An Empirical Investigation on the Dynamic Effects of Mergers

Evidence from 50 Major Mergers in the US (2005-2015)

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Abstract

Existing research on the antitrust analysis of mergers establishes theoretical and statistical associations between mergers and innovation but does not control for dynamic factors that simultaneously reveal the effects of mergers on innovation and productivity. This paper studies the dynamic effects of mergers using unique longitudinal data of 50 major mergers between 2005 and 2015 in the US. The results from Pooled OLS regressions suggest that there are positive cross-company associations running from mergers and market shares to innovation and production while the findings from fixed-effects estimators under several estimation strategies confirm the causal effects of mergers to innovation and efficiency.

Keywords: Antitrust, Mergers, Innovation, Market Share, Productivity

JEL Classification: L12, L22, L44, O31, O34

1. Introduction

According to the Federal Trade Commission (FTC)[1], the US antitrust merger policy relies on three legal statutes: The Sherman Antitrust of 1890 Act, The Clayton Antitrust Act of 1914, and the Federal Trade Commission Act of 1914. The FTC and the Antitrust Division of the Department of Justice are the responsible antitrust agencies for antitrust merger analysis and merger policy including reviewing, suing, and blocking M&As (Hovenkamp, 2012). This institutional setting basically outlaws "*monopolization, attempted monopolization, ... or combination to monopolize*" by the Sherman Act and "*unfair methods of competition*" and "*unfair or deceptive acts or practices*" by the FTC Act. Finally, the Clayton Act bans M&As where their effect "*may be substantially to lessen competition, or to tend to create a monopoly*". On the other hand, the Merger Guidelines and the Integration of Efficiencies into Antitrust Review of Horizontal Mergers of the Department of Justice in the US clearly states that "*it is efficiency, not competition, that is the ultimate goal if the antitrust laws or efficiency is the goal, competition is the process*". Under this institutional setting, there are two approaches to the antitrust merger analysis. The first approach focuses on market share or monopolization while the second one takes efficiency gains into account.

However, the US antitrust merger policy *de facto* has long relied on a presumption that a merger which considerably increases market share/power is likely to be anti-competitive[2] and it has mostly neglected the effects of mergers on innovation and/or efficiency. Market definition

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[1] https://www.ftc.gov/tips-advice/competition-guidance/guide-antitrust-laws/antitrust-laws
[2] See the Supreme Court decision on the Philadelphia National Bank case in 1963.

has been used to examine the effect of mergers on monopolization under a hypothetical monopolist test in the relevant market. Antitrust agencies and researchers have employed different techniques from traditional tools such as Lerner index, market shares, and concentration ratios to the estimation of demand elasticities (Çetin, 2017). As is well-known now, market definition has the shortcomings in the analysis of monopolization and it does not suffice to investigate the efficiency- and/or innovation-related effects of mergers[3] (Schmalensee, 2000; Farrell and Shapiro, 2010; Hovenkamp, 2012). For that reason, market share itself can be completely meaningless in an antitrust analysis of mergers[4]. Instead, a dynamic and comprehensive approach is needed to evaluate mergers. This approach should reveal the meaning of *changes* in market shares on the *changes* in innovation and efficiency as the effects of mergers in terms of antitrust policy in the antitrust merger analysis. The most direct way of doing that is to measure both productivity and innovation gains in the presence of increased market shares under economies of scale realized following a merger (Roller et al., 2010). As a matter of fact, the contemporary literature on the antitrust analysis of mergers suggests that the most crucial component of the current antirust merger policy analysis is the relationship between mergers and innovative market activities in the post-merger term. Even though there is less interest in it there are also some other studies analyzing the effect of mergers on productivity (Bernad et al., 2010; Yan et al., 2019).

In this sense, one of the most influential contributions to the antitrust merger analysis comes from the dynamic approach of Schumpeter to the market power-innovation nexus (Schumpeter, 1942; Sidak and Teece, 2009). The existing literature finds a positive correlation between market concentration (mergers) and R&D investment (innovation) (Katz and Shelanski, 2007). This statistical association between mergers and innovation establishes a contemporary theory of the Schumpeterian antitrust merger analysis. Similarly, one of the most remarkable empirical regularities in the contemporary antitrust merger analysis is the relationship between mergers and efficiency. Accordingly, an antitrust merger analysis should focus on the effects of mergers on innovation and efficiency in addition to the merger-market share nexus. we call this interaction the dynamic effects of mergers, and an empirical effort to the investigation of the dynamic effects of mergers is the cornerstone of a more influential antitrust merger policy.

In this paper, addressing the shortcomings in the current antitrust merger analysis, we investigate the dynamic effects of selected major mergers in the US. Following the relevant literature and the merger analysis of antitrust institutions, we employ cutting-edge estimation strategies for the antitrust merger analysis on a longitudinal data to reveal the causal effects of mergers on innovation and efficiency in addition to the statistical associations among mergers, market shares, innovation, and efficiency. The paper proceeds as follows. Section 2 discusses the relationships between mergers, innovation, and efficiency to better understand the dynamic effects of mergers. Section 3 presents the Schumpeterian antitrust associations based on the

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[3] The old and current approaches of both US and UE antitrust guidelines have been criticized from different perspectives. Some scholars argue that market definition does not work for mergers in differentiated markets since production differentiation can make defining the relevant market problematic.

[4] In some cases, even 100% market share can be meaningless from the perspective of antitrust merger analysis. For a detailed analysis and information about such cases. Çetin (2017) introduces a novel economic and econometric approach to market definition under 100% market share case.

hypotheses developed in this paper and empirical design based on data visualization, which is unique to this paper. Section 4 presents econometric empirical findings. Section 5 checks robustness of the models. Section 6 introduces antitrust policy suggestions. Section 7 concludes.

2. Dynamic Effects of Mergers

In neo-classical theory, the economic rationale for mergers is to gain benefits from economies of scale along with increased market share[5] (Hagedoorn and Duysters, 2002; Atallah, 2016). However, merging firm(s) with increased market power can dominate market and increase price. That is, it is assumed that the gains from merger come with some losses such as reduction in competition and increase in price. On the other hand, the merging firms with higher market shares or market power in the post-merger term can cause more innovation and productivity. Accordingly, the central issue in the antitrust merger analysis is the tradeoff between possible efficiency or productivity improvements through innovation arising from a merger and any reduction in competition due to economies of scale or increased market share/power. For that reason, investigating the effect of mergers is an arduous task since even the literature itself is controversial (Mueller, 1985). In *Capitalism, Socialism, and Democracy*, Schumpeter argues that firms with market power bring about more innovation even if they dominate the market. The Schumpeterian relationship between market power and innovation is called creative destruction. In other words, the Schumpeterian perspective on mergers claims that more concentrated markets necessarily do not create the abuse of market power and a decrease in consumer welfare. Conversely, large firms with higher market share might lead to more innovation and efficiency through creative destruction using their market power.

Following the Schumpeterian perspective on market power and innovation, some researchers argue that less competition or more market power lead to innovative market activities such as research and development investments due to the presence of economies of scale (Schumpeter, 1942; Gilbert and Newbery, 1982; Aghion and Tirole, 1994). On the other hand, some other researchers claim that more competition creates more innovation increasing economic efficiency and decreasing production costs (Arrow, 1962). In other words, the theoretical literature concerning the mergers-innovation nexus is not clear even though it introduces some base to account for the relationship between market structure and innovation (Gilbert and Sunshine, 1995; Entezarkheir and Moshiri, 2018; Federico et al., 2018). Empirical literature on mergers is also controversial. It is possible to find evidence that supports conflicting views on the effects of mergers on innovation and efficiency/productivity[6]. Some studies suggest that more innovation is positively correlated with less concentrated industries and the higher competition brings about patenting and IT intensity (Blundell et al., 1999; Pavcnik, 2002; Czarnitzki and Kraft, 2004; Loecker, 2011; Bloom et al., 2015). In the Schumpeterian camp, there are some empirical studies showing the relationship between lower innovation and higher competition (Riordan, 1992). Also, there is an inverted U-shaped relationship between innovation and competition in some

[5] Those gains are improved efficiency, expanded R&D efforts, investment ustment, firm growth, risk reduction, and speedy market entry.
[6] For more detailed information on this literature, see Entezarkheir and Moshiri (2018).

studies suggesting that innovation increases with competition along the low levels of competition while it declines at the higher competition levels (Aghion et al., 2005; Levin et al., 1985).

Clearly, the central issue in the antitrust merger analysis is the tradeoff between gains and losses from merger. While the gains from mergers refer to innovation and efficiency, the losses are represented by a reduction in competition stemming from high market share. For that reason, the analysis of the effect of mergers on innovation and efficiency is one of the most influential analytical tools in the antitrust analysis of mergers since such an investigation reveals the trade-off between the gains and losses of mergers. Following the literature, this paper studies the effect of mergers using the dynamic relationships among mergers, market shares, innovation, and efficiency since the economic foundations of antitrust merger analysis rely on static analysis and such static analysis might be illogical and socially harmful (Ordover and Willig, 1985; Sidak and Teece, 2009).

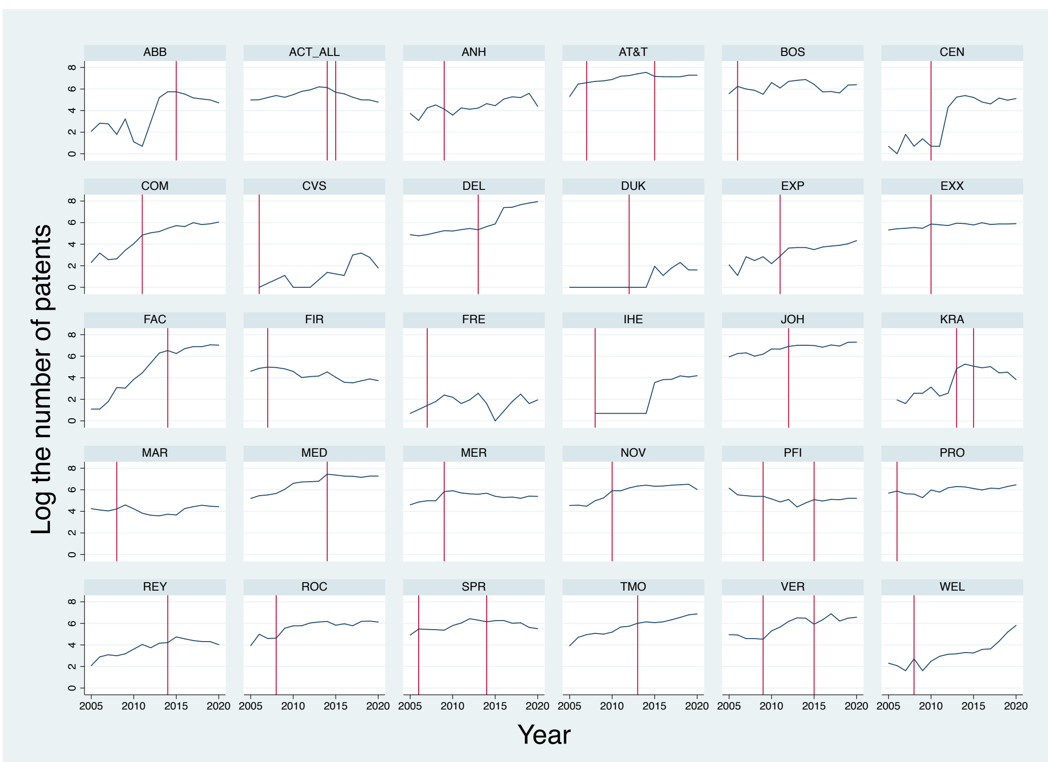
For this aim, it first analyzes the effect of mergers on innovation proxied by patents counts including market shares and R&D expenditures to the analysis. The aim is to better understand the dynamic relationships among mergers, market shares, and innovation in addition to some other variables such as investment and R&D expenditures because mergers change market shares and R&D expenditures, and those changes are influential in the innovation decisions of merging firms. Later, the paper investigates the effect of mergers on efficiency using the changes in market shares and the changes in the measure of innovation because the effect of mergers on efficiency is more dynamic than the simple inclusion of market shares and dummy variables representing mergers to the model, as explained in detail below. In the paper, following the relevant literature, efficiency is measured by productivity (Rezitis, 2008; Bernad et al., 2010; Cummins and Xie, 2008; Haynes and Thompson 1999; Odeck, 2008). Accordingly, the paper basically examines the dynamic effects of mergers since the simultaneous and multi-dimensional relationships between mergers, innovation, and efficiency/productivity are analyzed. Such an investigation to the effect of mergers is particularly important in the antitrust merger analysis since both the relevant literature and antitrust agencies aim to reveal the effects of mergers on innovation and productivity separately in their analyses. Because this paper empirically investigates all the relationships between mergers, innovation, and productivity concurrently it introduces comprehensive findings set to both literature and antitrust merger policy.

3. Schumpeterian Antitrust Associations and Empirical Design

In this section, using the relationships among mergers, market shares, patent counts, and productivity illustrated in the figures below, some hypotheses will be introduced to clarify the empirical approach. Later, equation(s) will be specified to empirically test those hypotheses following the relevant literature (Entezarkheir and Moshiri, 2019; Cloodt et al, 2006). We use a large dataset on the 50 largest mergers between 2005 and 2015 in the US. Table A1 reports the list of mergers and the code for merging companies that are used in the empirical analysis. The analysis of major mergers is particularly important since antitrust issue regarding mergers is basically whether mergers create market power through higher market shares in the post-merger period and it is difficult to analyze the technological performance of each individual transaction in the small mergers (Hagedoorn and Duysters, 2002). Note that the value of mergers in Table A1 changes from $15.1 billion to $130.3 billion. This refers to an expectation in which the merging companies should make more investments and R&D expenditures and thus, the increases in investment and R&D expenditures should lead to more innovation and productivity. Also note that the effects of major mergers on innovation and productivity should stem from an increase in market shares for merging companies. Lastly, the effect of mergers is analyzed at the level of companies that are involved in mergers since the effect of mergers on innovation or technological performance is generally analyzed at the level of individual firm but not merger itself because indicators, which are used to measure innovation, are registered at the level of firm.

We are mainly interested in the effect of mergers on economic performance, which is measured by innovation and productivity in the antitrust analysis of mergers. For that reason, the paper studies the impact of mergers on innovation and productivity to reveal the antitrust effect of a merger. The number of patents is considered as the main indicator of innovation in many studies analyzing the effect of mergers on innovation (Haucap et al., 2019). Similarly, productivity is proxied as the ratio of sales/revenue as output to the number of employees as input. The paper follows those approaches and analyzes the effect of mergers on innovation through patent counts and efficiency through productivity proxied by productivity per employee. Figures 1 depicts the pre- and post-merger changes in the number of patents for merging companies whereas Figure 2 illustrates the pre- and post-merger changes in productivity per employee for merging companies.

Figure 1. The number of patents for merging companies

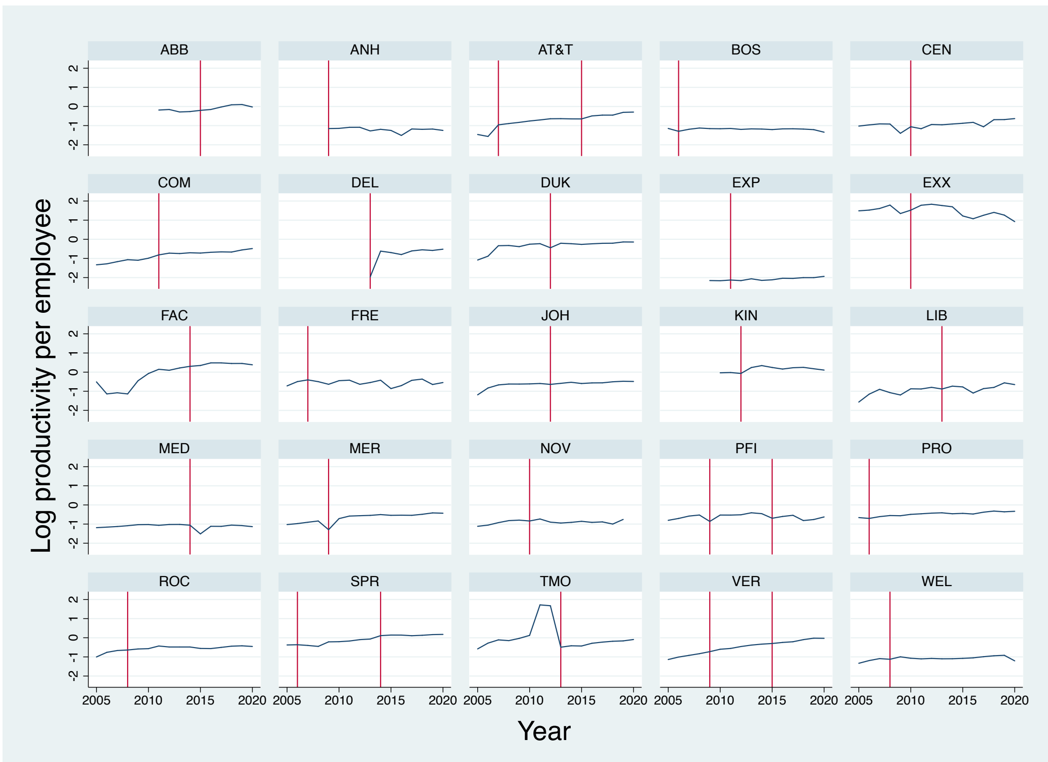


* The values for patent counts are used in logarithmic form to reduce possible uncertainties in the charts representing merging companies due to large differences between numbers.

** Instead of company names, codes are used to represent merging companies. Please see company names and their codes in Table A1.
** Red vertical lines represent merger years for merging firms.

As depicted in Figures 1 and 2, there is an increase in the number of patens and productivity for merging companies in the post-merger period. As a general trend, mergers bring about more innovation and productivity for the companies.

Figure 2. Productivity per Employee for Merging Companies

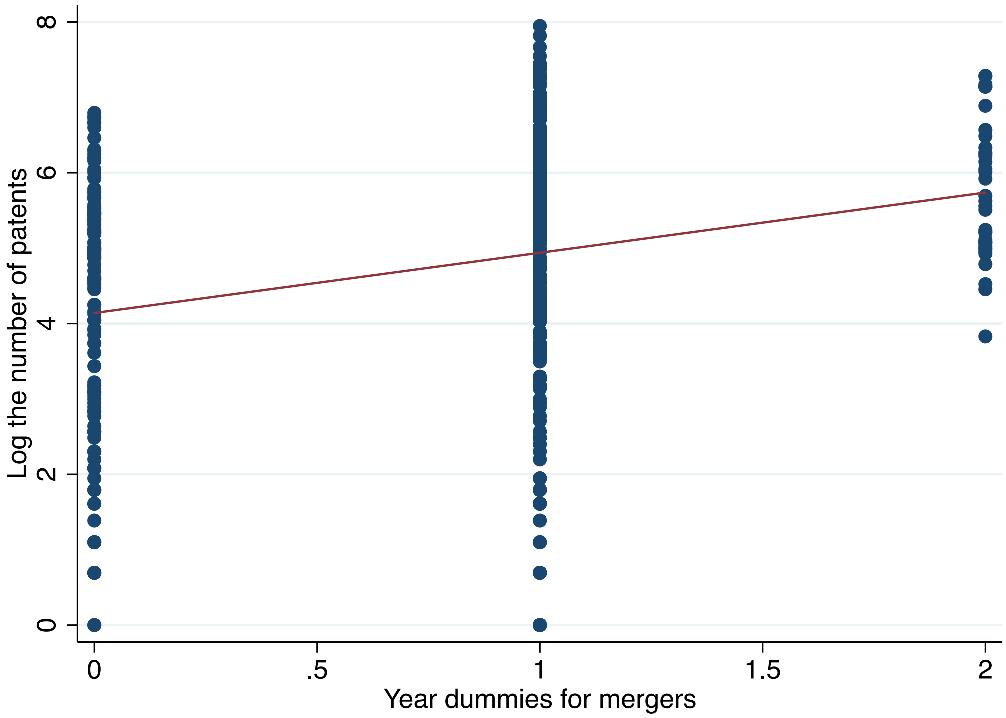


* The values for productivity are used in logarithmic form to reduce possible uncertainties in the charts representing merging companies due to large differences between numbers.
** Instead of company names, codes are used to represent merging companies. Please see company names and their codes in Table A1.
** Red vertical lines represent merger years for merging firms.

Figure 3 shows the relationship between mergers and innovation across time for merging companies. In the horizontal axis, year dummies for mergers are represented. If there is no merger for companies, it takes the value of zero for those non-merger years. If there is merger, it takes the value of one or two for those merger years since there are two mergers for some companies. Not surprisingly, as firms merge, the innovative effort of those companies increases. This is a long-term positive relationship between mergers and innovation for merging companies, which is also called a statistical association. This statistical association corroborates the Schumpeterian view on the relationship between mergers and innovation for the analyzed mergers in the paper. Using this association, we introduce the first and central hypothesis to test in *H1*:

H1: There is a long-term positive relationship between mergers and innovation running from mergers to innovation.

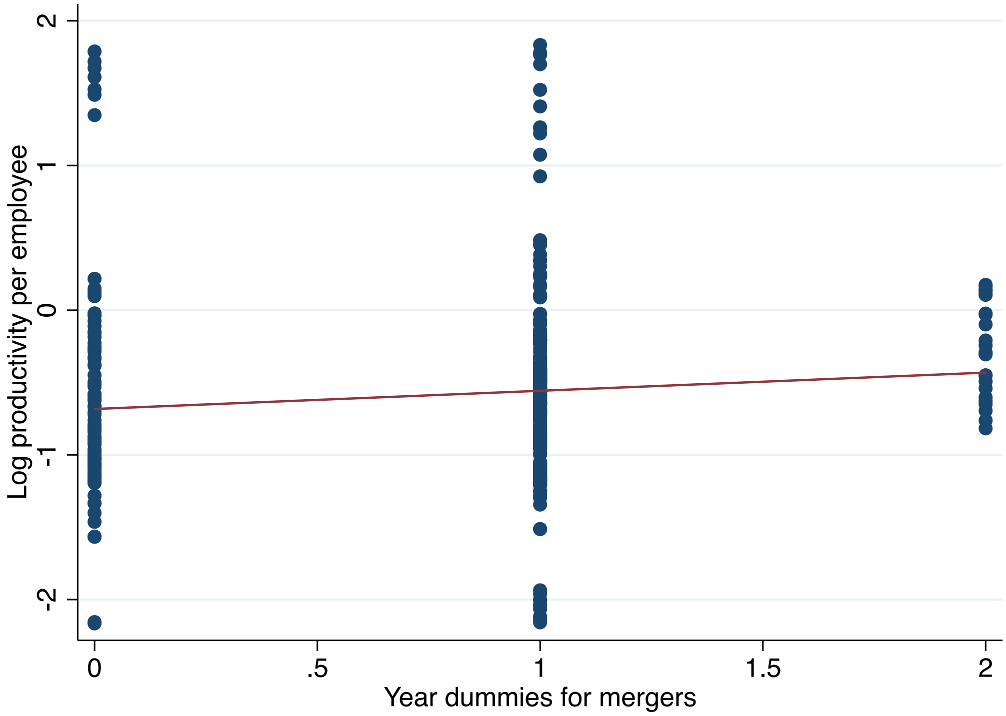
Figure 3. Mergers and innovation



As stated earlier, in the antitrust analysis of mergers, both antitrust agencies and the relevant academic literature focus on the effect of mergers on efficiency, which is represented by productivity, through economies of scale (Salant et al., 1983). Following this literature, the paper studies the effect of mergers on productivity. Figure 4 shows that there is a positive relationship between mergers and productivity. Accordingly, the second hypothesis is as follows:

H2: There is a long-term positive relationship between mergers and efficiency/productivity running from mergers to efficiency/productivity.

Figure 4. Mergers and Productivity



Because the effect of mergers on innovation and productivity is related to the relationship between mergers and market share for merging companies, another assumption in the antitrust analysis of mergers is about the relationship between market shares and the economic performance of merging firms. Accordingly, it is assumed that mergers lead to higher market shares for merging firms and using higher market shares or economies of scale, those firms increase their innovative efforts. On the other hand, it is argued that high market share brings about (in)efficiency for merging companies. In order to test the validity of those assumptions, the paper analyzes the relationships between innovation, productivity, and market share. Figure 5 shows the positive relationship between mergers and market shares[7]. Market share for merging companies increases along with merger. Using this relationship, the paper focuses on the relationship of market shares with innovation and productivity since the relevant Schumpeterian literature assume that firms with higher market share have more incentives for innovation since they might commercialize innovation more effectively (Blundell et al., 1999). Also, there should be relationship between market share and productivity if, as argued, higher market shares cause (in)efficiency. Accordingly, to empirically investigate those relationships, the following two hypotheses are introduced.

H3: There is a long-term positive relationship between market shares and innovation running from market shares to innovation.

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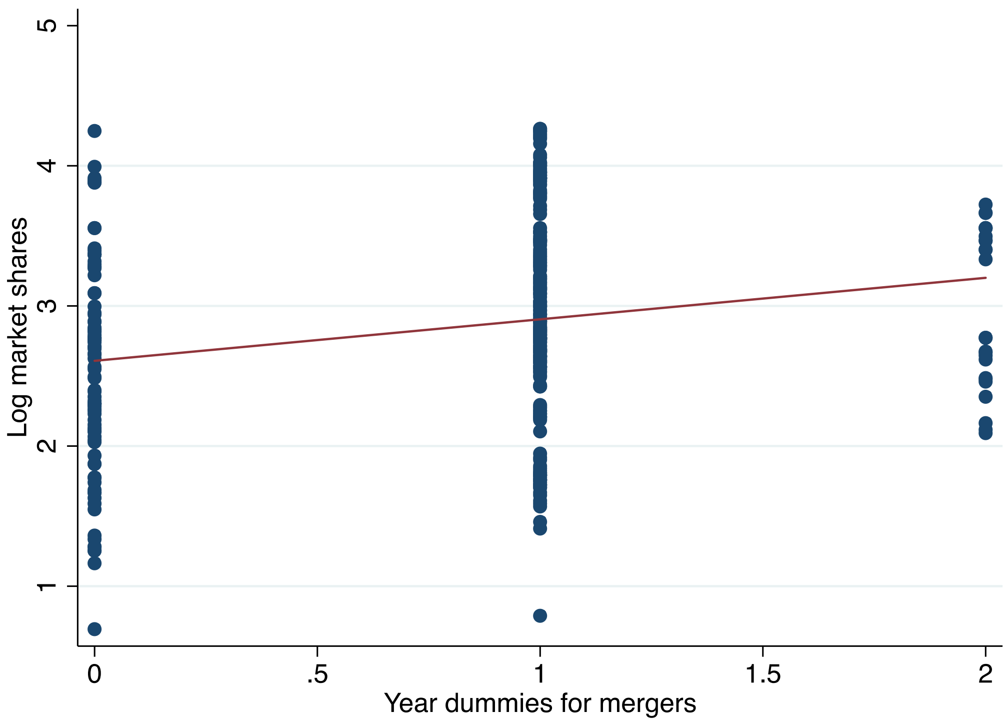
[7] However, the paper does not empirically investigate the relationship between merger and market share. In the antitrust merger analysis, market shares are taken as given. For that reason, there is less research on the effect of mergers on market share (Mueller, 1985).

Accordingly, the focus of the paper is on an empirical investigation of the causal effect of mergers on innovation and productivity under the changes in market shares occurring along with merger. The main variable in the antitrust merger analysis is market share since merger is an antitrust issue when there is a significant increase in market share along with merger. For that reason, antitrust agencies and researchers first take into account the change in market share in the merger antitrust analysis. Following this tradition in antitrust merger analysis, the paper includes market shares for merging firms to the empirical analysis since the relationship between mergers, innovation, and productivity occur along with an increase in market shares.

H4: There is a long-term positive relationship between market shares and efficiency/productivity running from market shares to efficiency/productivity.

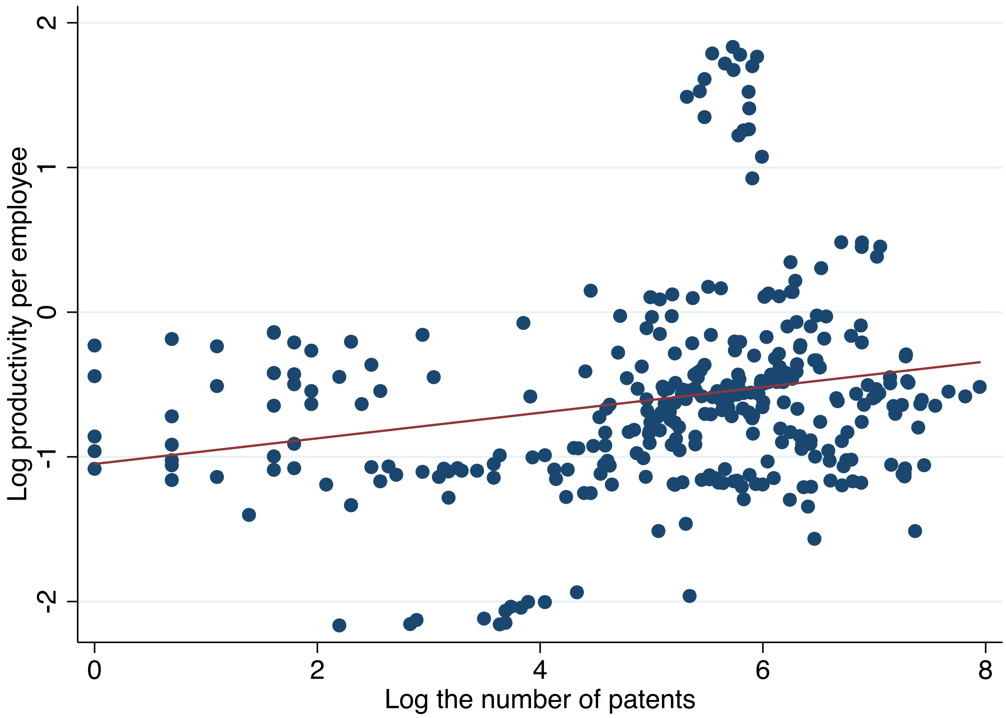
Figure 5. Mergers and Market Shares



The last relationship to test regarding the dynamic effects of mergers is about the innovation-productivity nexus since it is argued that there is a strong relationship between innovation and productivity (Morris, 2018; Ugur and Vivarelli, 2021; Aboal et al., 2019; Aiello et al., 2020). In order to analyze the relationship between innovation and productivity, the long-term innovation-productivity relationship is illustrated in Figure 6. Using this finding, the last hypothesis is introduced as follows:

H5: There is a long-term positive relationship between innovation and efficiency / productivity running from innovation to efficiency/productivity.

Figure 6. Innovation and Productivity



We have discussed the effect of mergers on economic performance and presented statistical associations and hypotheses based on those relationships. Basically, those statistical associations and hypotheses summarize the dynamic effects of mergers. However, even though it is possible to infer those statistical associations as the long-term effects of mergers on innovation and productivity since the figures above depict the cross-company associations, they are still needed to be investigated empirically to reveal the causal effects of mergers on economic performance. For that reason, using those hypotheses and statistical relationships, we will empirically investigate the dynamic effects of mergers below.

3.1. Model Specification

In order to study the dynamic effects of mergers, the paper constructs two baseline models to estimate: Innovation and production models. The aim is to investigate the effect of mergers on innovation in innovation models, while productivity models analyze the impact of mergers on the productivity for merging companies. The main idea with those models is to reveal the effects of mergers on economic performance and thus to introduce empirical evidence to antitrust merger analysis. Accordingly, the paper estimates two different regression equations for innovation and productivity models, respectively.

Innovation models aim to test *H:1* and *H:3* using market shares and year dummies representing mergers. R&D and investment expenditures are included to the model as control variables. In Eq. 1, which will be the baseline model for all estimation strategies, the paper estimates:

$$Patent_{it} = \beta_0 + \beta_1 MS_{it} + \beta_2 inv_{it} + \beta_3 RD_{it} + \beta_4 t1_{it} + \mathcal{E}_{it} \qquad (1)$$

where $Patent_{it}$ is the number of patents, MS_{it} is market shares, inv_{it} and RD_{it} are investment and R&D expenses for merging companies as individual *i* in period *t*. In order to represent pre- and post-merger terms, dummy variables are employed as $t1_{it}$ taking a value of 1 or 2 if the firm *i* merges in period *t* and 0 otherwise. $\mathcal{E}_{it}$ is the error term. In this equation, parameters β_0, β_1, β_2, β_3, and β_4 are estimated coefficients. In *ln* variable data models, those coefficients are interpreted as elasticities since the variables are used in logarithmic form. Accordingly, in Eq. 1, regression models specify the numbers of citations as a function of market shares, investment expenses, research and development expenses, and dummy variables representing merger years.

In productivity models, in order to analyze the effect of mergers on productivity, we test the hypotheses *H:2*, *H:4*, *and H:5* mergers, following the literature suggesting that there is strong relationship between innovation and productivity (Morris, 2018; Hall, 2011). Accordingly, in Eq. 2, we estimate:

$$prod_{it} = \beta_0 + \beta_1 MS_{it} + \beta_2 RD_{it} + \beta_3 t1_{it} + \ \mathcal{E}_t \tag{2}$$

where $prod_{it}$ is productivity, MS_{it} is market shares, RD_{it} is R&D expenses for merging companies as individual *i* in period *t*. In order to represent pre- and post-merger terms, we use dummy variables $t1_{it}$ taking a value of 1 if the firm *i* merges in period *t* following the literature (Yan et al., 2019; Sung and Gort, 2006). $\mathcal{E}_{it}$ is the error term. In Eq. 2, parameters β_0, β_1, β_2, β_3, and β_4 are estimated coefficients. In *ln* variable data models, it is possible to interpret those coefficients as elasticities since those variables are used in logarithmic form. Accordingly, in Eq. 2, productivity is the function of market shares, R&D expenses, and dummy variables representing merging years. First, we estimate Eqs. 1 and 2 as baseline models and then introduce some alternative estimates of models for robustness check using the findings from baseline models to the original measure of merger effects.

3.2. Data

As reported in Table A1, the paper focuses on the major 50 mergers between 2005 and 2015 in the US. In this sense, the dataset in this paper is unique since all data were gathered from different data sources. Another importance of the dataset in this paper is that it includes both target and acquiring firms in the pre-merger terms and the merging years in addition to the ones in the post-merger periods for the analyzed mergers. As clarified before, the paper uses two different estimation functions and/or models. Following the relevant literature, the number of patents is used to proxy innovation while productivity is calculated by the ratio of the number of employees as input to the total annual revenues of merging firms as output (Entezarkheir and Moshiri 2018; 2019; Blundell et al., 1999). In innovation models, innovation is proxied by the number of patents for individual companies. Patent data are retrieved as the number of patents granted by the United States Patent and Trademark Office (USPTO) from USPTO, Patent Guru, Patent Scope, and annual reports in Patent Docs. Productivity data are calculated as the ratio of revenue as output to employee as input by using total annual revenue and the annual number of employees for each analyzed firm. Those data are obtained from Macro Trends, the Securities and Exchange Commission (SEC), and the financial reports of companies. Market shares are calculated using subscriber, sale, and revenue data based on annual company reports, annual reports on Mobile Wireless Competition at the Federal Communication Commission

(FCC) for telecom companies, Energy Statistics at the International Energy Agency (IEA) for energy companies, and SEC. Data on investment and R&D expenditures are obtained from FCC, Industrial Research and Innovation data of European Commission, annul company reports, Finbox, and Macro Trends. Lastly, year dummy variables are included in dataset to represent pre- and post-merger periods. Dummy variables take a value of 1 and/or 2 if the firm merges and 0 otherwise.

Table 1 reports descriptive statistics for the variables used in the estimation models and shows that the variables differ from each other for both logarithmic and non-logarithmic values.

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
patent	480	297.863	398.318	0	2826
MS	352	21.961	16.305	0	71.1
inv	340	19841.665	66140.249	16	488372
prod	372	.761	.942	.115	6.251
RD	258	2838.717	2823.821	.249	10753
t1	480	.765	.552	0	2
lnpatent	457	4.764	1.749	0	7.947
lnMS	347	2.845	.742	.693	4.264
lninv	340	8.253	1.832	2.773	13.099
lnRD	258	6.805	2.435	-1.39	9.283
lnprod	372	-.583	.679	-2.165	1.833
lnpatlag	457	4.763991	1.748897	0	7.946618
lnprodlag	372	-.5831898	.678708	-2.165145	1.832698

Tables 2 reports the correlation coefficients for non-logarithmic variables. Note that correlation values are less than .5 for all the variables. This suggests that there is no correlation between the variables. Accordingly, there is no intercollinearity among independent variables so that we can include them to the models to estimate.

Table 2 Matrix of correlations

Variables	patent	MS	inv	RD	prod	t1
patent	1.000					

MS	0.217	1.000				
inv	0.257	0.061	1.000			
RD	-0.163	-0.317	0.186	1.000		
prod	-0.039	0.164	0.135	0.410	1.000	
t1	0.290	0.223	0.300	0.056	0.146	1.000

Tables 3 reports the correlation coefficients for logarithmic variables. As explained before, we use the variables in logarithmic form to estimate the long-term elasticities. Note that correlation values are still small for all the variables. This suggests that there is no correlation between the variables. Accordingly, there is no intercollinearity among independent variables so that we can include them to the models to estimate.

Table 3 Matrix of correlations (log)

Variables	lnpatent	lnMS	lninv	lnRD	lnprod	t1
lnpatent	1.000					
lnMS	0.258	1.000				
lninv	0.349	0.013	1.000			
lnRD	0.135	-0.146	0.421	1.000		
lnprod	0.184	0.091	0.499	0.551	1.000	
t1	0.327	0.231	0.201	-0.007	0.137	1.000

4. Results

We introduce different estimation models using different estimators under different estimation scenarios to increase the robustness of models for both estimation equations and to attain more reliable results. The estimators employed in the empirical analysis are reported in the regression result tables as Pooled OLS (1), random effect GLS (2), fixed effects (within) (3), first-difference (between) effect (4), and maximum likelihood (5), respectively, following the literature on longitudinal data (Acemoglu et al., 2008; Angrist et al., 2009; Kniesner et al., 2012; Entezarkheir and Moshiri, 2018; 2019; Imai and Kim, 2019). In particular, fixed-effects estimators are used to control for company-specific factors affecting both mergers and/or market shares and innovation and/or productivity. This helps us find the causal effects of mergers on innovation and productivity especially in the absence or exclusion of time-varying omitted variables influencing the dependent variable and correlated with the right-hand-side variables in the models[8].

Accordingly, the main source of potential bias in our estimation models is merging company-specific factors. Such company-specific time-variant factors can impact on both innovation and productivity as dependent variables and market shares and merger decisions as right-hand-side variables. For instance, if we compare Duke Energy and AT&T as individual merging companies we will see company-specific time-varying factors influencing the individual decisions of those companies on innovation and productivity as well as their merger decisions. In such a simple cross-company comparison, AT&T has both higher innovation rates and higher market shares whereas Duke Energy has both lower market shares and innovation rates over time. If an estimation strategy does not fix such company-specific factors, it will introduce biased results. To avoid this, the paper uses fixed-effects estimators and include control and dummy variables to control for company-specific factors, which will help us remove such bias from the models. The aim is to find the causal effects by analyzing 'within-company variation', which is also called fixed-effects estimator. Fixed-effects or within-effect estimators will reveal if Duke Energy is more likely to innovate (relatively) more as it has (relatively) higher market shares. In other words, this estimation strategy will enable us to better understand in the sense of causal inference if individual-merging companies will be more innovative if they have higher market shares, not simply that companies with high market shares are innovative. This means that fixed-effect estimators will provide more robust and reliable results including the causal inference of findings instead of cross-company statistical associations. As a matter of fact, when dummy variables and fixed effects are included to the estimated models, the relationships between mergers, innovation, and productivity remain statistically significant. This suggests that the fixed-effect regressions confirm the existence of casual effects in the estimated models.

4.1. Innovation Models

First, in innovation models, three different scenarios are used: non-logarithmic values for all the variables, full-logarithmic value for dependent variable but non-logarithmic values for independent variables, and full-logarithmic values for all the variables, respectively. Those scenarios are called non-log, LogDepVar, and full-logarithmic models, respectively. Differently, productivity models use two different scenarios: full-logarithmic values for dependent variable but non-logarithmic values for independent variables and full-logarithmic values for all the variables since those two scenarios provide more reliable and robust results compared to non-logarithmic models in innovation models. Second, the variable *inv* is removed from innovation models to test possible endogeneity problem between *inv* and *RD*[9].

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[8] For a detailed analysis and discussion on the use of fixed-effects estimators to reveal causal effects in the longitudinal data, see (Wooldridge, 2002; Acemoglu et al., 2008; Angrist and Pischke, 2009; Imai and Kim, 2019; Bennato et al, 2021).

[9] As another strategy, using the same methodology with non-inv models, *RD* is removed from the models instead of *inv* to see whether non-*RD* or non-*inv* models give more reliable results. non-*inv* models were more significant statistically and economically probably because R&D is more related to innovation. For that reason, instead of non-*RD* models, non-*inv* models are used in the paper.

Tables 4a, 4b, and 4c report the results from non-log, LogDepVar, and full-logarithmic innovation models, respectively. In all the estimated models under three different scenarios, the signs of estimated coefficients are mostly as expected with some exceptions. On the other hand, when we compare the statistical significance of estimated coefficients from different estimators, we attain different results. In Pooled OLS models (1) in the first columns of the Tables 4a, 4b, and 4c, the best results are from Scenario 3 in Table 4c using all the variables in logarithmic form. The findings from all estimators in this estimation strategy suggest that there is statistically significant and positive relationship between the number of patents and dummy variables, market shares, and R&D. However, as reported in the tables, some coefficient signs for *RD* especially in Scenario 2 and Scenario 3 are negative and the estimated coefficients for *inv* are almost zero.

Regarding the relationship between market shares and innovation, the results in all models under three different estimation strategies confirm the presence of a cross-company positive relationship since coefficient signs for *MS* are positive in Tables 4a, 4b, and 4c. This finding suggests that there is a statistical association between market shares and innovation. Moreover, the estimated coefficients for MS in LogDepVar and Full-Logarithmic models in Table 4b and Table 4c are mostly statistically significant. In particular, the estimated coefficient (.442*) from fixed-effects regression in Table 4c confirms the causal effect of market shares on innovation since it is positive and statistically significant at 90% significance level. Because variables are used in their logarithmic forms in those models, it is possible to interpret this evidence as a long-term electricity between market shares and innovation. Accordingly, a 10% increase in market shares causes a 4.4% rise in innovation. Note that this evidence is not only a statistical association between market shares and innovation but also the causal effect of market shares on innovation. Also, note that the increase in market shares for merging companies in the models stem from mergers. This suggests that the merging companies with higher market shares occurred along with mergers innovate more. It is possible to infer that merger improves the innovative efforts of merging companies by increasing market shares for those companies.

Table 4a. The Innovation Effect of Mergers (Non-log Models)

	(1)	(2)	(3)	(4)	(5)
patent	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML
MS	3.214	7.004	7.321	2.261	6.901
	(1.71)	(1.30)	(1.13)	(.20)	(1.34)
inv	.018*	.011	.011	.035	.011
	(2.47)	(1.82)	(1.78)	(.85)	(1.85)
RD	-.026*	.052**	.061**	-.042	.05**
	(-2.11)	(3.00)	(3.30)	(-.67)	(2.86)
t1	231.552***	127.167*	112.68*	-66.162	130.605*

	(3.58)	(2.39)	(2.07)	(-.08)	(2.47)
cons	260.195**	35.676	-4.601	488.714	42.313
	(3.36)	(0.19)	(-0.03)	(0.78)	(0.25)
N	146	146	146	146	146
R-sq	.186	.244	.245	-.315	

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

As a matter of fact, the findings from the estimated coefficients for *t1* are compatible with the finding on the causal effect of market shares on innovation through mergers since the most significant coefficient from all the models belongs to dummy variable representing mergers. In particular, in Table 4c, all the signs of coefficients for *t1* are positive and those coefficients are statistically significant above 99% significance level in four models. Moreover, in all the result tables, the estimated coefficients from within-effect regressions are both positive and statistically significant. This evidence confirms both the statistical association between mergers and innovation and the causal effect of mergers on innovation. In other words, when companies merge, this leads to more innovation. When these results are evaluated along with the findings for the relationship between market share and innovation, it is possible to infer that both merger activities and higher market shares stemming from the merger deals cause more innovation. Consequently, the results from the first estimation strategy reported in Tables 4a, 4b, and 4c confirm *H1* and *H3*. There is a long-term positive relationship running from mergers and market shares to innovation for merging companies analyzed in this paper.

Table 4b. The Innovation Effect of Mergers (LogDepVar Models)

	(1)	(2)	(3)	(4)	(5)
lnpatent	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML
MS	.012**	.025*	.027	.014	.024*
	(2.91)	(2.02)	(1.87)	(.47)	(2.07)
inv	.01*	-.01	-.01	.01	.01
	(2.27)	(-.02)	(-.012)	(.92)	(.02)
RD	-.01	.01***	.01***	-.01	.01***
	(-.05)	(4.19)	(4.22)	(-.10)	(4.15)
t1	.549***	.334***	.319***	-.298	.339***
	(3.09)	(2.86)	(2.67)	(-.14)	(2.93)

cons	4.929***	4.39***	4.413***	5.198**	4.405***
	(18.45)	(9.71)	(14.51)	(3.21)	(10.91)
N	146	146	146	146	146
R-sq	.175	.307	.308	.179	

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Remember that, under the first estimation strategy in Tables 4a, 4b, and 4c, investment and R&D expenditures are also used to control for company-specific factors. While the results from non-log and LogDepVar models are mostly insignificant and unreliable, the findings from full-logarithmic models confirms the statistical association of *lninv* and *lnRD* with *lnpatent*. Moreover, the fixed-effect estimator in Table 4c finds a causal effect of *lninv* and *lnRD* on *lnpatent* at a 90% significance level. Accordingly, the findings from company-specific control variables are compatible with the previous findings on the effect of *t1* and *(ln)MS* on *(ln)patent* in the same models. However, the results for *inv* and *RD* are more interesting in terms of the selection and validity of estimation strategies. Note that the coefficient signs for *RD* and *inv* are positive only in Full-logarithmic models in Table 4c. First, this finding suggests that full-logarithmic models for all estimators are more reliable and robust. Second, this can be caused by an endogeneity problem between *inv* and *RD*. For that reason, taking into those findings account, the paper introduces another estimation strategy to see if there is improvement in the estimated models by dropping the variable *inv* from the models, but not *RD* since R&D expenditures are more closely related to innovation as explained in footnote 9. The models in which *inv* is dropped are called non-inv models and the results from those models are reported in Tables 4d and 4e below.

Table 4c. The Innovation Effect of Mergers (Full-logarithmic Models)

	(1)	(2)	(3)	(4)	(5)
lnpatent	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML
lnMS	.345**	.406*	.442*	.413	.397*
	(.114)	(.233)	(.265)	(.571)	(.222)
lninv	.248**	.056	.007	.386	.072
	(.093)	(.092)	(.1)	(.357)	(.091)
lnRD	.049	.123**	.112*	.09	.126**
	(.049)	(.058)	(.06)	(.34)	(.057)
t1	.524**	.53***	.543***	.16	.525***
	(.167)	(.105)	(.107)	(1.609)	(.105)

cons	2.02**	2.814***	3.251***	.701	2.689***
	(.951)	(1.057)	(1.119)	(2.709)	(1.023)
N	146	146	146	146	146
R-sq	.247	.250	.239	.365	

Standard errors are in parentheses

***** p<.01, ** p<.05, * p<.1*

First of all, the results from Table 4d and Table 4e are less significant and reliable in the non-*inv* models since the coefficients for *MS* are mostly negative and not significant statistically. However, other than this, especially, the findings (Table 4e) from fixed-effects estimator within all the models show the most significant estimated coefficients, even for *MS*. While the signs for coefficients are positive for all the variables as expected, the results for all the variables *MS*, *RD*, and *t1* in full-logarithmic models are statistically significant at 95%, 99%, and 99% significance levels, respectively, as reported in Table 4e. This suggests that the fixed-effects non-*inv* models with full-logarithmic variables are still robust and reliable. In other words, this corroborates the estimation strategies used in the paper since the findings from the non-*inv* estimation strategy models confirms that there is no reason to exclude *inv* from the models. On the other hand, the findings from full-logarithmic models under the new estimation strategy are still mostly compatible with results from full-logarithmic models in the previous models.

Table 4d. The Innovation Effect of Mergers (without-*inv* Models)

	Non-inv Pooled OLS			Non-inv random effects		
	(1)	(2)	(3)	(4)	(5)	(6)
	patent	lnpatent	lnpatent	patent	lnpatent	lnpatent
MS	-3.373**	-.014		3.244	.01	
	(1.437)	(.018)		(4.248)	(.011)	
RD	-.006	.007***		.067***	.004***	
	(.011)	(.003)		(.017)	(.001)	
t1	308.87***	.763***	.587***	199.667***	.482***	.66***
	(63.337)	(.209)	(.189)	(52.186)	(.117)	(.105)
lnMS			-.022			.385*
			(.16)			(.202)
lnRD			.467***			.194***
			(.087)			(.059)

cons	324.373***	4.39***	1.583*	12.578	4.099***	2.329***
	(57.486)	(.53)	(.835)	(155.925)	(.521)	(.807)
N	189	146	186	189	186	186
R-sq	.114	.151	.298	.288	.350	.315

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

If we analyze the results for the variables one by one, the signs and coefficients for *MS* are mostly positive and statistically significant in the non-*inv* full-logarithmic models, but not in the other models. This suggests that there is still a positive relationship between market share and innovation. Also, note that it is possible to interpret the results as long-term elasticities. Accordingly, the long-term elasticity between *lnMS* and *lnpatent* is 0.4 on average from the significant logarithmic models. This finding is compatible with the previous finding on the MS and patent relationship and suggests that if there is a 10% increase in market share this increase in market share will cause 4% increase in innovation on average for those merging companies. This finding clearly confirms *H3* that there is a positive relationship between market share and innovation running from market share to innovation. In other words, the findings from innovation models confirm that a merging company with higher market share stemming from merger make more innovation. Note that innovation increases along with an increase in market shares meaning that even though mergers lead to market power this increase in market power simultaneously brings about more innovation since positive relationship between *patents* and *MS* is statistically significant especially in the full-logarithmic fixed-effects estimator models.

Similarly, the signs and coefficients for *RD* are mostly significant statistically and economically. This suggests that there is a positive relationship between R&D expenditures and innovation for merging companies. An increase in the R&D expenditures of merging companies bring about more innovation. More specifically, when we analyze the statistically significant coefficients as long-term elasticities in the fixed-effects full-logarithmic models those findings suggest that a 10% increase in R&D expenditures cause a 1.2% rise in innovation for merging companies. This finding for *RD* corroborates the other findings on the effect of mergers and market shares on innovation. In other words, the evidence from innovation models is compatible with the Schumpeterian literature on the antitrust merger analysis of innovation.

Table 4e. The Innovation Effect of Mergers (without-*inv* Models)

	Fixed Effects			Between-Group			Maximum Likelihood		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	patent	lnpatent	lnpatent	patent	lnpatent	lnpatent	patent	lnpatent	lnpatent
MS	4.401	.014		-3.954	-.021		3.215	.009	
	(5.303)	(.012)		(8.012)	(.032)		(4.208)	(.011)	

RD	.081***	0***		-.02	0		.067***	0***	
	(.019)	(0)		(.047)	(0)		(.018)	(0)	
t1	176.6***	.472***	.663***	316.03	1.446	.735	200.23***	.485***	.66***
	(53.48)	(.119)	(.105)	(472.77)	(1.886)	(1.608)	(52.357)	(.116)	(.104)
lnMS			.478**			-.024			.384*
			(.215)			(.65)			(.202)
lnRD			.171***			.592*			.194***
			(.06)			(.277)			(.059)
cons	-35.46	4.10***	2.32***	367.739	4.279**	.501	13.889	4.11***	2.33***
	(128.5)	(.279)	(.741)	(386.7)	(1.54)	(2.937)	(154.266)	(.471)	(.797)
N	189	186	186	189	186	186	189	186	186
R-sq	.289	.350	.317	-.252	-.139	.381			

Standard errors are in parentheses

*** $p<.01$, ** $p<.05$, * $p<.1$

4.2. Productivity Models

Estimating Eq. 2 and using the same estimation strategies (Pooled OLS (1), random effect GLS (2), fixed effects (within) (3), first-difference (between) effect (4), and maximum likelihood (5)) in innovation models, the paper investigates the effect of mergers on efficiency/productivity. In all the models, following the literature and using the hypotheses discussed and constructed in detail above, *t1* and *MS* are employed to test *H2* and *H4* and to reveal the effect of mergers and market shares on productivity, respectively. *Patent* and *RD* are included to the models to reveal the effect of innovation on productivity and to test *H5*. The Tables 5a, 5b, and 5c report the results from productivity models. In Table 5a, the paper uses LogDepVar and Full-Logarithmic models with all the variables including *inv*. According to the LogDepVar Models (1-5), the effect of mergers and innovation on productivity is not significant statistically. There is only one statistically significant result in Model 1 (Pooled OLS) for *RD*. On the other hand, the signs for *inv* are as expected and coefficients are mostly significant statistically. However, the effect of *RD* and *inv* on productivity from the significant results is close to zero in all the LogDepVar Models. In the Full-Logarithmic Models (6-10) in Table 5a, while the findings from Models 7, 8, and 10 suggest that there is a statistically significant finding for *t1*, coefficients are not significant for *patent* in all the models and there are only two statistically significant coefficients for *MS* (Models 1 and 6).

The findings from Table 5a suggest that estimation strategy with *inv* does not provide significant results statistically. This refers to a possible endogeneity between *inv* and *RD*. To test this and to see if there is improvement in the results, *inv* is dropped from the estimation models. Additionally, following the literature, we also drop *patent* from some models (1-5 in both tables) to test if those models only with *RD*, which still refers to the innovative efforts of companies, improve estimated coefficients. Tables 5b and 5c report the results from Non-Inv LogDepVar and Non-Inv Full-Logarithmic Models. First of all, the findings strongly suggest that the exclusion of *inv* from the models improves the empirical results whereas there is almost no difference between the models with *patent* and the models without *patent*. This means that the new estimation strategy is statistically more reliable and robust.

Table 5a. The Productivity Effect of Mergers (LogDepVar and Full-Logarithmic Models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lnprod	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML
patent	0	0	0	0	0					
	(0)	(0)	(0)	(0)	(0)					
MS	.009***	.006	.006	.008	.006					
	(.002)	(.004)	(.004)	(.012)	(.004)					
RD	0***	0***	0**	0	0***					
	(0)	(0)	(0)	(0)	(0)					
inv	0*	0***	0***	0	0***					
	(0)	(0)	(0)	(0)	(0)					
t1	-.008	.038	.044	.638	.036	.049	.089**	.096***	.794	.089***
	(.062)	(.036)	(.037)	(1.363)	(.036)	(.052)	(.035)	(.035)	(1.197)	(.034)
lnpatent						-.017	.032	.032	0	.032
						(.035)	(.026)	(.026)	(.127)	(.025)
lnMS						.1**	.072	.093	.005	.073
						(.047)	(.074)	(.081)	(.241)	(.073)
lninv						.111***	.126***	.114***	-.019	.125***
						(.037)	(.028)	(.029)	(.21)	(.027)
lnRD						.136***	.013	.004	.329	.012
						(.048)	(.018)	(.018)	(.183)	(.018)
cons	-1.34***	-1.23***	-1.19***	-2.139	-1.23***	-2.95***	-2.39***	-2.26***	-3.84***	-2.38***
	(.115)	(.168)	(.092)	(1.2)	(.146)	(.37)	(.333)	(.338)	(1.015)	(.329)

N	138	138	138	138	138	138	138	138	138	138
R-sq	.303		.201	-.003	.125	.394		.15	.448	.446

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Accordingly, under this estimation strategy, there are significant coefficients for *t1* (Models 2, 3, 5, 6, 8, and 9 in Table 5b and Models 1, 2, 3, 5, 6, 7, 8, and 10 in Table 5c). This finding confirms *H2* meaning that there is a long-term positive relationship between mergers and productivity running from mergers to productivity. The coefficients for both *patent* and *RD* are mostly highly significant statistically. This finding confirms *H5* meaning that there is a long-term relationship between innovation and productivity represented by *patent* and *RD* in the models. However, there is less evidence to confirm *H4* and/or the existence of a relationship between *MS* and *prod* since the coefficients for *MS* in the models are mostly not significant statistically except with Models 1 and 7 in both tables.

Table 5b. The Productivity Effect of Mergers (Non-Inv LogDepVar Models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lnprod	Pooled OLS	Random -effects	Fixed-effects	First-difference	ML	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML
patent						.018**	.011	.014**	.011**	.001
						(.001)	(.004)	(.001)	(.004)	(.002)
MS	.01***	.001	.012	.011	.002	.004	.011***	.009	-.002	.013
	(.001)	(.003)	(.004)	(.008)	(.003)	(.003)	(.001)	(.003)	(.004)	(.009)
RD	.05***	.012***	.032***	.033**	.011***	.043***	.04***	.012***	.014**	.03**
	(.015)	(.012)	(.043)	(.123)	(.103)	(.203)	(.111)	(.133)	(.234)	(.139)
t1	.05	.071**	.077**	.335	.07**	.058*	.04	.058*	.064*	.257
	(.048)	(.034)	(.034)	(.54)	(.033)	(.033)	(.051)	(.034)	(.034)	(.584)
cons	-1.3***	-1.05***	-.97***	-1.74***	-1.05***	-1.04***	-1.34***	-1.04***	-.95***	-1.79**
	(.083)	(.142)	(.088)	(.526)	(.138)	(.14)	(.097)	(.146)	(.087)	(.559)
N	175	175	175	175	175	175	175	175	175	175
R-sq	.316	.105	.109	.207	.102	.105	.313	.122	.133	.135

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Lastly, full-logarithmic models provide more reliable and robust results. Also, if we evaluate the results in terms of long-term elasticities, it is possible to say that a 10% rise in patent counts or innovation level causes a 5% increase in productivity on average because the coefficients for patent in Models 6, 7, 8, and 10 in Table 5c are statistically significant. Note that the results from the innovation models suggest that mergers lead to this increase in the number of patents for merging companies. We can infer that merger increases efficiency or productivity through innovation for merging firms used in the analysis.

Table 5c. The Productivity Effect of Mergers (Non-Inv Full-Logarithmic Models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lnprod	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML
lnpatent						.055**	.045**	.05**	-.115	.047**
						(2.18)	(1.96)	(2.10)	(-1.3)	(2.05)
lnMS	.19***	.048	.044	.21	.047	.17***	.035	.021	.171	.031
	(.039)	(.066)	(.071)	(.182)	(.065)	(.038)	(.066)	(.072)	(.173)	(.066)
lnRD	.125***	.027	.019	.231**	.026	.159***	.022	.012	.305**	.019
	(.032)	(.016)	(.017)	(.08)	(.016)	(.042)	(.017)	(.017)	(.092)	(.017)
t1	.087*	.12***	.125***	.326	.121***	.131***	.101***	.103***	.558	.101**
	(.046)	(.031)	(.031)	(.5)	(.031)	(.043)	(.033)	(.033)	(.494)	(.033)
cons	-2.3***	-1.2***	-1.1***	-3.3***	-1.2***	-2.2***	-1.4***	-1.3***	-3.4***	-1.3**
	(.314)	(.248)	(.235)	(.947)	(.251)	(.353)	(.252)	(.24)	(.901)	(.256)
N	175	175	175	175	175	172	172	172	172	172
R-sq	.260	.090	.050	.318	.378	.310	.094	.077	.393	.289

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

5. Robustness

Remember that the findings from baseline models above suggest that full-log models (Table 4c) and random effect (2) and fixed effect (3) estimators provide more reliable and robust results. Also, note that fixed-effect models are widely used for causal inference with longitudinal data (Angrist et al., 2009; Imai and Kim, 2019). Even in full-log models, *inv* is the only variable, which is statistically insignificant except with the Pooled OLS estimations. Using this feature of the estimation results, we introduced another estimation strategy in which we removed *inv* from the models to see whether there is improvement in the estimation results. As a matter of fact, the findings from Tables 4d and 4e suggest that there is improvement in the results.

Accordingly, estimated coefficients for *RD* is more significant statistically in the new estimation models. Also, random effect and fixed effect estimators obtain more robust and reliable results under this scenario as well. Note that the effect of mergers, market shares, and R&D expenditures on innovation is positive and statistically significant in all specifications in full-log models (Model (6) in Table 4d and Model (3) in Table 4e). The findings from the models under new estimation strategy in Tables 4d and 4e suggest that innovation, market share, and R&D expenses rise along with mergers.

At this point, using those empirical findings, we introduce a different estimation strategy including the lagged values of dependent variable as explanatory variable on the right-hand side since there should exist a strong positive relationship between the number of patents and its lagged values due to persistency in innovation. The aim is to increase the explanatory power of baseline models and to see if there is any improvement in the results. For that reason, we estimate Eq. 3:

$$lnpatent_{it} = \alpha lnpatent_{it-1} + \gamma lnMS_{it} + \beta x'_{it} + \mu_{it} + \ e_{it} \quad (3)$$

where $lnatent_{it}$ is the log of patent counts of merging firm *i* in period *t*. The log of lagged value of patent counts $lnpatent_{it-1}$ as explanatory variable is included to capture persistence in innovation and to see if it will improve the explanatory power of baseline models above. The main variable of interest $\gamma lnMS_{it}$ is *lnMS* for merging firm *i* in period *t*. All other potential covariates are included in the vector x'_{it}. μ_{it} proxies a full set of time effects as dummy variable to capture the effect of merger shocks to the innovation effort of all merging companies. e_{it} is an error term capturing all possible omitted factors for all *i* and *t*. Coefficient parameters α, γ, and β measure the causal effect of variables on innovation.

Because of the presence of lagged innovation in the models, *RD* is also dropped from some models as another estimation strategy under the lagged value estimation. Accordingly, with- and without-*RD* results are reported in Table 6. The coefficients for *lnpatlag1* are highly significant in all models, as expected, and suggest that there is strong persistency in the innovation efforts of merging companies. Note that, in the fixed-effects results using both with- and without-*RD* models, there is strong evidence showing the causal effect of mergers on innovation since the coefficients (.35 and .58), standard errors (3.83 and 7.79), and their *p* values (for both $p<.01$) refer to highly strong statistical significance levels. Also, note that there is remarkable increase in R^2. A remarkable causal effect evidence to the market share-innovation nexus comes from fixed-effect estimator using without-*RD* estimation strategy in Model 8 even though *lnMS* is still significant and suggests a strong positive relationship between market share and innovation in Model 3 using with-*RD* estimation. In short, in this new estimation strategy, the relationships with fixed-effects estimators remain statistically significant. This also suggests that the baseline models are valid.

Table 6. The Innovation Effect of Merger (Lagged-Value Models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)

lnpatent	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML	Pooled OLS	Random-effects	Fixed-effects	First-difference	ML
lnpatlag1	.88***	.82***	.54***	1.09***	.56***	.87***	.74***	.35***	1.08***	.39***
	(15.97)	(20.63)	(9.52)	(23.36)	(10.11)	(20.24)	(22.11)	(9.12)	(32.03)	(9.91)
lnMS	-0.03	-.039	.18	-.01	.06	.06	.12	.40***	.07	.36**
	(-0.39)	(-0.47)	(1.03)	(-0.03)	(0.37)	(.049)	(1.37)	(2.90)	(.98)	(2.79)
lnRD	0.08	0.10**	.010*	-0.02	0.12**					
	(1.69)	(2.63)	(2.06)	(-0.40)	(2.58)					
t1	0.02	.08	.35***	-.45	.29***	.19	.31***	.58***	-.32	.53***
	(0.20)	(.87)	(3.83)	(-2.16)	(3.25)	(1.77)	(3.53)	(7.79)	(-1.60)	(7.50)
cons	.244	.367	1.311*	.104	1.149*	.375	.693*	1.677***	-.344	1.463**
	(.63)	(.98)	(2.15)	(.28)	(2.01)	(1.13)	(2.30)	(3.85)	(-1.19)	(3.11)
N	184	184	184	184	184	306	306	306	306	306
R-sq	.833		.901	.987		.769		.703	.981	

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Using the same strategy in Eq. 3., we include the lagged value of productivity to the baseline models of productivity. Accordingly, we estimate Eq. 4:

$$lnprod_{it} = \alpha lnprod_{it-1} + \gamma Y_{it} + \beta x'_{it} + \mu_{it} + \ e_{it} \qquad (4)$$

where $lnprod_{it}$ is the log of patent counts of merging firm *i* in period *t*. The log of lagged value of productivity scores $lnprod_{it-1}$ as explanatory variable is included to capture persistence in productivity scores and to see if it will improve the explanatory power of baseline productivity models. The main variables of interest γY_{it} are *lnMS* and *lnpatent* for merging firm *i* in period *t*. All other potential covariates are included in the vector x'_{it}. μ_{it} proxies a full set of time effects as dummy variable to capture the effect of merger shocks to the innovation effort of all merging companies. e_{it} is an error term capturing all possible omitted factors for all *i* and *t*. Coefficient parameters α, γ, and β measure the causal effect of variables on productivity.

Accordingly, following the same strategy in the estimation of Eq. 3, we drop *RD* from some models. With- and without-*RD* results are reported in Table 7. Except with the statistical significance levels of Maximum Likelihood estimations in both with- and without-*RD* models, all models confirm a strong persistency in productivity for merging firms. There is only one statistically significant coefficient from Pooled OLS estimators in Model 1 showing the positive relationship between market shares and productivity. However, all other results in other models still confirm the same relationship between market share and productivity. The results from fixed-effects estimators in both with- and without-*RD* models confirm the causal effect of mergers on productivity. While the results from the estimation of Eq. 4 show that the baseline models of the effect of mergers on productivity are valid, fixed-effects estimators provide the most robust and reliable findings. This is strong evidence on the causal effect of mergers on productivity.

Table 7. The Productivity Effect of Merger (Lagged-Value Models)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
lnprod	Pooled OLS	Random -effects	Fixed-effects	First-difference	ML	Pooled OLS	Random -effects	Fixed-effects	First-difference	ML
lnprod_lag	.81***	.64***	.32***	1.03***	.81	.84***	.84***	.39***	.99***	.84
	(9.82)	(13.55)	(6.11)	(14.65)	(0)	(10.29)	(26.75)	(7.59)	(34.13)	(0)
lnpatent	0.003	0.006	.002	.029	.008	.020*	.020*	.035	.022*	.020
	(.30)	(.39)	(.010)	(1.56)	(.054)	(2.34)	(2.02)	(1.46)	(2.65)	(1.83)
lnMS	.050*	.512	.069	.007	.037	.026	.026	.089	.009	.028
	(2.27)	(1.48)	(1.21)	(0.19)	(1.14)	(1.43)	(1.19)	(1.54)	(.44)	(1.14)
lnRD	.028	.031*	.011	-.016	.015					
	(1.61)	(2.22)	(0.85)	(-.058)	(1.12)					
t1	.021	.028	.075**	.028	.013	.028	.028	.073*	.048	.028
	(.071)	(.099)	(2.81)	(.027)	(.048)	(.072)	(.092)	(2.15)	(.79)	(.85)
cons	-.52*	-.69***	-.86***	-.03	-.41*	-.31*	-.31***	-.92***	-.18*	-.31***
	(-2.31)	(-3.87)	(-4.08)	(-.11)	(-2.54)	(-2.51)	(-3.74)	(-4.81)	(-2.20)	(-3.52)
N	164	164	164	164	164	164	257	257	257	257
R-sq	.804		.254	.975		.747		.232	.985	

Standard errors are in parentheses

**** p<.01, ** p<.05, * p<.1*

Even though the paper tested the robustness of findings using different estimation strategies, more typical robustness checks are introduced in this section. In particular, the estimation models employed for Eqs. 3 and 4 confirm the robustness of previous models. The findings from different models under various estimation strategies are compatible with each other at high statistical significance levels. More specifically, the findings from fixed-effects estimators under different estimation strategies are highly significant and consistent in addition to random-effect estimators. However, in addition to the robustness check in the previous models, the paper also uses Hausman test to see if there is difference between random effects and fixed effects models. The Hausman tests for the lagged value estimations of both innovation and productivity models suggest that null hypothesis is rejected, and alternative is accepted since *Prob>chi2* is equal to zero for both models. This confirms that fixed-effects models are valid. (All the results from those models are available upon request).

Note that the results from the lagged value estimations of both innovation and productivity models are the most reliable and robust findings compared to the previous models under different estimation strategies. Accordingly, when we take into consideration only fixed-effects models the results confirm the causal effect of mergers on innovation and productivity since fixed-effects models are used to account for causal effects due to its focus on within-individual differences instead of between-individual changes[10]. In other words, the findings strongly confirm the causal effect of dummy variables proxying mergers on patent counts and productivity per employee in both innovation and productivity models.

6. Antitrust Implications

Traditionally, the main antitrust concern regarding mergers is whether they cause market power with higher market shares stemming from the deal. However, the simple inclusion of market shares to the antitrust merger analysis has been rather controversial. As discussed in the relevant literature in detail, even under a 100% market share in some cases, high market share or power does not necessarily mean the abuse of competition and this situation makes market delineation more complicated in such industries[11]. For that reason, the contemporary antitrust merger analysis relies on new approaches to mergers including the Schumpeterian perspective on the mergers-innovation nexus rather than a typical market definition analysis. In that sense, what matters with mergers is all about their effect on economic gains or losses. In order to reveal those dynamic effects of mergers, this paper introduced a dynamic estimation strategy using a dynamic panel data for selected major mergers between 2005 and 2015 in the US. The results suggest that mergers improve economic gains for merging companies in terms of the effect of mergers on innovation and efficiency/productivity. Nota that this is a causal effect running from mergers to innovation and efficiency/productivity.

Accordingly, the main finding in this paper is the causal effect of mergers on innovation. In innovation models, the findings from fixed-effects estimators are statistically significant, robust, and reliable. This evidence strongly confirms that mergers cause more innovation. In other words, this finding shows that the Schumpeterian statistical association on the mergers-innovation nexus is actually causal effect. In terms of antitrust merger policy, taking into account the causal effect of mergers on innovation found in this paper, there is no reason to ban mergers by law since mergers improve economic performance in the markets. Also, note that this effect exists under an increase in market shares for merging companies. As a matter of fact, the findings from different valid estimation models confirm that an increase in market shares lead to an increase in innovation for merging companies. Clearly, taking advantage of high

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[10] For that reason, fixed-effect models provide more robust and reliable results (Wooldridge, 2002).
[11] For a detailed discussion on the use of market share in the analysis of market definition, see Çetin (2017).

market shares or economies of scale along with merger, merging companies make more innovation. The findings regarding the causal effect of R&D expenditures on innovation are also consistent with the causal inferences on mergers, market shares, and innovation nexus. On the other hand, note that there are more positive cross-sectional relationships between market shares and innovation from pooled OLS regression models under different strategies. The positive cross-company relationship between market shares and innovation suggests that merging companies with higher market shares are also the ones that make more innovation.

Another main finding from the estimations is the causal effect of mergers on efficiency. The productivity models show that there are both positive cross-sectional long-term relationship and causal relationship between mergers and productivity. The fixed-effect estimation results in productivity models mostly confirm the existence of causal relationship between mergers and productivity. However, even though it is difficult to infer the pooled OLS regression results as the causal effects of mergers on productivity, those findings still confirm the cross-sectional statistical association between mergers and productivity. There is no causal relationship between market shares and productivity again if we consider only fixed-effect models as causal effect models. On the other hand, the pooled OLS results in all the models still confirm the presence of positive statistical relationship between market shares and productivity.

All in all, the findings are strongly compatible with the Schumpeterian literature on the antitrust merger analysis. There is strong evidence showing the causal effect of mergers on innovation and productivity. Mergers cause more innovation and more efficiency along with an increase in market power stemming from mergers. As a matter of fact, the findings on the positive cross-company relationship between market shares, innovation, and efficiency suggest that even if mergers lead to an increase in market shares for merging firms in the post-merger term, any benefits from an increase in market share are used for innovation and efficiency/productivity. Under those conditions, there is no reason to ban mergers by antitrust institutions and organizations. Instead, antitrust agencies can make antitrust inferences and decisions using the analysis introduced in this paper without conducting an analysis of market definition.

7. Conclusion

Evidence presented in this paper confirms the Schumpeterian statistical association between mergers and innovation in addition to the one between mergers and productivity. While the Pooled OLS models find the positive cross-company relationships between mergers, innovation, and productivity, the results from fixed-effects estimators confirm the causal effects of mergers on innovation and productivity. Accordingly, the findings confirm the statistical association of mergers with innovation and productivity in the meaning of both positive cross-sectional relationship and causal effect. However, there is less evidence on the causal effect of market shares on productivity even though there is still a strong positive cross-company relationship between market shares and productivity.

Accordingly, the paper presents two remarkable findings regarding the antitrust analysis of mergers. First, there is no reason for the traditional analysis of market definition in the antitrust analysis of mergers. Antitrust agencies should perform the empirical investigations introduced in this study to reveal the dynamic effects of mergers on economic performance to better understand the antitrust results of mergers. Also, antitrust regulations should be revised so as to include more contemporary analysis tools. Second, there is a strong evidence and contribution from this study to the Schumpeterian literature on the antitrust merger analysis since evidence of the causal effect of mergers on innovation and productivity is compatible with the Schumpeterian literature.

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Appendix

Table A1. List of Mergers

Code	Year	Acquirer Name	Target Name	Value ($billions)
VER	Feb-14	*Verizon*	Vodafone (Wireless)	130.3
AT&T	Mar-06	*AT&T Inc*	BellSouth Corp	85.8
ACT_ALL	May-15	Actavis PLC	*Allergan Inc*	68.5
PFI	Oct-09	*Pfizer Inc*	Wyeth	67.3
AT&T	Jul-15	*AT&T Inc*	DirecTV	67.1
PRO	Jan-05	*Procter & Gamble Co*	Gillette Co	55
ANH	Jan-09	InBev NV	*Anheuser-Busch*	52.3
BAN	Dec-08	*Bank of America Corp*	Merrill Lynch & Co Inc	48.7
ROC	Jul-08	*Roche Holdings AG*	Genentech Inc	46.6
KRA	Mar-15	Hj Heinz Co	*Kraft Foods*	46.1
MED	Jun-15	*Medtronic Inc*	Covidien PLC	42.7
MER	Nov-09	*Merck & Co.*	Schering-Plough	41.1
EXX	Jun-10	*ExxonMobil*	XTO Energy	41
NOV	Jan-10	*Novartis*	Alcon	39
EQU	Nov-06	*The Blackstone Group*	Equity Office	36
CON	Jan-06	*ConocoPhillips*	Burlington Resources	35.6
SPR	Feb-05	Sprint Corporation	Nextel Communications	35
BAN	Jan-06	Bank of America	*MBNA*	34.2
KOH	Feb-07	Kohlberg Kravis Roberts, Texas Pacific Group	*TXU/Energy Future Holdings*	31.8
COM	Jan-11	Comcast	*NBCUniversal*	30
TMO	May-13	*T-Mobile US*	MetroPCS	29.6

EXP	Mar-12	*Express Scripts*	Medco Health Solutions	29.1
FIR	Oct-07	Kohlberg Kravis Roberts	*First Data/Fiserv*	29
VER	Jan-09	*Verizon*	Alltel	28.1
REY	Jul-14	*Reynolds American*	Lorillard Tobacco Company	27.4
BOS	Jan-06	*Boston Scientific*	Guidant	27.2
CLE	Nov-08	Thomas H. Lee Partners, Bain Capital	*Clear Channel Broadcasting*	26.7
BNS	Feb-10	Berkshire Hathaway	*Burlington Northern Santa Fe Corp.*	26.3
HIL	Jul-07	The Blackstone Group	*Hilton Hotels Corp*	26
DUK	Jul-12	*Duke Energy*	Progress Energy Inc	26
FREE	Mar-07	*Freeport-McMoRan*	Phelps Dodge	25.9
WAC	May-06	*Wachovia*	Golden West Financial	25.5
HAR	Jan-08	Apollo Management, Texas Pacific Group	*Harrah's Entertainment*	25.1
DEL	Oct-13	Dell, Silver Lake Partners	*Dell*	24.4
CEN	Apr-10	*CenturyLink*	Qwest Corporation	24
LIB	Feb-13	Liberty Global	*Virgin Media*	23.3
KRA	Feb-13	Berkshire Hathaway	*Heinz*	23
MAR	Apr-08	*Mars, Incorporated*	Wm. Wrigley J	23
FAC	Oct-14	Facebook, Inc	*WhatsApp Inc.*	22
ALL	Apr-07	Kohlberg Kravis Roberts, Stefano Pessina	*Alliance Boots*	22
SPR	Jul-13	Softbank Group	*Sprint Corporation*	21.6
JOH	Jun-12	*Johnson & Johnson*	Synthes	21.3
KIN	May-12	*Kinder Morgan*	El Paso Corporation	21

BAN	Oct-07	*Bank of America Corp*	LaSalle Bank/ABN AMRO	21
ABB	Mar-15	*AbbVie*	Pharmacyclics	21
CVS	Nov-06	*CVS*	Caremark RX	21
ACT_ALL	Jul-14	*Actavis/Allergan*	Forest Laboratuars	20.7
SAN	Feb-11	*Sanofi-Aventis*	Genzyme	20.1
PFI	Sep-15	*Pfizer Inc*	Hospira	17
WEL	Dec-08	Wells Fargo	Wachovia	15.1