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Abstract This paper contributes further empirical evidence on the effects of mergers on innovation using company level data. Evidence on this issue has implications for the relationship between innovation and market concentration. Our departure from previous work is that we focus on a sample of horizontal mergers whose market concentration impacts were flagged by U.S. antitrust authorities as potentially posing a problem for antitrust law compliance. We employ propensity score matching and difference-in-differences estimation to compare the innovation activities of challenged and non-challenged merger firms to a control group of non-merged firms. We use R&D, patent grants, and citation-weighted patent grants to measure the innovation activities of firms before and after a merger. Our results indicate that the post-merger innovation outcomes of firms whose mergers were challenged are lower than they would have been had the firms not merged. But for non-challenged mergers, or mergers that do not raise concerns about market concentration, post-merger innovation outcomes are not significantly different from what they would have been without a merger.

Keywords patenting \cdot Research and Development (R&D) \cdot mergers \cdot challenges \cdot concentration

JEL Codes G34 · L40 · O30

1 Introduction

The purpose of this paper is to provide an empirical analysis of the effects of recent horizontal mergers on the research and development (R&D) expenditures and patent grants of large U.S. companies. Since the drafting of the Gilbert and Sunshine innovation markets approach and the Department of Justice (DOJ) and Federal Trade Commission (FTC) *Antitrust Guidelines for the*

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Licensing of Intellectual Property, it is a practice of antitrust policy to examine the innovation consequences of mergers.¹ In many merger review proceedings, regulators must ask not only whether a proposed combination will likely affect consumer welfare and competition, but also whether it will reduce innovation in a relevant innovation market.

The innovation market construct has stirred some controversy (see Carlton and Gertner 2003). First, the harm to competition is anticipatory. Current R&D, for example, affects future new products or improvements of existing goods. Thus, any merger impacts on research and development affect future product markets—or affect potential competition. Thus one option is to challenge market conduct later, to see if product markets become concentrated, rather than take anticipatory action. One response to this is that waiting is not optimal if the harm to innovation affects the path of product market development. Another response is that if the innovation market is concentrated, innovation can be harmed if firms exercise market power over the products of R&D and limit the diffusion of important technological inputs, or if firms scale back on R&D projects because they face weaker pressures to compete.

A second issue related to incorporating innovation considerations in antitrust policy is that the relationship between market concentration and innovation is not firmly established. Economic theory provides for different possibilities. For example, leading work by Schumpeter (1950) has argued that innovation increases with market concentration and firm size, while Arrow (1962) contended that incentives to innovate are greater under competition than under monopoly. Our objective in this paper is to address this second issue concerning innovation markets and contribute to the empirical literature on innovation and market concentration.

In this paper, we do not measure market concentration directly. Instead we use merger challenges by policy authorities to help us identify cases of concerns about increased market concentration. The authorities follow specific guidelines to determine the mergers that are to be challenged, including criteria related to the scope of the market, ease of entry or collusion, or any efficiency gains; they look at both the levels and expected changes in the Herfindahl-Hirschman Index (HHI) and consider the degree of overlap in the product markets of the acquirer and acquiree. Thus, to infer the effect of market concentration on innovation, we compare the innovation behavior of a sample of R&D-intensive challenged mergers to a similar sample of non-challenged mergers and to a control group of non-merged firms. We exploit the fact that the sample of horizontal mergers *challenged* by the antitrust authorities consists of those mergers deemed by them to result in a significant increase in market concentration. To our knowledge, this type of sample selection analysis has not been done in previous work.

The paper is organized as follows: the next section reviews previous theory and evidence. Section 3 discusses our empirical approach, and Section 4 discusses our dataset, along with some descriptive statistics. Section 5 contains our main results, and Section 6 concludes. Overall, we find substantial differences in the innovation behavior of challenged merger firms and non-challenged merger firms. Compared to a control group of non-merged firms, firms whose mergers were challenged have a statistically significant lower growth in R&D and patenting post-merger, while firms whose mergers were not challenged exhibit no appreciable difference in post-merger R&D and patenting growth compared to a control group.

¹ See Gilbert and Sunshine (1995). For the Intellectual Property Guidelines, see http://www.ftc.gov/bc/0558. pdf.

2 Literature review

2.1 Theoretical background

The theoretical basis for our empirical analysis centers on the relationship between market concentration and innovation. Specifically, we are testing the theory that elevated levels of market concentration adversely affect firm-level R&D and patenting post-merger by augmenting the combined firms' market power in product and innovation markets.

However, it should be acknowledged that market power can be conducive to innovation. Since innovation has the characteristics of a public good—non-excludable and non-rivalrous in use—market failure in the innovation market may arise in the absence of some form of property rights to innovation outputs. Hence, the patent system provides innovators a temporary right to exclude others (for example, business rivals) from commercially exploiting their innovations. As a result, innovators enjoy some market power over the products, components, or production processes that are protected by patents. This degree of market power is recognized as an important tradeoff for stimulating innovation.²

On the other hand, market power can also harm innovation. The higher prices for technological goods due to 'monopolistic' supply reduce technology diffusion and increase the cost of conducting R&D. Furthermore, market power due to increased market concentration, given limited entry and competition, may also lower incentives to innovate by relaxing pressure on the dominant supplier to introduce new products or improve existing ones vis-à-vis competitors. How these opposing influences of market power on innovation play out for the merging firms in our sample is a key issue. These firms are very large and are among the top patenting firms in the U.S., whose very mergers can increase market concentration considerably.

The theoretical literature on market concentration and innovation is mixed.³ Schumpeter (1950) argued that firms in more concentrated markets are more innovative. Facing less imitation risk, they are better able to appropriate the returns to their R&D efforts. In addition, large firms have resource advantages in financing high fixed-cost R&D and the capacity to diversify risk among a larger number of research projects. Arrow (1962) countered this argument with his view that competitive firms have greater incentives to innovate because the marginal change in expected profits (i.e., between post-innovation and pre-innovation profits) is larger than that for monopolists. Furthermore, a monopolist's innovation may render existing innovations obsolete (i.e., the replacement effect), which dampens incentives to innovate. The follow-on theoretical work, post-Schumpeter and Arrow, is also varied. For example, the literature on patent races suggests that in more concentrated markets, firms may slow down or delay the introduction of new innovations so as to enjoy economic rents on existing innovations longer (see Loury 1979; Dasgupta and Stiglitz 1980; and Takalo and Kanniainen 2000). On the other hand, there are theoretical models which suggest that incumbent firms operating in imperfectly competitive markets have the greater incentive to innovate in order to preserve their market power and pre-empt entry (see Gilbert and Newbery 1982; Tirole 1989).

More recently, Aghion et al. (2005) develop a theoretical model which captures the possibilities of both positive and negative effects of market concentration on innovation. In particular, the model yields a nonlinear relationship between market concentration and

² It should be noted, however, that patents are not always necessary to stimulate innovation, as in the case of open source software innovation.

³ See de Man and Duysters (2005), Gilbert (2006), and Schulz (2007) for surveys of previous work

innovation. As discussed earlier, some market power promotes innovation. Thus, some market concentration helps prevent competition from eroding the economic rents from innovation. But too much concentration hinders innovation because post-innovation rents would not be that much higher than pre-innovation rents. Thus, the effect of market concentration on innovation depends on the degree of competition within an industry. We build upon this insight by looking at two sub-samples of mergers: challenged and non-challenged, where the former has a bigger potential effect on product market competition than the latter.

In addition to the theoretical literature on market concentration and innovation, there is also theoretical work that directly examines the relationship between *mergers* and innovation. These studies provide additional factors to consider. For example, mergers enable companies to better access each other's intangible assets (Bresman et al. 1999), create knowledge synergies (Hall 1990; Ornaghi 2009), or increase internal funding for R&D (Hall 1999). Mergers may also increase R&D efficiency by enabling the combined firm to spread the fixed costs of innovation across more R&D outputs and/or across more R&D projects (see Cassiman et al. 2005). On the other hand, mergers may impact innovation negatively if the reorganization of the firm should result in the loss of key scientific personnel (Ernst and Vitt 2000). Of course, a key limitation of focusing simply on mergers and innovation is that not all mergers result in significant changes in market concentration or market power for the combined company. In this paper, we focus on those horizontal mergers that do create concentration concerns.

Thus, while the theoretical effects of market concentration on innovation are in general ambiguous, our empirical work identifies two important gaps in the theoretical literature which may help account for the varied predictions. First, as we stressed, some market power is conducive to innovation. Most likely, it is when market concentration results in excessive market power that innovation is harmed. Thus, theoretical models need to control for initial market power. We address this by focusing on a sample of large R&D firms that already possess some market power, and observe the effects of a merger that increases that power.⁴ Second, existing theories focus predominantly on *product* market concentration, when in fact the impact on innovation may be partly or mostly attributed to increased innovation market concentration; that is, where too few firms compete in a given technology space. We confront this issue by focusing on a sample of challenged mergers. These mergers were deemed by the DOJ/FTC to result in increased product market concentration, and were resolved by requiring the merging companies to divest a line of business or some assets. These actions were aimed at deterring a significant rise in product market concentration, but not necessarily that of innovation market concentration. It is likely that the post-merger innovation market, among challenged merger firms, was more concentrated. Thus, theoretical models should pay more attention to both the product and innovation market consequences of a merger.

2.2 Previous empirical work

The empirical evidence on mergers and innovation is mixed as well. Ravenscraft and Scherer (1987), Hall (1990), Hitt et al. (1991), and Hosono et al. (2009), for example, find a negative or insignificant impact of mergers and acquisitions on post-merger R&D. Studies that find a positive impact on innovation include Bresman et al. (1999) and Ernst and Vitt

⁴ For example, in the merger challenges of Glaxo-SmithKline (1998) and Pfizer-Pharmacia (2002), the FTC cited concerns about the anticompetitive effects of the patents owned by these firms.

(2000). Other studies find the impacts on innovation outcomes to be conditional on the relatedness of the knowledge assets or products of the merging companies (see Ahuja and Katila 2001; Cassiman et al. 2005; Cloodt et al. 2006, and Ornaghi 2009). There are post-merger innovation benefits if the assets are similar enough to allow for easy integration of the knowledge bases of the companies, but differentiated enough to create new learning opportunities.

Bena and Li (2011) further show that post-merger innovation outcomes and market performances depend on the extent to which merging firms have overlapping innovation activities. They measure the degree of technological overlap using patent data and examine the extent to which merger partners cite each other's patents. Stahl (2010) also uses patent citation data to trace whether mergers affect sequential innovation (i.e. whether later innovators cite earlier innovators). Using an empirical framework that allows market structure to be endogenous to innovation, Stahl (2010) finds that firms increase their rate of sequential innovation before a merger but decrease it after a merger. Stahl (2010), therefore, argues that mergers are driven more by the desire to dampen competition than to exploit knowledge spillovers between firms. Patent citation data are used in Zhao (2009) as well to examine both the quantity and quality of innovations (i.e. the latter correlates positively with forward citations). Zhao (2009) finds that technological innovation is not only impacted by acquisition activity but also motivates it. For example, when internal innovative efforts are deficient, a firm seeks to develop its innovative capacity externally (through merger).

Our main criticism of prior empirical work is that previous studies do not make as sharp a distinction between mergers that could significantly affect market concentration and combinations that have only marginal effects on market concentration. This is important since not all mergers have a significant impact on market concentration. We thus compare innovation activities between merged firms that were challenged by the DOJ/FTC and those that were not. This allows us to isolate the innovation impacts of those horizontal mergers that have raised market concentration concerns. As in previous work, we also compare the postmerger innovation activities of merged firms to a control group of non-merged firms.⁵ Furthermore, we also use both R&D and the patents of firms as our measures of innovation. This is especially useful in that if mergers enhance the efficiency of R&D activities – that is, reduce duplicative investments and enable economies of scale to be achieved in spreading the fixed costs of R&D—the post-merger expenditures on R&D may be lower,⁶ in which case this scaling back of expenditures should not be interpreted as a reduction in innovative activities. An examination of firm patents—the outputs of research and development—can better confirm whether innovation outcomes have fallen. As in Stahl (2010) and Zhao (2009), we also take into account the potential endogeneity between mergers and innovative activity by treating the self-selection bias of merging firms, as described in the next section.

3 Methodology

As an overview, our empirical strategy is to determine how the innovation levels of merged firms shift after a merger compared to those of a control group of firms that did not merge.

⁶ See Cohen and Levin 1989 and Roller et al. 2006.

⁵ See Hall (1999), Danzon et al. (2007), Bertrand and Zitouna (2008), and Ornaghi (2009). As in these studies, we use propensity score matching methods to select a control group of non-merging firms.

To that end, we employ a difference-in-differences approach and use propensity score matching methods to choose a sample of control group firms.

To illustrate, let I be a measure of innovation, such as research and development or patentable innovations. Consider a merger event as a kind of 'treatment' (e.g. change in business organization) and let Treat={Yes, No} indicate whether a firm has merged or not. Thus, two types of firms exist in the sample: Type={0, 1}, where 1 indexes the treated group (i.e. firms that merged during the sample period) and 0 the control group (i.e., firms that never merged during the sample period). Let Period={0, 1}, where period 1 denotes the post-merger period and period 0 the pre-merger. We are interested in measuring the impact:

$$\Delta = E(I^{\text{Treat}=\text{Yes}}|\text{Type} = 1, \text{Period} = 1) - E(I^{\text{Treat}=\text{No}}|\text{Type} = 1, \text{Period} = 1)$$
(1)

where E denotes average or expected value. In other words, Δ captures, for the merged firm (Type 1), the difference between its level of innovation under merger and its level of innovation had it not merged in period 1. (Our hypothesis is that Δ is significantly negative for challenged mergers.) However, the level of innovation had the firm not merged is a counterfactual. It is not observed in the data (since in period 1, the firm merges).

To help identify this counterfactual mean, we use matching methods which provide an estimate for $E(I^{Treat=No}|Type = 1, Period = 1)$ based on the statistical independence of potential outcomes and treatment status. Specifically, if the characteristics of firms are equally distributed between merged and control groups, we can make the identifying assumption that the treated and non-treated firms would have been identical in the absence of a merger:

$$E(I^{\text{Treat}=\text{No}}|\text{Type} = 1, \text{Period} = 1) - E(I^{\text{Treat}=\text{No}}|\text{Type} = 1, \text{Period} = 0)$$

= $E(I^{\text{Treat}=\text{No}}|\text{Type} = 0, \text{Period} = 1) - E(I^{\text{Treat}=\text{No}}|\text{Type} = 0, \text{Period} = 0)$ (2)

That is, both types of firms would have the same change in innovation levels over time. Thus, we can substitute $E(I^{Treat=No}|Type = 1, Period = 1)$ from (2) into (1), and rearrange:

$$\Delta = \left[E(I^{\text{Treat}=\text{Yes}} | \text{Type} = 1, \text{Period} = 1) - E(I^{\text{Treat}=\text{No}} | \text{Type} = 1, \text{Period} = 0) \right] - \left[E(I^{\text{Treat}=\text{No}} | \text{Type} = 0, \text{Period} = 1) - E(I^{\text{Treat}=\text{No}} | \text{Type} = 0, \text{Period} = 0) \right]$$
(3)

But $E(I^{Treat=No}|Type = 1, Period = 0)$ in (3) is just the (combined) pre-merger innovation levels of the firms that merged. Likewise, $E(I^{Treat=No}|Type = 0, Period = 0)$ and $E(I^{Treat=No}|Type = 0, Period = 1)$ are the innovation levels of the control (non-merged) firm over the same period—that is, before and after the corresponding merger firms merged, respectively. Thus, we can rewrite Δ more compactly as the following difference:

$$\Delta = (I_{\text{Type1.After}} - I_{\text{Type1.Before}}) - (I_{\text{Type0.After}} - I_{\text{Type0.Before}})$$
(4)

that is, the difference between the differences in innovation levels after and before the period of merger. If $\Delta < 0$, the merged firm has a lower shift in innovation compared to that of a control group firm that does not merge; and the opposite if $\Delta > 0$.

To find Δ , we can estimate the following equation:

$$I_{it} = \beta_0 + \beta_1 \operatorname{Treatment}_{it} + \beta_2 \operatorname{Type}_i + \beta_3 \operatorname{Treatment}_{it} \times \operatorname{Type}_i + \beta_4 \operatorname{X}_{it} + \mu_i + \delta_t + \epsilon_{it}$$
(5)

where Type=1 for a merged firm (and 0 for a non-merged firm) and Treatment=1 for the post-merger period and 0 for the pre-merger for both the treated and untreated firm. The

coefficient estimate of β_3 , the interaction term, will be our estimate of Δ .⁷ In (5), X is the vector of control variables, μ_i individual fixed effects, δ_t year effects, and ε_{it} a spherical random disturbance term.

The question then is how to pick our control group of firms so that (2) can hold—that is, to select a group of non-merged firms that is "similar" to the group of merged firms. Otherwise, the treated and untreated firms may differ not only by treatment type but by other characteristics that affect both the merger event and innovation outcomes, creating a selection bias where we only observe the innovation activities of a non-random sample; for example, as discussed in Section 2, the less innovative firms might be the ones who seek mergers in order to address their technological deficiencies. For our selection task, we turn to propensity score matching, whereby we estimate the probability of merging:

$$Pr(Treatment_{it} = 1) = z_{it}'a + v_{it}$$
(6)

where z is a vector of characteristics and v the error term. The estimation of Eq. 6 generates the probability or propensity score of merging for each observation. We then match a merged firm to a non-merged firm with a similar propensity score. We use the nearest neighbor matching with caliper as the matching algorithm. The non-merged firms that are matched to the merged firms comprise our control group. We discuss the estimates of Eqs. 5 and 6 later.

To summarize, we have a sample of merged firms and control group firms. Our outcome variable of interest is innovation. The measures of innovation we consider are research and development (R&D) and patent grants (PAT). For patent grants, as we discuss in the next section, we consider both counts of patent grants as well as patent grants weighted by forward citations to account for the potential 'value' of patents (PAT-W). In Eq. 5, when R&D is the dependent variable, Sales is one of the control variables X, as this is a key determinant in previous work (Hall 1990; Hitt et al. 1991). When patents are the dependent variable, R&D is one of the control variables, as this too is a key determinant of patenting in prior work (for example in knowledge production function studies (Pakes and Griliches 1984)).⁸

Other control variables include dummy variables for firm size, industry growth, income tax rate (corporate taxes divided by income), and leverage (debt-equity ratios). Tax policy affects the appropriation of profits of firms and potentially their incentives to invest in innovation. We also use employment as a proxy for firm size. But employment is highly correlated with sales, which we control for to help capture the size of the market facing firms. Thus, in order to capture the effects of *firm size* on innovation, and avoid collinearity with sales, we put all the firms into one of four groups or quartiles, based on their number of employees. In this way, we create four 'Firm Size' dummies.⁹ Finally, we control for

 $^{^{7}}$ To see this, we can plug in the different values that the dummy variables can take on and compute the innovation level associated with each case. For example, assume for simplicity that all other determinants are zero (i.e. X=0):

$I_{1.After} = \beta_0 + \beta_1 + \beta_2 + \beta_3$	if Treatment = Type = 1
$I_{1.Before} = \beta_0 + \beta_2$	if Treatment $= 0$ and Type $= 1$
$I_{0.After} = \beta_0 + \beta_1$	if Treatment $= 1$ and Type $= 0$
$I_{0.Before} = \beta_0$	if Treatment = Type = 0

Thus $\Delta = (I_{1.After} - I_{1.Before}) - (I_{0.After} - I_{0.Before}) = \beta_3$.

⁸ When both sales and R&D are included in the patenting equation, we find either the coefficient of sales to be insignificant or the coefficient of R&D and sales to be significant and opposite in sign, indicating that the two variables are highly correlated.

 9 The first group has fewer than 7661 employees, the second has more than 7661 and fewer than 32,766, the third has more than 32,766 and fewer than 79,400, and the fourth has more than 79400 employees.

leverage (debt/equity) since innovation may be affected by the source of funds. Innovation and leverage may be inversely related because R&D investments generally have highly uncertain returns and therefore cannot be financed extensively with debt (Rajan and Zingales 1995).

4 Dataset and sample statistics

Our sample period is 1989 to 2008.¹⁰ Our dataset consists of 78 firms, of which 47 of them merged between 1996 and 2008. The Appendix contains a list of companies in our sample along with the data sources. We first discuss the firms in our sample and then discuss the outcome variables and some sample statistics.

4.1 Mergers and non-mergers

Of the 47 mergers in the sample, 27 of the acquisitions were challenged by the DOJ and FTC for concentration concerns. In the U.S., the Hart-Scott-Rodino Antitrust Improvements Act of 1976 (or HSR Act) requires firms with intent to merge with or acquire another firm to notify antitrust authorities.¹¹ After firms initially file a notification, a 30-day waiting period ensues to provide regulatory agencies an opportunity to examine whether the proposed transaction will violate antitrust statutes and to request additional information if the transaction appears to be anti-competitive, particularly if the acquirer and acquiree strongly overlap in the product market.¹² The request for additional information is referred to as a 2nd request and typically extends the waiting period an additional 30 days. The government may then choose to allow the merger, seek injunctive relief, or negotiate a settlement that often involves the divestment of key assets. Thus, the group of challenged mergers refers to those proposed acquisitions that are publicly challenged by the government after a HSR 2nd request. Second requests are issued by the FTC and DOJ for approximately 10% of mergers reviewed annually if the government suspects the transaction to be in violation of antitrust laws. The parties then submit further documentation, and the government decides whether to challenge the merger formally. When a merger is publicly challenged, a complaint and/or competitive impact statement is issued. These documents contain evidence, such as market share, market concentration, and the definition of the contested market.

Between 1996 and 2008, there were approximately 800 mergers challenged by the FTC or DOJ. Most of these mergers were not suitable for this study because they did not involve R&D-intensive firms¹³ and/or related only to privately held firms or divisions of public companies. The 27 challenged mergers in our sample account for about 75% of all R&D-

¹⁰ The sample period is shorter (1989–2006) when we study the patenting of firms.

¹¹ The HSR Act requires specific filings for all mergers over a certain size threshold. This amount is \$63.4 million as of February, 2010. The amount is adjusted annually based on the change in the gross national product.

product. ¹² In the 1997 merger guidelines the government specified three different Herfindahl Hirschman Index (HHI) levels and change in HHI index values that would result in a likely challenge. First, if a merger results in an HHI level below 1,000, the merger will likely not be challenged. Mergers resulting in an HHI level between 1,000 and 1,800 and causing the index to increase by more than 100 points were noted to raise significant competitive concerns. Similarly, mergers resulting in an HHI level above 1,800 and causing the index to increase by more than 50 points were also noted to raise significant competitive concerns.

¹³ For the purposes of this study, high R&D-intensity is defined as an R&D/sales ratio of two percent or higher. Only companies with high R&D intensities were used in this study. R&D expenditures are often not reported for companies with low R&D intensity levels.

intensive mergers challenged during that period. The other 25% of R&D-intensive mergers challenged were not included because of the difficulty of gathering R&D and patenting information or because the merger consisted of a very large company acquiring a very small company, which makes the impact on R&D expenses minimal (e.g. General Electric's \$150 million acquisition of InVision). In addition, the merger may have been abandoned (e.g. Compuware—Viasoft) and thus cannot be studied.

The other 20 of the 47 mergers were not challenged. These mergers consist of large transactions, exceeding \$1.5 billion, among R&D-intensive firms. The number of non-challenged mergers is smaller than the number of challenged since there are just a few mergers of large R&D-intensive companies that occur each year, and many of these mergers are challenged by the government.

The non-merger sample, totaling 31 firms, consists of relatively large companies that did not engage in a major acquisition, valued at \$1.5 billion or greater, during the sample period. The companies in this sample were pulled from the list of the top 500 firms ranked by revenue in the 2009 Fortune 1000 listing of companies.¹⁴ Using propensity score matching, non-merged firms are selected based on their comparability, in terms of innovation intensity and other characteristics, to the firms that engaged in a merger over the sample period.

Our sample of firms operates in three broad sectors, based on their primary product lines: life sciences (38% of the sample), computer technology-related (27%), and industrials (35%). The life sciences firms include pharmaceutical, biotech, and medical device companies. They include the top 10 pharmaceutical companies and seven of the top 11 biotech companies ranked by revenue. The computer technology-related sector includes software, telecommunications, and computer hardware. They include seven of the 13 largest global technology companies. Industrial includes aerospace, defense, electrical and electronic equipment, and chemical companies. The regression analyses in this paper will include dummies for these three broad sectors.

4.2 Innovation measures

We examine both the R&D expenditures performed by a firm and the patentable innovations of firms. Both provide important perspectives on innovation activity. R&D represents inputs into innovation while patents represent the outputs of innovation. As such, if the merged firms conduct their innovation activities more efficiently, their post-merger expenditures on R&D may be lower, but their patentable outputs higher. Hence it is useful to examine both the inputs and outputs of innovation.

Our measure of patents is that of patents granted, as opposed to just applications (which do not all meet standards of patentability or inventiveness). However, we count the patents granted by date of application, rather than date of grant. The advantage of using the application date is that it may more accurately capture the timing of innovations. Patent grants occur with some delay. They therefore represent innovations that occurred some time ago. An empirical analysis of the impact of mergers on innovation, based on dates of patent grants, would need to estimate, or make additional assumptions about, the lag between innovation and the issuance of a patent right. Historically, in the U.S., the lag between patent application and patent grant (if approved) has averaged 2–3 years, though patent pendency has increased recently due to the increase in the volume of patent filing activity. Our data on

¹⁴ We examined the largest companies by industry as listed in the 2009 Fortune 1000 (see http://money.cnn. com/magazines/fortune/fortune500/2009/performers/industries/fastgrowers/).

patent grants by date of application end in 2006; thus, our patent equations are estimated up to 2006.

Of course, patent data have well-known limitations. Not all research outputs are patented; some are kept as industrial secrets and some are not patentable, such as basic knowledge outputs. Hence, measures of innovation input such as R&D are useful to consider. Patents also vary in quality in terms of their impacts on productivity or on the enhancement of further technological innovations. To partially account for quality differences among patents, we take into account the number of citations that a patent has received, adjusting for the age of the patent grant (since patents can receive more citations as time passes). Specifically, for each firm in our sample, we examine the number of patent grants it has received by year of patent application.¹⁵ For each patent, we count the number of 'forward' citations it has received (from other firms). We then address the 'truncation' problem. Patents that were granted towards the later years in our sample are likely to have fewer citations than patents that were granted earlier in the sample period. Those older patents have had more time to be cited. Thus the citations received by a patent are themselves adjusted to take into account the patent's age.

These adjustment factors are available in the *National Bureau of Economic Research* patent data project. The methodology is developed in Hall et al. (2001). Essentially, given an estimate of the citation lag distribution, we divide the observed citations of a patent by the fraction of the predicted lifetime citations that occurs in the time interval for which citations have been observed. For example, if a given time interval accounts for one-third of the lifetime citations, we can multiply the observed citations in that interval by three to estimate the total citations associated with that patent. In this way, we can not only count the total number of patent grants per firm per application year but also weight each of the patents granted by its total *estimated* lifetime citations to get an indication of the value of the underlying innovation.¹⁶

4.3 Sample statistics

Table 1 presents our sample statistics of the key variables of interest. R&D and sales data are converted into real 2005 dollars using a chain-type price index for private industry value added.¹⁷ Four different groupings are shown: the full sample of firms, non-merged firms, merged firms that were challenged by the authorities, and those merged firms that were not challenged. Firms whose mergers were not challenged conducted, on average, the most real R&D and patenting per year, and also had the highest average annual sales. Non-merged firms whose mergers were challenged have the least number of patent grants on average. The firms whose mergers were not challenged have the lowest debt-equity ratios while the non-merged firms had the highest. Interestingly, the mean debt-equity ratios vary inversely with the mean R&D; for example, the non-merged firms are in the high 30% range.

¹⁵ We use the National Bureau of Economic Research (NBER) patent database. This database consists of patents awarded by the U.S. Patent and Trademark Office during 1976–2006. Through patent identification numbers, the awards are matched to the firms in *Compustat*, which are in turn matched to our merger dataset.

¹⁶ The predictions of lifetime citations of a patent are based on the median citations received by patents in the same technology class and grant year as the patent in question. The citation lag distribution is also assumed to be stationary or time-invariant.

¹⁷ The deflators are from the U.S. Bureau of Economic Analysis, Annual Industry Accounts.

Variables	All firms	Non merged firms	Merged firms challenged	Merged firms non challenged
R&D	1,283 (1,718)	1,032 (1,371)	1,346 (1,913)	1,615 (1,885)
Patents (PAT)	299 (529)	278 (414)	151 (118)	534 (893)
Patents -Weighted (PAT-W)	2,532 (7,745)	2,851 (5,998)	962 (1,831)	4,246 (12,691)
Sales	16,173 (18,682)	11,970 (10,611)	14,989 (16,269)	24,872 (27,534)
Income Tax Rate	0.378 (2.18)	0.392 (0.99)	0.364 (3.61)	0.377 (0.39)
Leverage (Debt-equity Ratio)	0.39(1.39)	0.45 (2.01)	0.41 (0.52)	0.29 (0.32)
Product Overlap			17.8 (27.3)	
R&D and Sales are in millions of rea	il constant 2005 dollars			
PAT refers to numbers of patents gra	nted and PAT-W to the citation	n-weighted patent grants		
The income tax rate is the ratio of co	rporate income taxes to corpc	rate income		
Leverage is the ratio of debt to equit	λ			
Product overlap is the weighted aver.	age percent of sales accounted	I for by the challenged product li	ine for the noticed 1080-2008 where dote	e available
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Table 1 Descriptive statistics: means and standard deviations

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In Table 1, the ratio of citation-weighted patents (PAT-W) to patent grants (PAT) provides us with an idea of the average citations per patent. For all firms, the typical patent receives 8.44 citations.¹⁸ In our sample, merged firms that were challenged have the lowest average number of citations per patent of 6.4. Non-merged firms have the highest average number of citations per patent of 10.3.

Table 2 shows the correlations among the variables considered in our study. The innovation variables (R&D and patenting) are positively correlated among one another for the samples of both merged and non-merged firms. The innovation variables are also positively correlated with sales, especially R&D. Leverage (debt-equity ratio) and the tax rate are generally negatively correlated with the measures of innovation. The growth rate of sectoral value-added is also positively correlated with firm level R&D and patenting, and positively with the sales of merged firms only. No pairs of variables are so very highly correlated as to raise concerns about multicollinearity.

5 Empirical results

In this section, we first discuss the estimates of the probability of mergers. We next discuss the impacts of mergers on innovation outcomes using the sample of merged firms only. This compares the post-acquisition and pre-acquisition innovation levels of the merged firms, without the control group of firms. We then incorporate the matched non-merged firms and discuss the results of our difference-in-differences analysis, which allow us to examine the innovation impacts of mergers relative to a control group of non-mergers. Throughout, our key focus is on whether innovation outcomes are different for the mergers that were challenged.

5.1 Propensity score step

Table 3, Part A shows the estimates of the probit Eq. 6 from which the propensity scores are obtained. The key factors used to explain mergers are measures of innovation intensity: R&D/Sales ratio and patents/R&D ratio, and their quadratic terms.¹⁹ The nonlinear terms aided in achieving a balanced distribution of the covariates between the merged and comparison firms. Other variables were tried, such as the level and growth rate of sales, but were found to be statistically insignificant and to result in the balancing condition not being satisfied. The RHS variables are lagged one period to avoid endogeneity (i.e., mergers influencing innovation intensity). To check for robustness, we use two different measures of patents: counts of patents granted and citation-weighted patent grants. The propensity scores generated from either measure is highly correlated (0.962) and hence it makes little difference which model estimates (column 1 or 2) we use. We used the propensity scores generated by the second model, using citation-weighted patent grants, to match merged and control group firms based on the proximity of their scores.

Propensity score matching requires the satisfaction of the *balancing condition*, in which the characteristics of firms are equally distributed between merged firms and

¹⁸ This is line with previous findings; for example, Hall et al. (2005) finds the median citation to be about eight.

¹⁹ See Sonenshine (2010) for a discussion of how innovation intensity influences deal premia which reflect the attractiveness of mergers. Bena and Li (2011) and Zhao (2009) also use innovation measures to explain merger propensities.

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Table 2 Sample (conclations						
	R&D	PAT	PAT-W	Sales	Tax Rate	Leverage	Δ Value Added
Non-Merged Firm	IS						
R&D	1						
PAT	0.3331	1					
PAT-W	0.1312	0.3432	1				
Sales	0.6837	0.2017	0.0965	1			
Tax Rate	-0.0352	-0.0524	0.0332	0.0484	1		
Leverage	-0.1277	-0.1170	-0.0877	0.0372	0.0238	1	
Δ Value Added	0.0766	0.3805	0.2358	-0.0675	-0.0971	-0.1444	1
Merged Firms							
R&D	1						
PAT	0.3413	1					
PAT-W	0.2702	0.5370	1				
Sales	0.6972	0.6892	0.3980	1			
Tax Rate	-0.0214	-0.0236	-0.0143	-0.0487	1		
Leverage	-0.1785	-0.0903	-0.0129	0.1247	0.0295	1	
Δ Value Added	0.1185	0.3460	0.1952	0.1062	-0.0532	-0.1709	1

Table 2 Sample correlations

The variables are as defined in Table 1. Δ Value Added is the growth rate of sectoral value added for three sectors: life sciences, computer-related, and industrial (as discussed in Section 4.1 of the text)

non-merged firms, and the *common support condition*, whereby the supports of the propensity scores of the merged and non-merged firms should overlap.²⁰ Part B of Table 3 shows the results of testing the balancing condition. Overall, after matching, the differences in the mean values of the various measures of innovation intensity are not statistically significant and the selection bias is reduced significantly. To test the common support condition, we conducted the Kolmogorov-Smirnov test for equality of distributions and could not reject the null hypothesis that the distribution of propensity scores for the merged and non-merged firms are drawn from the same distribution (p-value=0.44).

5.2 Innovation among merging firms

As a prelude to our difference-in-differences estimation, we examine the impact of mergers among the merged firms only. Our objective is to first study innovation levels after a merger relative to before a merger, while controlling for other variables. Table 4 presents these results, obtained from least squares dummy variable (LSDV) regressions.²¹ Robust standard errors are reported throughout.

As column 1 of this table shows, a merger is significantly associated with a decline in post-merger R&D. However, we see from columns 2–4 that this result is driven by the sample of firms engaged in challenged mergers. Controlling for other factors, we find that the post-merger levels of R&D are lower among the sample of firms whose mergers were

²⁰ See Rosenbaum and Rubin (1985) and Guo and Fraser (2010) for more details of propensity score analysis. ²¹ We have a manageable number of firm dummies – i.e., N=27 for challenged merger firms and N=20 for nonchallenged merger firms – and T=30 years.

·····	0	I				
A. Probit Estimates	of the Propensit	y to Merge				
Dependent	Merger = $\{0, 1\}$	1}				
Variable:	(1)			(2)		
Constant	-0.31			-0.83*		
	(0.45)			(0.47)		
ln (R&D/Sales) _{t-1}	0.39**			0.32*		
	(0.16)			(0.18)		
ln (R&D/Sales) ²	0.05*			0.03		
t-1	(0.03)			(0.03)		
ln (PAT/R&D) t-1	0.18*					
	(0.10)					
ln (PAT/R&D) ² t-1	0.04***					
	(0.01)					
ln (PAT-W/R&D)				0.10**		
t-1				(0.05)		
ln (PAT-W/R&D) ²				0.03***		
t-1				(0.01)		
Firm Size Dummies	Included			Included		
Year Dummies	Included			Included		
Industry Dummies	Included			Included		
Pseudo-R squared	0.19			0.17		
Log-Likelihood	-339.1			-267.9		
Observations	691			583		
B. Comparison of M	leans of Selected	d Variables f	for Matched	and Unmate	hed Samples	
Variable	Sample	Treated	Control	% Bias	%Bias Reduction	Mean Difference (p-value)
R&D/Sales	Unmatched	0.061	0.087	-34.0		0.000***
	Matched	0.065	0.069	-5.6	83.5	0.666
PAT/R&D	Unmatched	0.052	0.086	-27.9		0.002***
	Matched	0.054	0.065	-10.7	61.8	0.414
PAT-W/R&D	Unmatched	0.398	0.653	-22.9		0.029**
	Matched	0.362	0.359	0.4	98.3	0.970

Table 3 Propensity score matching procedure

R&D denotes real research and development expenditures (in constant 2005 dollars), Sales the firm level sales also in constant 2005 dollars, PAT the number of patents granted, and PAT-W the citation weighted (age-adjusted) patent grants. The RHS variables are lagged one period. The sample period is 1989–2006.

In part A, the propensity scores obtained from the models shown in columns (1) and (2) have a correlation of 0.962. In part B, bias is the difference of the sample means in the treated and control samples as a percentage of the square root of the average of the sample variances in the treated and control groups. The last column of part B reports the test of equality of means between the treated and control groups.

challenged; in contrast, there is no statistically significant difference between post- and premerger R&D expenditures among firms engaged in mergers that were not challenged. This result is robust to the inclusion of a variable measuring product overlap, the weighted average percentage of sales of the target firms' product line(s) that induced the merger to be challenged.²² This helps measure the degree to which the companies challenged in a merger compete in the same product market. We have data on product overlap only for the challenged mergers. In general, the challenged mergers do tend to operate in the same product market, but to varying degrees. The results in column (3) indicate that higher degrees of product overlap are associated with reduced R&D. This may be due to merger partners eliminating duplicate projects. But the main point of including the product overlap variable is to show that the effects of challenged mergers are not merely picking up the effects of product overlap, as the coefficient estimate and significance of the merger variable are essentially unaffected.

Columns 5–6 repeat the analysis using patents as the dependent variable, and to conserve space, we consider only the challenged merger sample. Column (5) uses the natural log of the quantity of patent grants as the dependent variable, while column (6) uses the natural log of citation-weighted patent grants. In either case, among challenged mergers, no statistically significant differences in patenting before and after a merger exist, controlling for other influences on patenting. We find the same insignificant effect of mergers on patenting if we lag the RHS variables by one, two, or three periods, or use the sample of non-challenged mergers (results not shown). Thus, it remains to be seen if mergers affect the patenting of merging firms *relative* to a control group over the same period, rather than merely within a merged firm's own history. The product overlap variable has a positive association with the patenting of challenged mergers. In this case, having some similarity in products may enable merger partners to build upon common knowledge bases and thereby enhance research productivity.

Before proceeding, it should be noted that sales is an important determinant of R&D, and that R&D is an important determinant of patenting. The sectoral growth rate of value added, the tax rate, and leverage variables are not statistically significant influences on innovation. Dummy variables for firm size are important for R&D, indicating that smaller firms, with fewer employees, have in general lower levels of R&D than larger firms. The industry dummies tend not to be statistically significant while the year dummies are generally significant; however, an F-test indicates joint significance of all these fixed effects.

5.3 Difference-in-differences estimation

In Table 5, we estimate Eq. 5 using the natural log of R&D expenditures as the dependent variable. Here, we compare the R&D investment behavior of merged firms before and after a merger to the R&D investment behavior of the matched non-merged firms before and after the same date. The coefficient of the interaction term, Treatment x Firm Type, as shown in Section 3, captures the post- and pre-merger difference in R&D levels between the two different types of firms. Column 1 shows the results for the full sample, column 2 for the challenged merger firms, and column 3 for the non-challenged merger firms. The main finding is that compared to the

²² For example, in the challenged merger between Viasoft and Compuware, two of Viasoft's product lines totaling 29% of Viasoft's sales were involved in the merger challenge (see chart below). Therefore, the product overlap between the two firms is 29%:

Compuware Product Lines	% of Viasoft Sales
Mainframe Testing And Debugging	19%
Mainframe Software	10%
Total	29%

Dependent Variable	ln(R&D)	ln(R&D)	ln(R&D)	ln(R&D)	ln(Pat)	ln(Pat-W)
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
	Full sample	Challenged	Challenged	Non-challenged	Challenged	Challenged
Constant	-4.10***	-3.74***	-3.84***	-1.84***	-4.2***	3.06***
	(0.53)	(0.56)	(0.57)	(0.60)	(0.75)	(0.85)
ln (Sales)	0.78***	0.85***	0.82***	0.75***		
	(0.05)	(0.05)	(0.05)	(0.06)		
ln (R&D)					0.38***	0.15
					(0.14)	(0.18)
ln (Tax Rate)	0.04	0.01	0.02	0.06	-0.07	-0.23*
	(0.03)	(0.04)	(0.04)	(0.04)	(0.09)	(0.13)
ln (Leverage)	-0.01	-0.03	-0.03	0.01	0.01	0.05
	(0.02)	(0.02)	(0.02)	(0.04)	(0.07)	(0.09)
Merger	-0.12**	-0.15**	-0.15**	-0.06	-0.06	0.39
	(0.05)	(0.06)	(0.06)	(0.06)	(0.16)	(0.26)
Firm size 1	-0.35**	-0.48***	-0.48***	-0.33	0.07	-0.36
	(0.15)	(0.16)	(0.16)	(0.23)	(0.60)	(0.75)
Firm size 2	-0.24**	-0.38***	-0.38***	-0.23	-0.12	-0.80
	(0.10)	(0.10)	(0.10)	(0.16)	(0.48)	(0.56)
Firm size 3	-0.05**	0.12**	0.12**	-0.01	0.41*	0.02
	(0.05)	(0.05)	(0.05)	(0.09)	(0.24)	(0.24)
Δ Value Added	-0.34	-0.51	-0.51	-0.15	1.56	2.06
	(0.25)	(0.35)	(0.35)	(0.40)	(1.44)	(1.74)
In Product Overlap			-0.04**		0.21***	0.25***
			(0.02)		(0.04)	(0.09)
Observations	640	389	389	251	282	250
R-squared	0.97	0.97	0.97	0.96	0.85	0.83

 Table 4
 Merger analysis, merged firm sample only

Robust standard errors are in parentheses. Estimation is by least squares dummy variables (LSDV), controlling for year, industry, and firm dummies. ***, **, and * indicate statistical significance levels of 1%, 5%, and 10% respectively. The sample period is 1989–2008 for columns 1–4, and 1989–2006 for columns 5–6.

Firm Size refers to four dummies (4th is dropped) in which Firm Size 1=1 if employment levels are under 7661, Firm Size 2=1 if employment levels are between 7661 and 32766, Firm Size 3=1 if employment levels are between 32,766 and 79,400, and Firm Size 4=1 if employment levels exceed 79,400. Δ Value Added is the sectoral growth rate of value added. All other variables are as defined in Table 1.

control group of non-merged firms, the challenged merger firms do have a lower growth in real R&D post-merger, controlling for other variables (see columns 1 and 2); the negative impact of mergers on the R&D of merged firms relative to non-merged firms is driven by the sample of challenged mergers. The change in R&D of firms whose mergers were not challenged is insignificantly different from that of similar non-merged firms in the aftermath of a merger, controlling for other factors. Thus, the results on the R&D impacts of mergers are consistent with our findings using only the sample of mergers (recall Table 4). The results could imply a decline in innovation effort among firms whose mergers were challenged or suggest that a merger led to cost savings in R&D. We will investigate further using patent data.

As for the other variables, the coefficient on Firm Type is significantly positive for challenged merger firms and significantly negative for non-challenged merger firms,

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	Dependent Variable	e: ln (R&D)	
	(1) Full sample	(2) Challenged	(3) Non-challenged
Constant	-5.32***	-3.10***	-3.99***
	(0.44)	(0.38)	(0.43)
ln (Sales)	0.75***	0.77***	0.72***
	(0.04)	(0.04)	(0.05)
ln (Tax Rate)	0.01	0.02	0.01
	(0.02)	(0.03)	(0.03)
ln(Leverage)	-0.015	-0.026*	-0.01
	(0.013)	(0.014)	(0.02)
Treatment	-0.04	-0.05	-0.02
	(0.04)	(0.04)	(0.04)
Firm Type	1.95***	1.90***	-0.97***
	(0.12)	(0.12)	(0.14)
Treatment x Firm Type	-0.07*	-0.08**	-0.07
	(0.04)	(0.04)	(0.05)
Firm size 1	-0.37***	0.43***	-0.34**
	(0.11)	(0.11)	(0.15)
Firm size 2	-0.27***	-0.34***	-0.27***
	(0.06)	(0.03)	(0.08)
Firm size 3	-0.08**	-0.12***	-0.08**
	(0.03)	(0.03)	(0.04)
Δ Value Added	-0.18	-0.25	-0.04
	(0.19)	(0.22)	(0.03)
Observations	1,057	806	668
R-squared	0.97	0.97	0.96

Table 5	Difference-in-differences	estimation	matched	sample	R&D	as a	measure	of i	innovation
Table 5	Difference-in-uniterences	commanon,	matcheu	sample,	Rad	as 0	measure	011	movation

Robust standard errors are in parentheses. Estimation is by least squares dummy variables (LSDV), controlling for year dummies, industry dummies, and firm dummies. ***, **, and * indicate statistical significance levels of 1%, 5%, and 10% respectively. The sample period is 1989–2008.

Firm Size refers to four dummies (4th is dropped) in which Firm Size 1=1 if employment levels are under 7661, Firm Size 2=1 if employment levels are between 7661 and 32766, Firm Size 3=1 if employment levels are between 32766 and 79400, and Firm Size 4=1 if employment levels exceed 79400. Δ Value Added is the sectoral growth rate of value added. All other variables are as defined in Table 1.

indicating that the former, in general, conduct more R&D than the control group does while the latter conducts less—holding other factors constant. The coefficient on Treatment is insignificant, suggesting that for the control group of firms, there is no statistically significant difference in their R&D before and after the acquisition activities of their counterparts (i.e., if we substitute in Treatment=1 and Type=0 into Eq. 5, we simply obtain the change in the control group's R&D, controlling for other factors). As before, 'sales' is an important determinant of R&D. The elasticity of R&D with respect to sales is quite similar for both challenged and non-challenged firms. Firm size also matters: smaller firms tend to conduct less R&D. Industry growth, the tax rate, and leverage have weak effects on firm R&D. Tables 6 and 7 repeat the difference-in-differences analysis using the natural log of patents as the dependent variable. In the results for Table 6, we used the count of patent grants (PAT), and for Table 7, we used the citation-weight patent grants (PAT-W). As before (Table 5), we look at three samples: the full sample, the challenged merger firm sample, and the non-challenged firm sample. Each of these samples includes the control group of non-merged firms. In addition, for each sample, we examine three different lag lengths for the RHS variables. The motivation for this is to account for the lag between R&D and patenting. The dependent variables are patent grants by date of patent application. They represent those applications filed in a certain year which later resulted in the issuance of a patent right. At the time of application, the underlying innovation was the result of a combination of current and prior R&D investments, but the exact lag structure between patent filings and R&D is not observable. Thus, we examine three different lag lengths: one period, two periods, and three periods. Likewise, the merger event could also affect innovation outcomes with a lag.

As Table 6 shows, we find consistently that the growth in patent grants of challenged merger firms from pre-merger levels are lower than those of a control group of non-merged firms over the same period (see the coefficient of the Treatment x Firm Type variable). This finding is robust to different lag lengths. Indeed, the coefficient estimate of the interaction term (Treatment x Firm Type) suggests that the merger is associated with a greater negative impact on relative patent grants three years later. Furthermore, the growth in patentable innovations of non-challenged merger firms from pre-merger levels is not significantly different from that of a control group of non-merged firms over the same period. Interestingly, controlling for other factors, we find that the patent grants of the *non-merged* firms rise over the same period (i.e., see the significant positive coefficient of Treatment). This means that even if a challenged merger firm's innovation were constant after a merger, the firm would lag behind the non-merged firm in terms of innovation.

Throughout, R&D is an important determinant of patenting, and all of the firms in the sample are large R&D intensive and innovating firms. The estimated sensitivity of patent grants to R&D is greater for challenged mergers than for non-challenged mergers, which may be why a drop in R&D for the challenged merger firms will translate into somewhat larger decreases in patentable outcomes for challenged firms.

One criticism with the results in Table 6 is that, even if firms engaged in challenged mergers patent less after a merger, holding other factors constant, they may be patenting fewer but *higher valued* innovations instead. However, the results in Table 7 show that there is also a reduction in quality-adjusted patents among challenged merger firms, relative to those of the control group, after a merger takes place. As expected, for challenged mergers, in the postmerger period, the growth in citation-weighted patent grants is lower than that of the control group; for non-challenged mergers, there is no statistically significant difference between their growth in citation-weighted patent grants and that of the control group. Again, for non-merged firms, their patentable innovations increased after their counterpart firms merged (which we can tell from the generally significant positive coefficient of the Treatment dummy). The influences of other control variables are similar—for example, R&D is an important determinant of patenting, but the coefficient estimate is slightly lower, indicating that expenditures on R&D have a slightly stronger quantitative impact on patent quantity than on patent quality. The main difference is that the leverage variable has a significant positive association with citation-weighted patent grants, but only when the lag length of the model is one period.²³

²³ Shyam-Sunder and Myers (1999) also find cases where innovation can be positively associated with leverage; that is, where firms turn to debt to finance innovation.

	Dependent Vari	ible: Natural log of I	atent Grants, In (PAT)						
Lag Length:	Full sample t-1	Challenged t-1	Non-challenged t-1	Full sample t-2	Challenged t-2	Non-challenged t-2	Full sample t-3	Challenged t-3	Non-challenged t-3
Constant	-4.13***	1.57*	-1.84	-4.00^{***}	-026	2.47**	-0.87	-6.72***	-2.92***
	(0.77)	(06.0)	(1.17)	(075)	(0.79)	(1.09)	(0.484)	(1.07)	(0.93)
ln (R&D)	0.47***	0.60***	0.45***	0.46**	0.66***	0.42***	0.41***	0.68***	0.34***
	(60.0)	(0.12)	(0.13)	(0.10)	(0.13)	(0.12)	(0.10)	(0.14)	(0.12)
ln (Tax Rate)	-0.04	-0.08	0.02	0.01	0.02	0.03	0.10	0.15	0.12
	(0.06)	(0.07)	(0.07)	(0.08)	(0.08)	(0.08)	(0.07)	(0.08)	(0.09)
ln(Leverage)	0.07*	0.05	0.05	0.04	0.05	0.01	0.03	0.06	-0.04
	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.07)
Treatment	0.33*	0.37**	0.30	0.55***	0.58***	0.53***	0.63***	0.64^{***}	0.65***
	(0.19)	(0.18)	(0.20)	(0.21)	(0.20)	(0.23)	(0.23)	(0.23)	(0.25)
Firm Type	0.35	0.39	-2.61***	0.14	-3.93***	0.58	2.46***	1.53***	-0.66
	(0.41)	(0.42)	(0.51)	(0.42)	(0.62)	(0.52)	(0.39)	(0.46)	(0.54)
Treatment x Firm	-0.53^{***}	-0.66***	-0.33	-0.58***	-0.89***	-0.23	-0.47*	-0.92***	-0.01
Type	(0.21)	(0.22)	(0.26)	(0.23)	(0.26)	(0.27)	(0.25)	(0.32)	(0.26)
Firm size 1	-0.306	-0.80^{***}	-0.01	-0.26	-0.84**	-0.46	-0.27***	0.39	-0.58
	(0.38)	(0.37)	(0.53)	(0.40)	(0.40)	(0.57)	(0.42)	(0.43)	(090)
Firm size 2	-0.07	-0.78***	-0.05	-0.28	-0.79***	-0.28	0.14	-0.54*	-0.23
	(0.26)	(0.29)	(0.32)	(0.27)	(0.30)	(0.33)	(0.28)	(0.29)	(0.34)
Firm size 3	0.12	-0.50***	-0.52^{**}	-0.26	-0.53***	-0.58***	0.26	-0.42**	-0.61^{***}
	(0.73)	(0.21)	(0.24)	(0.19)	(0.21)	(0.25)	(0.18)	(0.20)	(0.23)
∆ Value Added	-0.1	0.98	-0.32	0.82	1.43	-0.08	-0.4	0.07	-1.32
	(0.19)	(0.88)	(0.86)	(0.82)	(0.83)	(0.98)	(1.14)	(0.85)	(1.41)
Observations	748	563	487	696	525	455	645	486	424
R-squared	0.82	0.82	0.80	0.82	0.83	0.81	0.84	0.85	0.83

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	Dependent Varis	able: Natural log of (Citation Weighted Patent	Counts, (In PAT-W)					
Lag Length:	Full sample t-1	Challenged t-1	Non-challenged t-1	Full sample t-2	Challenged t-2	Non-challenged t-2	Full Sample t-3	Challenged t-3	Non-challenged t-3
Constant	3.70***	-0.88	0.09	-0.96	0.56	0.34*	3.90***	-1.25	1.89
	(0.76)	(1.17)	(1.40)	(0.92)	(1.15)	(1.07)	(0.87)	(2.37)	(1.77)
ln (R&D)	0.30^{***}	0.48^{***}	0.34^{**}	0.24**	0.48^{***}	0.21	0.26*	0.64^{***}	0.19
	(0.11)	(0.13)	(0.15)	(0.11)	(0.16)	(0.14)	(0.15)	(0.18)	(0.19)
ln (Tax Rate)	-0.10	0.09	-0.05	0.02	0.08	0.03	0.03	0.13	0.01
	(0.08)	(60.0)	(0.10)	(0.08)	(60.0)	(60.0)	(60.0)	(0.11)	(0.10)
ln(Leverage)	0.13^{***}	*60.0	0.12**	0.10*	0.08	0.11	0.12*	0.12	0.08
	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.07)	(0.07)	(0.07)	(0.09)
Treatment	0.50**	0.60***	0.41*	0.45*	0.54^{**}	0.36	0.35	0.48*	0.26
	(0.22)	(0.22)	(0.23)	(0.24)	(0.24)	(0.25)	(0.25)	(0.25)	(0.26)
Firm Type	-1.60^{***}	-1.76^{***}	-0.03	0.40	-2.85***	0.40	-1.06	-0.68	-1.94*
	(0.66)	(0.63)	(0.50)	(0.54)	(0.91)	(0.93)	(0.84)	(0.96)	(1.03)
Treatment x Firm	-0.45*	-0.56^{**}	-0.34	-0.46*	-0.59**	-0.31	-0.42	-0.51*	-0.33
Type	(0.27)	(0.27)	(0.29)	(0.26)	(0.28)	(0.32)	(0.27)	(0.29)	(0.33)
Firm size 1	-0.40	-0.75*	-0.58	-0.38	-0.43	-0.77	-0.25	-0.22	0.30
	(0.336)	(0.46)	(0.44)	(0.38)	(0.49)	(0.46)	(0.44)	(0.55)	(0.33)
Firm size 2	-0.70**	-1.09^{***}	-0.54*	-0.7***	-0.80***	-0.64**	-0.55**	-0.79**	-0.40
	(0.36)	(0.31)	(0.31)	(0.24)	(0.31)	(0.32)	(0.28)	(0.33)	(0.36)
Firm size 3	-0.46^{**}	-0.567^{***}	-067***	-0.5***	-0.60***	-0.64^{**}	0.50***	-0.60***	-0.67^{**}
	(0.19)	(0.22)	(0.26)	(0.19)	(0.22)	(0.27)	(0.20)	(0.23)	(0.27)
Δ Value Added	1.14	0.97	0.09	0.63	0.97	-0.55	1.46	1.16	0.95
	(0.87)	(1.08)	(1.11)	(1.11)	(1.01)	(1.37)	(1.14)	(1.25)	(1.42)
Observations	662	502	431	610	463	399	561	427	368
R-squared	0.82	0.81	0.82	0.82	0.81	0.81	0.83	0.81	0.81

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5.4 Discussion of results

To summarize, we find that horizontal mergers are associated with a decline in post-merger innovation, relative to the level of innovation that would have prevailed had a merger not occurred, only for the sample of mergers that were challenged by the antitrust authorities. We first compared challenged mergers and non-challenged mergers and found that firms engaged in challenged mergers had lower post-merger R&D than firms whose mergers were not challenged; this result, however, did not apply to patenting. This suggests that firms whose mergers were challenged may have been cutting back on duplicative R&D, so that overall innovation outcomes did not significantly differ between mergers that raised market concentration levels and those that did not. However, when we compare the innovation activities of challenged and non-challenged merger firms to a matched control group, we find that the growth in both the R&D and patenting of challenged firms from the pre-merger to the post-merger period was lower than that of nonmerged firms over the same period. For non-challenged merger firms, no statistically significant differences in innovation growth exist between them and non-merged firms. Thus, firms whose mergers increased market concentration levels had lower innovation outcomes than those nonmerged firms who were otherwise similar to the challenged merger firms (i.e., who had the same propensity to merge but did not). We infer, therefore, that the innovation outcomes of merged firms are expected to be lower (than they would otherwise be in the absence of a merger) in markets that, as a consequence of the merger, become more concentrated. For example, the combined company may not feel compelled to invest heavily in innovation after the merger in order to find the next breakthrough product or technology because competitive pressures are weaker. Our findings are robust to measuring innovation outcomes as either the quantities of patent grants or as the quality of such grants, as indicated by the age-adjusted citations received by the patent grants that we observed.

Our evidence adds to the mix of different empirical findings in the literature. As we pointed out in Section 2, existing empirical evidence is diverse. However, the reason we find a negative impact of mergers on post-merger innovation, while other studies might find a positive impact, is that we focused especially on those mergers that were screened by authorities to raise market concentration levels. For example, in Section 2, we discussed previous studies showing that mergers may enhance innovation if the merging partners overlap technologically or possess intangible assets that are related. We do not dispute nor contradict these findings. Rather, we argue that it is important to control for mergers that significantly raise concentration levels. The effects of higher concentration are likely to offset any positive benefits a merger may confer on innovation.

6 Conclusion

Research on the effects of mergers on innovation has important public policy implications. Due to new antitrust guidelines in the U.S., antitrust and regulatory interventions may become a more influential determinant of technological change, as antitrust authorities like the DOJ and FTC screen and challenge mergers that may adversely affect innovation markets; approximately, one-third of all merger challenges between 2000 and 2003 cited innovation effects as a reason for the challenge (Gilbert 2006). Hence, prevailing views on the relationship between innovation and market concentration have an important impact on policy decisions to challenge a merger. If, for example, market concentration promotes innovation, intervention by policy authorities to challenge mergers would not be appropriate if the mergers involved parties who would innovate further when operating in a more concentrated market.

In our paper, we used merger challenges to identify cases of increased market concentration. We find that merger challenges by the DOJ and FTC tended to correctly portend innovation concerns. Firms whose mergers were challenged, due to market power concerns stemming from high levels of concentration, undertook less innovative activity after a merger than they otherwise would have without a merger. Firms whose mergers were not challenged innovated no differently from what they would have done had they not merged.

Several directions exist for further research. First, our empirical analysis has some implications for theoretical research. Models studying the impact of market concentration on innovation should be conditioned on whether excessive market power results, perhaps due to the combination of mergers and barriers to entry. Models should also study the effects of mergers beyond product markets and analyze the resulting concentration in innovation markets. The ultimate impact on innovation may reside in what transpires in the innovation market.²⁴ Second, the empirical work could be extended to study the total factor productivity of challenged mergers versus non-challenged mergers (using the approach in Bertrand and Zitouna 2008) or to apply the innovation market analysis to cross border mergers and acquisitions.²⁵

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Appendix

Challenged:	Merger		Non-Challenged:	Merger	
Acquirer-Acquired	Year	Sector	Acquirer-Acquired	Year	Sector
3D Systems-DTM	2001	Computer	Adobe-Macromedia	2005	Computer
ABB-Elsag Bailey	1998	Industrial	Air Liquide-Messier	2004	Industrial
Allergan- Inamed	2005	Life Sciences	Arcelor-Mittal	2005	Industrial
Amgen-Immunex	2001	Life Sciences	BASF-Engelhard	2006	Industrial
Astra-Zeneca	1998	Life Sciences	Biogen-Idec	2003	Life Sciences
Boston Scientific-Guidant	2005	Life Sciences	Boeing-McDonnell Douglas	1997	Industrial
Cephalon-Cima	2003	Life Sciences	Cisco-Scientific Atlanta	2005	Computer
Computer Associates- Platinum T.	1999	Computer	Eaton-Vickers	1999	Industrial
Dow-Union Carbide	1999	Industrial	General Dynamics- Gulfstream	1999	Industrial

A) Company Information

 $^{^{24}}$ In the late 1990s, the DOJ disallowed the aerospace merger of Lockheed Martin and North Grumman on the grounds that their merger would significantly reduce the number of bidders for government (namely Pentagon) technology contracts. In other words, too few contractors will compete to develop innovations for defense-related needs.

²⁵ See work on this by Bertrand (2009) for French firms and Stiebale and Reize (2011) for German firms.

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Genzyme-Ilex	2004	Life Sciences	HP-Compaq	2001	Computer
Glaxo-SmithKline	1998	Life Sciences	IBM-Rational Software	2002	Computer
Halliburton-Dresser	1998	Industrial	J&J-Alza	2001	Life Sciences
Honeywell-Allied Signal	1999	Industrial	Juniper-NetScreen	2003	Computer
JDSU-Etek	2000	Computer	Millenium-Cor	2001	Life Sciences
Medtronics-Physio Control	1998	Life Sciences	Motorola-General Instruments	1999	Computer
Novartis-Eon Labs.	2005	Life Sciences	Novartis-Chiron	2006	Life Sciences
Oracle-Peoplesoft	2004	Computer	Teva-Sicor	2003	Life Sciences
P&G-Gillette	2005	Industrial	United Technologies- Sundstrand	1998	Industrial
Pfizer-Pharmacia	2002	Life Sciences	Veritas-Symantec	2005	Computer
Pfizer-Warner Lambert	2000	Life Sciences	Whirlpool-Maytag	2005	Industrial
Precision Cast-Wyman Gordon	2000	Industrial			
Rohm Haas-Morton	1999	Industrial			
Sanofi-Aventis	2004	Life Sciences			
Teva-IVAX	2005	Life Sciences			
Tyco-Mallinckrodt	2000	Industrial			
Valspar-Lilly	2000	Industrial			
Watson-Andrx	2006	Life Sciences			

Non-Merging	g Firms:				
Companies	Sector	Companies	Sector	Companies	Sector
3 M	Industrial	Genentech	Life Sciences	Pentair	Industrial
Abbott	Life Sciences	Gilead Sciences	Industrial	PPG	Industrial
Apple	Computer	Hoffman LaRoche	Life Sciences	Qualcomm	Computer
Baxter	Life Sciences	Intel	Life Sciences	Raytheon	Industrial
Caterpillar	Industrial	Johnson Controls	Computer	RIM	Computer
Cytec	Life Sciences	Lockheed Martin	Industrial	Sandisk	Computer
Deere	Industrial	Merck	Life Sciences	Schering Plough	Life Sciences
Dover	Industrial	Micron Technology	Computer	Texas Instruments	Computer
Eli Lilly	Life Sciences	Microsoft	Computer	Unisys	Computer
Emerson	Industrial	NCR	Computer	Wyeth	Life Sciences
Forest Lab.	Life Sciences				

B) Data Sources

Data	Source
Listing of challenged mergers and percent of sales overlap	Federal Trade Commission ²⁶ /Department of Justice ²⁷ web sites, complaint documents, annual reports
General Merger Information	Annual Congressional Research Service (CRS) Reports to

Annual Congressional Research Service (CRS) Reports to Congress.

²⁶ See http://www.ftc.gov/os/caselist/index.shtm for a list of Federal Trade Commission cases.
 ²⁷ See http://www.justice.gov/atr/cases.html for a list of Department of Justice cases.

Non-merging companies	Financial Times Global 1,000 Report
Patent Grants and Citations	National Bureau of Economic Research Patent Data Project, Files Pat76_06_Assg and Assignee, http://www.nber.org/ patents
Sales, R&D Expenditures, Employment, Debt, Equity, Income, and Income Taxes	Standard and Poors' Compustat Data Base, North America— Simplified Financial Extract Report
Sectoral Value Added and Price Indexes	U.S. Department of Commerce, Bureau of Economic Analysis http://www.bea.gov/industry/index.htm#annual

References

- Aghion P, Bloom N, Blundell R, Griffith R, Howitt P (2005) Competition and innovation: an inverted-U relationship. Quart J Econ 120(2):701–728
- Ahuja G, Katila R (2001) Technological acquisitions and the innovation performance of acquiring firms: a longitudinal study. Strat Manag J 22:197–220
- Arrow KJ (1962) Economic welfare and the allocation of resources for invention. In: Nelson R (ed) The rate of direction of inventive activity. NBER Conference Series. Princeton University Press, Princeton, NJ, pp 609–626
- Bena J, Li K (2011) Corporate innovations and mergers and acquisitions. University of British Columbia Working Paper.
- Bertrand O (2009) Effects of foreign acquisitions on R&D activity: evidence from firm-level data for France. Research Policy 38(6):1021–1031
- Bertrand O, Zitouna H (2008) Domestic versus Cross-border acquisitions: which impact on the target firms' performance? Appl Econ 40:2221–2238
- Bresman H, Birkinshaw J, Nobel R (1999) Knowledge transfer in international acquisitions. J Int Bus Studies 30:439–462
- Carlton D, Gertner R (2003) Intellectual property, antitrust, and strategic behavior. In: Jaffe A, Lerner J (eds) Innovation policy and the economy, vol 3. National Bureau of Economic Research, Cambridge, MA, pp 29–59
- Cassiman B, Paola G, Larissa R, Veugelers R (2005) The impact of M&A on the R&D process: an empirical analysis of the role of technological and market relatedness. Research Policy 34(2):195–220
- Cohen W, Levin R (1989) Empirical studies of innovation and market structure. In: Schmalensee R, Willig R (eds) Handbook of industrial organization. North-Holland Inc., Amsterdam, pp 1060–1107
- Cloodt M, Hagedoorn J, Van Kranenburg H (2006) Mergers and acquisitions: their effect on the innovative performance of companies in high-tech industries. Research Policy 35(5):642–654
- Danzon P, Epstein A, Sean N (2007) Mergers and acquisitions in the pharmaceutical and biotech industries. Manag Decis Econ 28:307–328
- Dasgupta P, Stiglitz J (1980) Industrial structure and the nature of innovative activity. Econ J 90:266-293
- de Man A-P, Duysters G (2005) Collaboration and innovation: a review of the effects of mergers, acquisitions and alliances on innovation. Technovation 25:1377–1387
- Ernst H, Vitt J (2000) The influence of corporate acquisitions on the behavior of key inventors. R&D Manag 30:105–119
- Gilbert R (2006) Looking for Mr. Schumpeter: where are we in the competition-innovation debate? In: Jaffe A, Lerner J, Stern S (eds) Innovation policy and the economy, vol 6. National Bureau of Economic Research, Cambridge, MA, pp 159–215
- Gilbert R, Newbery D (1982) Preemptive patenting and the persistence of monopoly. Am Econ Rev 72 (2):514–526
- Gilbert R, Sunshine S (1995) Incorporating dynamic efficiency concerns in merger analysis: the use of innovation markets. Antitrust Law J 63:569–603
- Guo S, Fraser M (2010) Propensity score analysis. Sage Publication, Los Angeles, California
- Hall B (1990) The impact of corporate restructuring on industrial research and development. Brookings Papers on Economic Activity: Microeconomics 3:85–124
- Hall B (1999) Mergers and R&D revisited. Prepared for the Quasi Experimental Methods Symposium, Econometrics Laboratory, U.C. Berkeley. http://elsa.berkeley.edu/~bhhall/papers/BHH99mergerR&D. pdf.
- Hall B, Jaffe A, Trajtenberg M (2001) The NBER patent citation datafiles: Lessons, insights and methodological tools. NBER Working Paper No. 8498.

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Hall B, Jaffe A, Trajtenberg M (2005) Market value and patent citations. Rand J Econ 36:16-38

- Hitt M, Hoskinsson R, Ireland D, Harrison J (1991) Effects of acquisitions on R&D inputs and outputs. Acad Manag J 34(3):693–706
- Hosono K, Takizawa M, Tsuru K (2009) Mergers, innovation, and productivity: evidence from japanese manufacturing firms. Research Institute of Economy, Trade and Industry (RIETI), Discussion Paper Series 09-E-017.
- Loury G (1979) Market structure and innovation. Quart J Econ 93:395-410
- Ornaghi C (2009) Mergers and Innovation in big pharma. Int J Ind Organ 27(1):70-79
- Pakes A, Griliches Z (1984) Patents and R&D at the firm level: a first look, In: Griliches Z (eds.) R&D, Patents, and Productivity. University of Chicago Press, pp. 55–72.
- Rajan R, Zingales L (1995) What do we know about capital structure? Some evidence from international data. J Finance 50:1421–1460
- Ravenscraft D, Scherer FM (1987) Mergers, sell-offs, and economic efficiency. Brookings Institution, Washington, DC
- Roller L, Stennek J, and Verboven, F (2006) Efficiency gains from Mergers, In: Ilzkovitz F, Meiklejohn R (eds) European merger control: Do we need an efficiency defense. Edward Elgar Publishing, pp. 84–201.
- Rosenbaum P, Rubin D (1985) Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. Am Stat 39:33–38
- Schulz N (2007) Review on the literature of mergers on innovation. Center for European Economic Research, ZEW Discussion Paper No. 07-061.
- Schumpeter J (1950) Capitalism, socialism, and democracy. Harper Inc., New York
- Shyam-Sunder L, Myers S (1999) Testing static trade-off against pecking order models of capital structure. J Finan Econ 51:219–244
- Sonenshine R (2010) The stock market's valuation of R&D and market concentration in horizontal mergers. Rev Ind Organ 37(2):119–140
- Stahl J (2010) Mergers and sequential innovation: evidence from patent counts. Paper presented at the American Economic Association meetings, Atlanta, January. http://www.aeaweb.org/aea/conference/program/retrieve. php?pdfid=444.
- Stiebale J, Reize F (2011) The impact of FDI through mergers and acquisitions on innovation in target firms. Int J Ind Organ 29:155–167
- Takalo T, Kanniainen V (2000) Do patents slow down technological progress? Real options in research, patenting, and market introduction. Int J Ind Organ 18:1105–1127
- Tirole J (1989) Theory of industrial organization. MIT Press, Cambridge
- Zhao X (2009) Technological innovation and acquisitions. Manag Sci 55(7):1170-1183