical results from quantile estimations with regard to recidivism variable (*REC*) when the dependent variables are TFP and LP in the market *i*.

In Appendix 2 we present the total empirical results from quantile estimations (Tables 2A and 2B).

It is evident from Tables 8 and 9 that recidivism negatively affects productivity growth in all quantiles (0.10, 0.20, 0.25 0.50. 0.75. 0.85. 0.90 and 0.99). Particularly, Table 9 reveals that from the second quantile (0.20) until the fifth quantile (0.75), the negative effect of recidivism on productivity growth under the dependent variable *GLP1* increases. Indeed, this effect reaches its peak at the fifth quantile (-0.135). In the sixth and seventh quantiles (0.85 & 0.90 respectively) the effect of recidivism on productivity growth continues to be negative, but at a lower rate than before, while in the eighth quantile (0.99) the negative effect rises again (from -0.0751 to -0,114). When we use the dependent variable *GLP2*, the effect of recidivism is still negative and statistically significant in the second, the third and the sixth quantiles respectively.

The highest effect of recidivism on productivity growth is estimated under the dependent variables *ΔLP1* and *ΔLP2* (Table 9). Especially, the negative effect of recidivism on productivity growth estimated under the dependent variable *ΔLP1* is statistically significant at 1% for the second and the third quantile. The same result we get when we use the dependent variable *ΔLP2*, but the magnitude of the negative effect of recidivism on productivity growth is lower than the one we estimate under the dependent variable *ΔLP1*.

Table 2B in Appendix 2 also reveals the statistically significant and positive relationship between human capital (*HC*) and productivity growth (*LP*). Under all dependent and independent variables, we use the estimated coefficients are positive. Particularly, when we regress the independent variables on *GLP1* and *GLP2*, the estimated coefficients are positive and statistically significant at 1% in all quantiles, but when we regress the independent variables on *ΔLP1* and *ΔLP2* the estimated coefficients continue to be positive and statistically significant in first, second, third, sixth and eighth quantiles.

Table 8 reveals that in the fourth, fifth and sixth quantiles, the negative effect of recidivism on productivity growth (*TFP*) is statistically significant. This negative effect rises from the second quantile until the fifth quantile and then drops until the eighth quantile (under the dependent variables *ΔTFP5* & *ΔTFP4*) or starts to rise again in the last two quantiles (under the dependent variables *GTFP5* & *GTFP5*). The highest effect of recidivism on productivity growth is estimated under the dependent variables *GLP1* and *GLP2* (Table 8) in the first and eighth quantiles, but the estimations are statistically insignificant.

Table 2A in Appendix 2 also reveals the positive relationship between labor productivity (*LP*) and productivity growth (*TFP*). Under all dependent and independent variables, we use the estimated coefficients are positive. Particularly, when we regress the independent variables on *GTFP5* and *GTFP4*, the estimated coefficients are positive and in some quantiles statistically significant at 5% and 10% levels of statistical significance, but when we regress the independent variables on *ΔTFP5* and *ΔTFP4* the estimated coefficients continue to be positive but statistically insignificant.

Table 8: Quantile regression analysis: Dependent variable TFP

	Q(0.10)	Q(0.20)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.85)	Q(0.90)	Q(0.99)
				Dependent Variable: GTFP5				
REC	**-0.0944**	**-0.00282**	**-0.0241**	**-0.0505*****	**-0.0625****	**-0.0578****	**-0.0401**	**-0.0995**
	(0.0735)	(0.0545)	(0.0385)	(0.0144)	(0.0248)	(0.0266)	(0.0323)	(0.0836)
				Dependent Variable: GTFP4				
REC	**-0.0963**	**0.000247**	**-0.0281**	**-0.0552*****	**-0.0671*****	**-0.0589****	**-0.0411**	**-0.0976**
	(0.0649)	(0.0445)	(0.0367)	(0.0208)	(0.0245)	(0.0234)	(0.0314)	(0.0929)
				Dependent Variable: ΔTFP5				
REC	**-0.0912**	**-0.00243**	**-0.0274**	**-0.0478****	**-0.0868*****	**-0.0574****	**-0.0363**	**-0.00166**
	(0.0724)	(0.0515)	(0.0416)	(0.0191)	(0.0281)	(0.0269)	(0.0327)	(0.117)
				Dependent Variable: ΔTFP4				
REC	**-0.0922**	**-0.00105**	**-0.0298**	**-0.0486*****	**-0.0878****	**-0.0584***	**-0.0373**	**-0.00107**
	(0.0725)	(0.0436)	(0.0368)	(0.0179)	(0.0339)	(0.0312)	(0.0307)	(0.100)

Notes: All the specifications are estimated using the sequential quantile regressions methodology at different quantiles Q (0.10, 0.20, 0.25 0.50. 0.75. 0.85. 0.90 and 0.99) allowing for 100 repetitions. The numbers in parentheses denote robust standard errors. Significant at ***1%, **5%, and *10% respectively.

Table 9: Quantile regression analysis: Dependent variable LP

	Q(0.10)	Q(0.20)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.85)	Q(0.90)	Q(0.99)
				Dependent Variable: GLP1				
REC	**-0.117**	**-0.0775***	**-0.0750***	**-0.0842****	**-0.135****	**-0.106*****	**-0.0751****	**-0.114****
	(0.0866)	(0.0425)	(0.0403)	(0.0410)	(0.0583)	(0.0294)	(0.0350)	(0.0548)
				Dependent Variable: GLP2				
REC	**-0.0986**	**-0.0799****	**-0.0734***	**-0.0555**	**-0.0519**	**-0.119****	**-0.0563**	**0.00109**
	(0.0780)	(0.0393)	(0.0392)	(0.0404)	(0.0786)	(0.0484)	(0.0539)	(0.0922)
				Dependent Variable: ΔLP1				
REC	**-7.829**	**-15.96*****	**-15.34*****	**-24.54**	**-47.19**	**8.555**	**38.07**	**104.4**
	(45.14)	(6.006)	(5.463)	(20.70)	(40.71)	(51.61)	(58.53)	(75.96)
				Dependent Variable: ΔLP2				
REC	**-4.470**	**-6.532****	**-8.316*****	**-15.54**	**-28.68**	**0.603**	**14.45**	**33.36**
	(32.65)	(3.019)	(2.939)	(10.12)	(22.18)	(28.45)	(32.63)	(31.17)

Notes: All the specifications are estimated using the sequential quantile regressions methodology at different quantiles Q (0.10, 0.20, 0.25 0.50. 0.75. 0.85. 0.90 and 0.99) allowing for 100 repetitions. The numbers in parentheses denote robust standard errors. Significant at ***1%, **5%, and *10% respectively.

7. Conclusions

Some of the academic empirical literature shows that repeated cartelists (offenders) are more common in the US than in the EU, but only half of them are defined as recidivists (Conor 2016). Other academic scholars failed to find at least two cartelistis and state that in the US, since 1999, recidivism has been eliminated (Werden et al. 2011). However, none of them have explored the relationship between recidivism and productivity growth.

The theoretical literature mainly concerns with the existence of recidivism, which may significantly affect Competition Authorities' performance, by decreasing their efforts to enhance the level of competition in product/service markets where cartel activity re-emerges (Katsoulacos et al. 2023). For others, repeated offenders constitute evidence that deterrence penalties in antitrust law are inadequate (Conor 2016).

This paper directly examines the effect of recidivism on productivity growth. The OLS and quantile estimations confirm the research hypothesis, that is, recidivism negatively affects productivity growth at the market level. We use as proxies of productivity growth both the TFP annual growth rate and labor productivity. We define a recidivist as a multiple offender with at least 2 cartel fines.

This paper does not examine the effect of recidivism on competition. However, we can infer indirectly that since the presence of recidivism restricts the efficiency of competition policy, which, in turn, negatively affects productivity growth, the higher the level of recidivism, the lower the level of productivity growth.

One way to foster productivity growth in markets with multiple offenders is to enhance deterrence against anticompetitive practices. Anti-cartel enforcement, especially in price–fixing cases, may be strengthened either by enforcing more the legislation on recidivism or by increasing the cartel penalties imposed by the Competition Authorities. Both in the US and the EU, the cartel fine can be increased for a repeated offender by an amount equivalent to 15% - 25% and 0% - 16% of the yearly sales respectively, but this increment seems not to enhance deterrence against repeated cartelists adequately. Moreover, recidivism penalties must be used in practice because, as Conor (2016) states, the recidivism penalties in the US have largely remained unused since 1990.

Therefore, both policymakers and competition authorities should treat recidivism with considerable caution not only because it significantly affects Competition Authorities' performance, but also because affects the growth of markets and the economy.

APPENDIX 1

Table 1A Product/Service markets and NAICS codes of 111 cartel cases in the US from 1966 to 2016

A/A	Product/Service Market	NAICS code
1	Citric Acid	325199
2	Lysine	334516
3	MCAA (monochloroacetic acid)	325120
4	MSG and Nucleotides (IMP, GMP)	334516
5	Abrasive grains (aluminum oxide (a/k/a alumina) and silicon oxide), US	334516
6	Sodium Gluconate	325412
7	Sorbates	325180
8	Doors, residential flush, wood, US	321911
9	Vitamin Premixes	325412
10	Aluminum Phosphide, US	325180
11	Corn Glucose Syrup, US	311221
12	High Fructose Corn Syrup, US	311221
13	Maltol, Synthetic, US + CA	325199
14	Tampico Fiber, US	325220
15	Construction, Nigeria liquid natural gas plants	333618
16	Diamonds, Industrial	339910
17	DRAMs (digital random access memory semiconductors)	334413
18	Graphite Electrodes	335991
19	Graphite, Isostatic (molded/specialty)	335991
20	Magnetic Iron Oxide Powder/Pigment	331110
21	Methylglucamine, Pharma Grade for X-rays	325199
22	Drill bits, oil drilling, US	333132
23	Nitrile Synthetic Rubber (NBR or acrylo-nitrile-butadiene rubber)	325212
24	Polychloroprene Synthetic Rubber (PCP)	325212
25	Rubber Processing Chemicals	325998
26	Stamp Auctions, Bid Rigging in US & UK	333318
27	Steel wool scouring pads, US	332999
28	Marine fenders, buoys, pilings (plastic), US	321114
29	Bromines	325180
30	Cable-stayed bridges, US [n]	331222
31	Cable-stayed bridges, California, US	331222
32	Construction, Heavy-Lift Marine	321114
33	Construction, USAID-financed Egypt Wastewater Plant, US	333120
34	Explosives mfg., commercial, Texas Group, US	325920
35	Ferrosilicon, US	331110
36	Foundry resins	333511
27	Spun yarn, open end, US	313110
38	Tactile tile, sold to Long Island Railroad, U.S.	327120
39	Tubes, laminated, US	332996

40	Steel, specialty, tubes and piping, US	331110
41	Orthopedic devices, US	339113
42	LCDs (Liquid Crystal Display Panels), TFP (thin film) type	334419
43	Metal sling hoist assemblies, US	332618
44	NANDs (flash memory chips)	334413
45	Marine hose (bid rigging vs. petrol. cos.& Navy)	313220
46	Cathode ray tubes, Color Display Tube type	334419
47	Concrete, ready-mix, central Indiana, US	327320
48	Tomatoes, processed, US	311423
49	Cathode ray tubes, Color Picture Tube type	334419
50	LCDs, TFT Type, sold to Dell	334419
51	LCDs, TFT Type, sold to Motorola (now Motorola Mobility)	334419
52	LCDs, TFT Type, sold to Apple	334419
53	Concrete, ready mix, Northwest Iowa, US	327320
54	Foodservice equipment, US	333241
55	Containerboard 2, US	322130
56	Freight forwarders, intl. air, NES fee from UK to ROW	333921
57	Freight forwarders, intl. air, CAF fee, China & ROW	333921
58	Freight forwarders, intl. air Hong Kong exports, PSS fee	333921
59	Battery cells, cylindrical lithium ion	335911
60	Auto parts, aftermarket lighting, US & CA	336310
61	Electricity and gas utilities, US	335312
62	Auto parts, anti-vibration devices	336310
63	Auto parts, speed sensor wire assemblies	336310
64	Auto parts, starter motors, alternators, ignition coils	336310
65	Auto parts, air flow meters	336310
66	Auto parts, valve timing controls	336310
67	Auto parts, fuel injection systems	336310
68	Auto parts, electronic throttle bodies	336310
69	Auto parts, inverters	336310
70	Auto parts, motor generators	336310
71	Auto parts, windshield washer systems	336310
72	Auto parts, windshield wipers and components	336310
73	Auto parts, window motors, power	336310
74	Auto parts, fan motors (engine-cooling)	336310
75	Auto parts, radiators & cooling fans	336310
76	Auto parts, ATF warmers	336310
77	Auto parts, steering assemblies, power	336310
78	Auto parts, driveshaft boots, constant-velocity	336310
79	Capacitors, electrolytic & aluminum, Global	335999
80	Doryx (doxycycline) Pay-for-Delay, US	325412
81	Auto Parts, spark plugs	336310
82	Auto Parts, oxygen Sensors	336310

83	Auto Parts, Air Fuel Ratio Sensors	336310
84	Auto parts, hoses, rubber	336310
85	Provigil (modafinil) generic pay-for-delay, US & EC	325412
86	Federal Creosote Superfund Cleanup, US	325194
87	Auto parts, brake hose, non-rubber	336310
88	Bandages, specialized military, US	339113
89	Heaters, parking & auxilliary, aftermaket	333414
90	Auto parts, steering columns, manual	336310
91	Canned tuna, US	311421
92	Digoxin, generic doxycycline, US	325412
93	Auto parts, shock absorbers	336310
94	Auto parts, rubber body seals	336310
95	Auto parts, alternators	336310
96	Auto parts, plastic interior trim	336310
97	Aluminum sulfate, liquid, ("alum"), US	333111
98	Auto parts, power window switches	336310
99	Posters sold online worldwide	323113
100	Auto parts, emission controls, ceramic substrates	336310
101	Auto parts, tubes, steel	336310
102	Auto parts, locks, keys, handles	336310
103	Pharmaceuticals, Generic, US	325412
104	Kapvay, no-authorized-generic drug, US	325412
105	Ovcon-35, no-authorized-generic, US	325412
106	Adalat, generic drug (Nifedopine), 30 & 60 mg., pay-for-delay, US	325412
107	Military services, pumps bid-rigging, US	333911
108	Silicone wristbands, sold online, US	325199
109	Rail industry, skilled employees, no-poach, US	321999
110	Dental supplies, US	325620
111	Saline, intravenous solution, US	325412

Source: Authors' elaboration of Conor's (2020) dadaset

Table 1B Start, end and duration of 111 cartels in the US from 1966 to 2016

	Start of the Cartel		End of the Cartel		Duration of Cartel	
A/A	month	year	month	year	Δ months	Δ years
1	3	1991	5	1995	50,0	4,2
2	7	1990	6	1995	59,0	4,9
3	1	1984	8	1999	187,0	15,6
4	11	1988	6	1998	115,0	9,6
5	1	1985	12	1994	119,0	9,9
6	2	1987	6	1995	100,0	8,3
7	1	1979	6	1997	221,0	18,4
8	3	1993	9	1994	18,0	1,5
9	1	1991	12	1997	83,0	6,9
10	1	1990	11	1990	10,0	0,8
11	1	1989	6	1995	77,0	6,4
12	1	1989	6	1995	77,0	6,4
13	12	1989	12	1995	72,0	6,0
14	1	1990	4	1995	63,0	5,3
15	-	1995	-	2004	108,0	9,0
16	11	1987	5	1994	78,0	6,5
17	4	1999	6	2002	38,0	3,2
18	3	1992	2	1998	71,0	5,9
19	3	1993	2	1998	59,0	4,9
20	1	1991	4	1998	87,0	7,3
21	11	1990	12	1999	109,0	9,1
22	3	1989	11	1989	8,0	0,7
23	12	1996	10	2002	70,0	5,8
24	5	1993	5	2002	108,0	9,0
25	1	1994	10	2002	105,0	8,8
26	-	1979	6	1997	222,0	18,5
27	1	1992	12	1992	12,0	1,0
28	12	2002	5	2003	5,0	0,4
29	1	1995	4	1998	39,0	3,3
30	12	1994	8	1996	20,0	1,7
31	12	1994	8	1996	20,0	1,7
32	-	1990	1	2007	205,0	17,1
33	6	1988	9	1996	99,0	8,3
34	9	1988	12	1993	63,0	5,3
35	10	1989	8	1991	22,0	1,8
36	1	2001	12	2003	36,0	3,0
27	10	2000	6	2001	8,0	0,7
38	3	1998	10	1998	7,0	0,6
39	-	1987	-	1995	96,0	8,0

40	-	1966	-	1987	252,0	21,0
41	1	2001	10	2005	57,0	4,8
42	1	1999	12	2006	96,0	8,0
43	11	2001	1	2005	38,0	3,2
44	11	2001	1	2005	38,0	3,2
45	-	1985	6	2007	270,0	22,5
46	3	1995	11	2007	152,0	12,7
47	7	2000	5	2004	46,0	3,8
48	1	2004	4	2008	51,0	4,3
49	3	1995	11	2007	152,0	12,7
50	4	2001	3	2004	36,0	3,0
51	9	2005	7	2006	10,0	0,8
52	9	2005	12	2006	15,0	1,3
53	1	2006	12	2009	48,0	4,0
54	12	2004	12	2008	48,0	4,0
55	2	2004	11	2010	80,8	6,7
56	10	2002	10	2007	60,0	5,0
57	7	2005	10	2007	27,0	2,3
58	6	2005	10	2007	28,0	2,3
59	1	2000	5	2011	137,0	11,4
60	7	2001	9	2008	85,3	7,1
61	1	2006	2	2010	49,2	4,1
62	3	1996	5	2012	194,0	16,2
63	1	2003	3	2010	86,0	7,2
64	1	2000	2	2010	121,0	10,1
65	1	2000	2	2010	121,0	10,1
66	1	2000	2	2010	121,0	10,1
67	1	2000	2	2010	121,0	10,1
68	1	2000	2	2010	121,0	10,1
69	1	2000	2	2010	121,0	10,1
70	1	2000	2	2010	121,0	10,1
71	1	2000	2	2010	121,0	10,1
72	1	2000	2	2010	121,0	10,1
73	1	2000	2	2010	121,0	10,1
74	1	2000	2	2010	121,0	10,1
75	11	2002	2	2010	87,0	7,3
76	11	2002	2	2010	87,0	7,3
77	1	2005	10	2011	81,0	6,8
78	1	2006	9	2010	56,0	4,7
79	9	1997	1	2014	196,0	16,3
80	9	2008	4	2012	43,3	3,6
81	1	2000	-	2013	155,0	12,9

82	1	2000	7	2011	138,0	11,5
83	1	2000	7	2011	138,0	11,5
84	2	2004	9	2010	79,0	6,6
85	-	2005	-	2006	12,0	1,0
86	12	2000	4	2010	112,0	9,3
87	11	2005	9	2006	10,0	0,8
88	-	1984	-	1985	12,0	1,0
89	10	2007	12	2012	63,0	5,2
90	9	2007	9	2012	60,0	5,0
91	7	2011	8	2015	48,2	4,0
92	10	2014	3	2016	17,0	1,4
93	-	1986	-	2012	312,0	26,0
94	1	2000	12	2012	155,0	12,9
95	1	2000	-	2012	143,0	11,9
96	6	2004	9	2012	99,0	8,3
97	1	1997	2	2011	169,9	14,2
98	-	2005	-	2013	96,0	8,0
99	9	2013	1	2015	16,0	1,3
100	1	1985	2	2010	301,0	25,1
101	12	2003	7	2011	91,3	7,6
102	1	2002	9	2011	116,0	9,7
103	1	2013	12	2015	35,0	2,9
104	5	2013	10	2015	29,7	2,5
105	4	2004	10	2006	30,7	2,6
106	12	2000	8	2002	20,5	1,7
107	1	2009	12	2013	59,0	4,9
108	-	2014	6	2016	30,0	2,5
109	1	2009	12	2015	83,0	6,9
110	7	2011	12	2015	53,0	4,4
111	9	2013	-	2016	27,0	2,3

Source: Authors' elaboration of Conor's (2020) dadaset.

Table 1C Summary statistics of the remaining variables of the empirical models (eq. 4 & 5)

Variable	Obs	Mean	Std. dev.	Min	Max
ΔVSHIP	111	1276.576	9246.061	-19876.9	31909.5
GVSHIP	111	.1015256	.3672392	-.4805186	1.35688
ΔHC	111	2.8007	3.428589	-19.61732	13.69662
GHC	111	.2374704	.4132652	-.7996191	2.884671
ΔINVEST	111	-18.33514	709.9334	-4172.7	2756.8
GINVEST	111	.0770266	.9560145	-1.722698	4.371542
GINVENT	111	.1333531	.3947419	-.5590724	2.169289
ΔINVENT	111	285.7631	893.5492	-1290.1	3607.5

APPENDIX 2

Table 2A: Quantile regression analysis: Dependent variable TFP

	Q(0.10)	Q(0.20)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.85)	Q(0.90)	Q(0.99)
				Dependent Variable: GTFP5				
REC	**-0.0803**	**-0.00128**	**-0.0221**	**-0.0442****	**-0.0506***	**-0.0578****	**-0.0386**	**-0.194****
	(0.0774)	(0.0507)	(0.0375)	(0.0191)	(0.0262)	(0.0286)	(0.0336)	(0.0763)
GLP1	0.0686*	0.0222	0.0275	0.0330**	0.0830*	0.0822	0.0168	-0.0372
	(0.0399)	(0.0270)	(0.0195)	(0.0154)	(0.0494)	(0.0559)	(0.0624)	(0.0789)
Trend	0.000758	3.60e-05	0.000267	0.000245	0.000724*	0.000420	-0.000456	-0.00205***
	(0.00105)	(0.000606)	(0.000503)	(0.000355)	(0.000370)	(0.000557)	(0.000795)	(0.000739)
Constant	-0.162	-0.0592	-0.0406	0.0193	0.0479	0.0758	0.171**	0.502***
	(0.0992)	(0.0557)	(0.0468)	(0.0198)	(0.0334)	(0.0494)	(0.0698)	(0.115)
				Dependent Variable: GTFP4				
REC	**-0.0829**	**-0.000685**	**-0.0248**	**-0.0466****	**-0.0516***	**-0.0588***	**-0.0396**	**-0.196****
	(0.0727)	(0.0538)	(0.0422)	(0.0194)	(0.0299)	(0.0329)	(0.0462)	(0.0833)
GLP1	0.0683	0.0226	0.0313	0.0340	0.0869*	0.0817	0.0165	-0.0376
	(0.0526)	(0.0286)	(0.0269)	(0.0245)	(0.0465)	(0.0493)	(0.0634)	(0.0830)
Trend	0.000705	5.33e-05	0.000242	0.000268	0.000718	0.000425	-0.000459	-0.00205*
	(0.00120)	(0.000631)	(0.000515)	(0.000340)	(0.000463)	(0.000659)	(0.00105)	(0.00104)
Constant	-0.157	-0.0618	-0.0384	0.0187	0.0479	0.0766	0.172	0.503***
	(0.119)	(0.0625)	(0.0514)	(0.0221)	(0.0419)	(0.0619)	(0.106)	(0.143)
				Dependent Variable: ΔTFP5				
REC	**-0.0839**	**-0.00222**	**-0.0112**	**-0.0449****	**-0.0455**	**-0.0314**	**-0.0216**	**-0.0162**
	(0.0739)	(0.0539)	(0.0412)	(0.0173)	(0.0319)	(0.0345)	(0.0390)	(0.0697)
ΔLP1	0.0642	0.0216	0.0307	0.0428	0.0737	0.0957	0.0707	0.0439
	(0.0495)	(0.0354)	(0.0328)	(0.0330)	(0.0613)	(0.0665)	(0.0764)	(0.0922)
Trend	0.000689	0.000359	0.000455	0.000220	0.000773	0.000792	-0	-0.00264**
	(0.00128)	(0.000747)	(0.000484)	(0.000335)	(0.000492)	(0.000689)	(0.000849)	(0.00109)
Constant	-0.151	-0.0666	-0.0608	0.0192	0.0464	0.0490	0.116	0.412***
	(0.124)	(0.0720)	(0.0495)	(0.0205)	(0.0394)	(0.0574)	(0.0718)	(0.120)
				Dependent Variable: ΔTFP4				
REC	**-0.0829**	**-0.000785**	**-0.0147**	**-0.0450****	**-0.0451**	**-0.0328**	**-0.0213**	**-0.0159**
	(0.0661)	(0.0493)	(0.0333)	(0.0210)	(0.0306)	(0.0361)	(0.0429)	(0.0591)
ΔLP2	0.0632	0.0218	0.0340	0.0431	0.0777	0.0972	0.0732	0.0446
	(0.0493)	(0.0285)	(0.0254)	(0.0281)	(0.0554)	(0.0609)	(0.0738)	(0.0921)
Trend	0.000656	0.000294	0.000417	0.000218	0.000769*	0.000813	0	-0.00264**
	(0.00122)	(0.000665)	(0.000497)	(0.000334)	(0.000398)	(0.000688)	(0.000797)	(0.00116)
Constant	-0.147	-0.0670	-0.0574	0.0194	0.0464	0.0478	0.116	0.412***
	(0.116)	(0.0540)	(0.0439)	(0.0207)	(0.0396)	(0.0629)	(0.0789)	(0.117)

Notes: All the specifications are estimated using the sequential quantile regressions methodology at different quantiles Q (0.10, 0.20, 0.25 0.50. 0.75. 0.85. 0.90 and 0.99) allowing for 100 repetitions. The numbers in parentheses denote robust standard errors. Significant at ***1%, **5%, and *10% respectively.

Table 2B: Quantile regression analysis: Dependent variable LP

	Q(0.10)	Q(0.20)	Q(0.25)	Q(0.50)	Q(0.75)	Q(0.85)	Q(0.90)	Q(0.99)
				Dependent Variable: GLP1				
REC	**-0.117**	**-0.0775***	**-0.0750***	**-0.0842****	**-0.135****	**-0.106*****	**-0.0751****	**-0.114****
	(0.0866)	(0.0425)	(0.0403)	(0.0410)	(0.0583)	(0.0294)	(0.0350)	(0.0548)
GHC	1.159***	1.247***	1.241***	1.296***	1.214***	1.226***	1.291***	1.360***
	(0.126)	(0.0920)	(0.0834)	(0.0695)	(0.0634)	(0.0885)	(0.116)	(0.149)
Trend	8.21e-05	0.000486	0.000673	-0.000474	0.000891	-0.000159	-0.000258	0.000465
	(0.00106)	(0.000634)	(0.000565)	(0.000726)	(0.000766)	(0.000859)	(0.000834)	(0.00116)
Constant	-0.0132	-0.0113	-0.00818	0.138***	0.247***	0.322***	0.321***	0.393***
	(0.111)	(0.0572)	(0.0535)	(0.0379)	(0.0659)	(0.0587)	(0.0578)	(0.0858)
				Dependent Variable: GLP2				
REC	**-0.0986**	**-0.0799****	**-0.0734***	**-0.0555**	**-0.0519**	**-0.119****	**-0.0563**	**0.00109**
	(0.0780)	(0.0393)	(0.0392)	(0.0404)	(0.0786)	(0.0484)	(0.0539)	(0.0922)
GHC	1.113***	1.225***	1.305***	1.284***	1.222***	1.244***	1.362***	1.238***
	(0.151)	(0.117)	(0.104)	(0.0610)	(0.0802)	(0.105)	(0.109)	(0.103)
Trend	0.000122	0.000591	0.000455	0.000308	0.000586	0.000460	-0.00105	-0.00399**
	(0.00109)	(0.000704)	(0.000627)	(0.000567)	(0.000962)	(0.00119)	(0.00147)	(0.00190)
Constant	-0.0327	-0.0300	-0.0196	0.0576	0.195**	0.298***	0.390***	0.675***
	(0.114)	(0.0558)	(0.0507)	(0.0422)	(0.0783)	(0.0833)	(0.100)	(0.145)
				Dependent Variable: ΔLP1				
REC	**-7.829**	**-15.96*****	**-15.34*****	**-24.54**	**-47.19**	**8.555**	**38.07**	**104.4**
	(45.14)	(6.006)	(5.463)	(20.70)	(40.71)	(51.61)	(58.53)	(75.96)
ΔHC	29.37*	29.71***	26.08***	19.53	-0.917	119.8*	90.04	430.7*
	(17.59)	(10.78)	(9.305)	(40.47)	(69.75)	(71.66)	(101.5)	(219.2)
Trend	0.0416	0.0202	0.102	0.0243	0.186	0.347	-0.0704	-0.372
	(0.191)	(0.128)	(0.109)	(0.330)	(0.663)	(0.720)	(0.721)	(0.423)
Constant	0.481	15.61*	15.88**	46.02*	123.4**	101.9*	150.1**	165.8***
	(15.27)	(8.857)	(7.611)	(27.71)	(52.16)	(59.70)	(64.46)	(44.08)
				Dependent Variable: ΔLP2				
REC	**-4.470**	**-6.532****	**-8.316*****	**-15.54**	**-28.68**	**0.603**	**14.45**	**33.36**
	(32.65)	(3.019)	(2.939)	(10.12)	(22.18)	(28.45)	(32.63)	(31.17)
ΔHC	16.05	15.16	14.08	11.92	1.522	59.39	41.06	282.2**
	(13.40)	(9.621)	(9.744)	(18.15)	(44.73)	(63.56)	(75.97)	(118.7)
Trend	0.00549	-4.81e-05	0.0316	0.0586	0.0785	0.185	0.127	0.353
	(0.103)	(0.0503)	(0.0472)	(0.158)	(0.346)	(0.421)	(0.383)	(0.288)
Constant	-0.333	6.595	8.499*	21.25	63.88**	49.13	77.43**	43.19*
	(8.700)	(4.126)	(4.434)	(13.89)	(27.73)	(34.71)	(33.72)	(25.23)

Notes: All the specifications are estimated using the sequential quantile regressions methodology at different quantiles Q (0.10, 0.20, 0.25 0.50. 0.75. 0.85. 0.90 and 0.99) allowing for 100 repetitions. The numbers in parentheses denote robust standard errors. Significant at ***1%, **5%, and *10% respectively.

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