# Revisiting the Missing R&D-Patent Relation: Challenges and Solutions for Firm Fixed Effects Models

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**Abstract**

The common practice to include firm fixed effects in empirical research may eliminate the explanatory power of important economic factors that are persistent in time – we use the intuitive R&D-patent relation to illustrate this point. Prior studies based on firm fixed effects models often present a "missing link" between R&D input and patent output. Our empirical evidence and simulations suggest that such a pattern is attributable to the persistence of R&D and patents that causes the between-firm variation to be absorbed by firm fixed effects. We present three solutions (with ready-to-use codes) for empiricists working with persistent variables: first, we recommend to report *between* and *within* R-squared as well as estimation results without firm fixed effects. Second, we develop adjusted Hausman-Taylor estimators for persistent regressors to help quantify the R&D effect. Third, we propose advanced machine learning methods to evaluate the R&D effect by separating informative and non-informative firm dummies. In our sample, only 10-20% of firm dummies are informative in regressions for the R&D-patent relation. This paper not only offers a "second opinion" for empirical researchers working with explanatory variables that strongly correlate with between-individual unobservables, but also facilitates their exploration of more important factors in finance and economics research.

**JEL Codes:** C01, C13, G30, O30
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## 1. Introduction

In the finance and economics literature, empirical researchers often focus on firm fixed effects models in their regression analyses to control or absorb all firm-specific, time-invariant factors. This approach is widely adopted because it is challenging for researchers to identify the "correct" regression models (and to address potential endogeneity); thus, to be conservative, they may choose to estimate firm fixed effects regressions and claim that their test results are not subject to the influence of firm-specific unobservables.[1] However, without theoretical modeling or appropriate econometric designs, such prevailing (almost by default) use of firm fixed effects may "throw the baby out with the bathwater" by eliminating the explanatory power of important economic factors that are persistent in time and mainly vary across firms. In this paper, we aim to propose feasible solutions for this important yet underexplored issue.

Our first challenge is the fact that no one knows the underlying data generating process of financial data, which makes it difficult for us to justify whether the explanatory power of variables of interest is indeed biased by the inclusion of firm fixed effects. We clear this concern by focusing on the positive relation between R&D input and patent output that is intuitive and has economic foundation (e.g., Hausman et al., 1984; Pakes and Griliches, 1984; Griliches, 1990; Kortum, 1993).

Moreover, the investigation of the driving forces of innovation output has recently developed into an important topic in finance research, possibly due to two reasons. First, accelerating technological advancement and intensifying business competition make it necessary for corporations to heavily invest in R&D.[2] Firms' intention to create patents to protect their intellectual property is certainly the most important incentive for their substantial R&D investments.[3] Second, the public availability of patent data leads to a surge of studies on "new factors" to explain corporate innovation performance (see the reviews of Ederer and Manso, 2011; He and Tian, 2018; Lerner and Seru, 2022). Given the important role of R&D input in the production of patents, these studies often include R&D-related proxies in their regressions as a control variable.

Our literature review suggests a surprising and puzzling pattern: the role of R&D input is often missing in prior studies because 40% to 50% of their estimates show insignificant or even

[1] This practice, as a solution for endogeneity concerns, has been discussed in Angrist and Pischke (2009), Imbens and Wooldridge (2009), and Roberts and Whited (2013).

[2] Amazon leads all U.S. public firms by spending $73 billion in 2022, followed by Alphabet and Meta which spent $40 and $35 billion, respectively, in the same year. Source: https://www.fdiintelligence.com/content/feature/global-innovation-leaders-2022-edition-82527

[3] Other reasons include the investment in the ability to absorb external knowledge and technology (Cohen and Levinthal, 1989; Arora, Belenzon and Sheer, 2017).

negative coefficients on R&D input (more details are provided in Section 2). These findings of an insignificant R&D-patent relation can be directly attributed to the prevailing use of firm fixed effects (Aghion et al., 2013; Balsmeier et al., 2017).[4] A more thorough discussion of this issue is found in Hall et al. (2005, p.26): "*We have chosen not to include fixed firm effects for a number of reasons... [b]ecause R&D tends to change slowly over time, a firm's R&D intensity is highly correlated with its individual effect; in fact, it is an important component of what creates differences across firms, so removing these effects would entail an overcorrection.*"[5]

In fact, the missing role of R&D input leads to two concerns. First, if R&D input cannot explain patent output in a regression model, then to what extent can we accept the explanatory power of those new factors? This issue can be easily fixed if prior studies also consider regression models without firm fixed effects and, in turn, recover the positive coefficient on R&D input. Unfortunately, most papers we review only report results from firm fixed effects models. This leads to our second concern: if the role of a new factor is only examined using firm fixed effects regressions, then the factor may only capture the time-series variation of patent output, which is relatively small when compared with the cross-sectional variation (Hausman et al., 1984; Hall et al., 2005). In addition, statistical inferences based on firm fixed effects regressions may be dominated by firms that are featured with larger within-firm variation (i.e., time-series variation) (Breuer and DeHaan, 2024). To the best of our knowledge, there is a lack of appropriate procedures to diagnose and solve the aforementioned issue for more reliable statistical inferences.

An even more thorny issue is the prominent possibility that unobserved heterogeneity exists in some firms but not others. For example, some firms may have a strong, innovation-oriented culture, while all the rest do not. To appropriately model the aforementioned plausible scenarios, we cannot resort to models that only allow (or disallow) the use of dummies for all individual firms. (Throughout this paper, we use the term "firm fixed effects" to denote the inclusion of dummies for *all* firms. On the other hand, we often use the term "firm dummies" when we discuss some dummies for *specific* firms.) Thus, an econometric methodology that can select which individual firm dummies are informative to the R&D-patent relation is called for.

To illustrate the aforementioned issues, we construct panel data of firm-year observations by

[4] Aghion et al. (2013) wrote: *"In the specifications where we include fixed effects, the coefficient on the R&D stock falls significantly."* Balsmeier et al. (2017) wrote *"Alternative regressions with R&D investments scaled by total assets reveal a significant positive effect only in specifications without firm fixed effects. Inclusion of controls for time-invariant firm heterogeneity leads to statistically insignificant results."*

[5] This issue is also pointed out in Hausman et al. (1984), Pakes and Griliches (1984), Blundell et al. (1995), Zhou (2001), Hall et al. (2007), and Noel and Schankerman (2013). Small variation in within-groups amplifies the measurement error issue (Griliches and Hausman, 1986; Jennings et al., 2024).

collecting patent data from the PatentsView database and by collecting accounting and financing data of publicly-listed firms from the CRSP and Compustat database. We then estimate the extent to which firm-level patent output (measured by the number of new patents filed or the number of forward citations of these patents) can be explained by an extensive list of economic variables including R&D input. Similar to most prior studies, we estimate OLS and Poisson regressions in which dependent variables are the logarithmic and raw values of patents/citations, respectively.

Our OLS regression results suggest a robust pattern that R&D input positively explains patent output when regression models include an extensive list of control variables but do *not* include firm fixed effects. The economic magnitude of this positive relation is eliminated or severely weakened when firm fixed effects are included in regressions ("firm FE models" hereafter), which is consistent with the concerns we discussed earlier.

We then present three solutions to resolve the missing R&D puzzle and to address time persistence issues in general. First, we report *between* and *within* R-squared – which are reported in modern statistical packages or can be easily computed based on dependent and explanatory variables' time-series averages and demeanded values, respectively (Cameron et al., 2010, 2022). We find that the between R-squared is much higher than the within R-squared (17% or above vs. 1% to 3.5%), regardless of the existence of firm fixed effects. This contrast confirms that the time-series variation of patent output (to which explanatory variables can only contribute in firm FE models) is fairly small relative to the cross-sectional variation. Moreover, the inclusion of firm fixed effects greatly reduces the between R-squared (by over 28%), confirming that they "absorb" the cross-sectional explanatory power of persistent variables including R&D. As a result, we recommend researchers to report models without firm fixed effects as well as between and within R squared, especially when the cross-sectional variation dominates the time series variation in their data.

Second, we propose the adjusted Hausman and Taylor estimator. Hausman and Taylor (1981) approach is well-known to address the time-invariant variable of interest to be correlated to firm heterogeneity. As shown in Wooldridge (2002, Ch. 11) and Hansen (2022, Ch. 17), the Hausman-Taylor estimator can be obtained using Generalized Method of Moments (GMM) in which demeaned independent variables form moment conditions. We implement the GMM using the moment conditions for demeaned independent variables. (The code is provided in footnotes in Section 5.) In our empirical analyses, the adjusted Hausman-Taylor method and the OLS without firm fixed effects deliver a positive R&D-patents relation. More importantly, the economic magnitude of the R&D effect based on the former method is much closer to that based on the OLS without firm fixed

effects and is far from that based on firm FE models.

Third, we consider advanced machine learning based on the Least Absolute Shrinkage and Selection Operator (LASSO, Tibshirani, 1996), which has been used to select predictors and control variables (Chinco et al., 2019; Feng et al., 2020; Gu et al., 2020; Erel et al., 2021) and individual dummies (Kock and Tang, 2019; Chan and Mátyás, 2022; Semenova et al., 2023). In particular, we use the post-regularization LASSO ("PRL" henceforth, Chernozhukov et al., 2015) estimation and its extension based on double machine learning ("DML" hereafter, Chernozhukov et al., 2018) to select firm dummies.[6] (The code is provided in footnotes in Section 6.) The intuition for such selections is that, if innovation culture is the only fixed effect in the panel and if only some firms have such cultures, our PRL and DML estimators can identify those *without* such culture and thus suggest us not to include those firms' dummies in regression estimations, as those firms are not subject to individual effects in R&D or patents.

We find that these two advanced methods select about 10% to 20% of firm dummies that are informative and should be included in regression models. In addition, the coefficients on R&D input based on the PRL and DML estimators are statistically significant, and their economic magnitude is much closer to that from models without firm fixed effects (and adjusted Hausman-Taylor method) than that from firm FE models. More importantly, our results suggest that the majority of firm dummies do not play a crucial role in explaining innovation process. These findings also highlight the possibility that the bias from adding all firm dummies can be costlier than that from not adding any dummies.

We then implement simulations based on the data generation process (DGP) of Cohn et al. (2022) to model between- and within-firm variations in panels and to examine the efficacy and efficiency of different estimators. As between-firm variation increases relative to within-firm variation, fixed effects estimators tend to have lower rejection rates and higher error rates than other estimators including OLS models without firm fixed effects, adjusted Hausman-Taylor estimators, and PRL estimators. This finding is consistent with prior studies' argument: the high correlation between persistent R&D and (unobservable) firm features hinders the ability of fixed effects estimators to capture the genuine R&D-patent relation. Moreover, we show that the proposed PRL methods outperform adjusted Hausman-Taylor estimators and OLS models without firm fixed effects, highlighting the advantage of machine learning in handling persistent explanatory variables.

[6] While Semenova et al. (2023) also employ LASSO for selecting individual dummies within the DML framework, our objectives differ remarkably. Semenova et al. (2023) aim to debias the Nickell (1981) bias in dynamic panel models, whereas our focus is on identifying the coefficients of time-persistent variables. For the oracle property of LASSO in the selection of fixed effects, see Kock and Tang (2019).

We also consider Poisson regressions that are common for count-based dependent variables in the economics and finance literature (Cohn et al., 2022). Our empirical evidence shows that, similar to our results in OLS regressions, Poisson models with firm fixed effects (Silva and Tenreyro, 2006; Correia et al., 2020a) fail to detect the R&D effect. When we implement PRL and DML methods for Poisson regressions, we again find that the estimated coefficients on R&D input are much closer to those from Poisson regressions without firm fixed effects than those with. Simulations suggest that Poisson regressions with firm fixed effects underperform those without in efficacy and efficiency, and that the PRL Poisson performs the best among all estimators. Thus, the bias that we attempt to highlight and solve in this paper is a general issue across different regression models.

This paper provides feasible solutions for empirical researchers who are concerned with persistent explanatory variables that likely correlate with important between-firm unobservables. These methods not only resolve the debate on whether firm fixed effects should be included or not, but also inform researchers which firm dummies are more important and are worth being added in regressions. In addition, our empirical evidence suggests that the bias from including firm fixed effects may overpower the bias from not adding any at all, at least for R&D investment. This challenges the claim that using firm fixed effects is a "conservative" choice.

At the very least, researchers should consider reporting both between and within R-squared as well as estimating regressions without firm fixed effects – all of these help readers understand the sources and weights of the explanatory power. When the economic magnitude and statistical significance of the coefficients of interest vary widely across models with and without firm fixed effects, researchers will have a chance to discuss how their variables of interest explain outcome variables along different dimensions.

This paper adds to the corporate finance, innovation economics, and applied econometrics literature as follows. First, noting that corporate finance studies tend to solve firm-specific, time-invariant unobservables issues by using fixed effects models, we illustrate the potential biases of such a practice by testing the intuitive R&D-patent relation. More importantly, we offer several feasible and easy-to-implement methodologies to enable corporate finance researchers to analyze the effects of economic variables that are persistent in time, such as ownership structure and managerial capability (e.g., Zhou, 2001). In particular, we provide explanations that they may use to justify their choice of regression specifications without firm fixed effects (or with only a limited set of firm dummies).

From a broader perspective, we demonstrate how to apply modern machine learning techniques to corporate finance research, in particular for the selection of relevant covariates (e.g., Chinco et al.,

2019; Feng et al., 2020; Gu et al., 2020; Erel et al., 2021) and individual dummies (Kock and Tang, 2019; Chan and Mátyás, 2022; Semenova et al., 2023). Without theoretical/structural models, it is often challenging for researchers to determine input variables to be included in regressions and to address endogeneity (e.g., Coles et al., 2012; Roberts and Whited, 2013). The PRL and DML methods we propose offer researchers a more objective approach for covariate selection; moreover, this approach is robust to the existence of between and within heterogeneity.

This study also adds to the literature by empirically justifying prior studies' choice of not including firm fixed effects to estimate knowledge production functions (Pakes and Griliches, 1984; Blundell et al., 1995; Hall et al., 2007; Noel and Schankerman, 2013). The advanced machine learning techniques we use to restore the positive R&D-patent relation facilitate economists' exploration of new factors in knowledge production. The fact that only a small portion of individual firm dummies are selected by the PRL and DML methods indicates that placing too much emphasis on firm fixed effects may restrict researchers' attention with respect to within-firm heterogeneity, which would cause them to miss important explanatory variables for between-firm heterogeneity.

The rest of our paper proceeds as follows. In Section 2, we review the literature on knowledge production functions and recent studies on new factors of firms' patent output. In Section 3, we present our data sources and empirical designs. In Section 4, we examine the R&D-patent relation in OLS regressions without and with firm fixed effects and discuss between vs. within R-squared. We then discuss the adjusted Hausman-Taylor estimators in Section 5 and the PRL and DML methods in Section 6. Simulations that highlight the weights of within and between variations are presented in Section 7. In Section 8, we examine the R&D-patent relation in Poisson regressions. We conclude this paper with Section 9. Technical details of between and within R-squared, PRL, and DML methods and supplementary tables and figures are provided in the Internet Appendix.

## 2. A Missing R&D-Patent Link in the Recent Literature

As an essential class of intangible capital and intellectual property, patents have been widely regarded as an important indicator of firms' innovation output (Kamien and Schwartz, 1975; Griliches, 1990).[7] With the surge of technology competition and patent lawsuits, researchers have gained more interest in identifying and analyzing the driving forces for firms' patent output. Their accumulated efforts in this direction have led to a burgeoning literature on the new factors of corporate innovation.

[7] Griliches (1998, chap. 13) noted *"[n]othing else even comes close in the quantity of available data, accessibility, and the potential industrial, organizational, and technological detail."*

The foundation for this literature can be traced back to a Cobb-Douglas production function for the creation of knowledge capital (e.g., Pakes and Griliches, 1984; Hall et al., 1986; Kortum, 1993). Such a knowledge production function can be tested using reduced-form OLS regressions with a patent-based dependent variable, and many explanatory variables that reflect different input factors (including R&D) that may contribute to knowledge accumulation. With some modifications, the function can also be tested using Poisson or negative binomial regressions.

After a thorough review of the literature,[8] we focus on 36 papers that are most relevant to the R&D-patent relation: they examine how patent output is explained by variables of interest and include R&D input as an independent variable. Table 1 provides an overview of these studies, which were published from 2007 to 2021. In these papers, patent output measures include the number of patents a firm produces in a period (patent counts), the number of forward citations received by these patents (sometimes referred to as "citation-weighted patent counts"), and their modifications (e.g., truncation-adjusted patent counts, forward citations per patent).[9] Among these papers, 30 include both patents and forward citations in their studies; of the rest, four studies use only patents, and two use only forward citations. Their R&D input measures can be classified as R&D intensity and R&D stock. R&D intensity includes R&D expenses (or their multi-year sum) scaled by total assets, sales, or market equity. R&D stock includes R&D expenses (or their multi-year sum) in logarithm. Among the 36 papers, 27 use R&D intensity and 10 use R&D stock (note: one paper uses both of them).

We find that 21 papers include at least one regression with firm fixed effects, and 15 studies do not consider firm FEs models. In addition, OLS regressions are more popular in the literature: 30 studies use OLS regressions as the major estimation method. Only six (four) studies use the Poisson (negative binomial) model.[10]

We analyze the statistical significance of the R&D-patent relation (i.e., whether the R&D

[8]We start our search with papers covered by the review papers of Ederer and Manso (2011), He and Tian (2018), and Lerner and Seru (2022) as well as our own reading lists. We then restrict the publications to 197 journal articles published in the following journals: Econometrica, Journal of Accounting and Economics, Journal of Financial Economics, Journal of Financial and Quantitative Analysis, Journal of Law and Economics, Management Science, Review of Financial Studies, The American Economic Review, The Journal of Finance, and The Review of Economics and Statistics. Among these journal articles, 1.52% were published in the 1980s, 4.06% in the 1990s, 15.74% in the 2000s, and 62.44% in the 2010s.

[9]We do not consider other patent-based variables such as basicness, exploration, exploitation, originality, and generality.

[10]For those studies that passed our screening conditions on R&D, patent, and citation definitions, we find only one paper that uses a random effect model (Gomes-Casseres et al., 2006), one that uses a Fama Macbeth procedure (Cohen et al., 2013), one that uses a hierarchical linear model (Griffin et al., 2021), and two that use Tobit models (Faleye et al., 2011; Celikyurt et al., 2014). We exclude those studies from our discussion.

coefficients are significantly positive at the 5% level or lower) in these selected studies that differ in estimation methods, dependent variables (patents or citations), and R&D input (intensity or stock). We first focus on studies using OLS estimation. Panels (a) and (b) of Figure 1 present an overview of studies using the number of patents as the dependent variable, and Panels (c) and (d) of Figure 1 present an overview of studies using the number of forward citations as the dependent variable.

As every article presents multiple estimates on the R&D-patent/citation relation, we design Figure 1 in two ways: an article-based counting method in Panels (a) and (c); and a regression-based counting method in Panels (b) and (d). For article-based counting, we present the number of articles in which at least one of the estimates satisfies the marked condition in each step (i.e., R&D intensity or stock, with or without firm fixed effects, and R&D coefficients being significantly positive or not). Thus, the numbers in the parentheses of the child nodes do not exactly add up to the numbers in the parenthesis of the parent node. For our regression-based counting method, we present the number of all regression estimates of all articles that satisfy the marked condition.

Panel (a) of Figure 1 starts with 28 papers that consider patent counts as the dependent variable. Among 24 studies that use R&D intensity as the input, 11 control for firm fixed effects. In this strand, 7 out of 11 papers (63.6%) include any significantly positive R&D estimates. On the other hand, 6 of 11 papers (54.5%) include any negative or insignificantly positive R&D estimates. Among the other 14 studies that do not control for firm fixed effects, all include at least one significantly positive R&D estimate (and only 2 out of 14 (14.3%) report any negative or insignificantly positive R&D estimates). As for the studies based on R&D stock tht appear in the lower part of this figure, we do not discuss them due to their small sample size (only five).

Panel (b) starts with 134 regression estimates and presents largely similar results. Among 122 regressions that use R&D intensity as the input, 66 control for firm fixed effects. Next, 28 out of 66 regressions (42.4%) post negative or insignificantly positive R&D coefficients. Among the other 56 regressions without firm fixed effects, only five regressions fail to discover a significant R&D-patent relation.

Panels (c) and (d) of Figure 1 analyze the R&D-citation relation in the same framework, and we find similar patterns as with the R&D-patent relation. As a result, we argue that the R&D-patent relation is missing in a substantial number (roughly half) of prior studies based on OLS regressions.

Figure IA.1 in the Internet Appendix offers an overview of prior studies based on count mod-

els (i.e., Poisson and negative binomial regressions).[11] A qualitatively similar pattern is found.

Our literature review connects the missing R&D effect to firm fixed effects. Figure 1 and Figure IA.1 collectively present a pattern that the important role of R&D input is not supported by a substantial part (40% to 50%) of prior studies' regressions with firm fixed effects. On the other hand, a positive R&D-patent relation is much more likely to hold in regressions without firm fixed effects. This pattern is consistent with the findings of Aghion et al. (2013) and Balsmeier et al. (2017), and supports our concern for "throwing the baby out with the bathwater." As discussed in the economics literature, controlling for firm FEs is problematic in the estimation of the R&D-patent relation because R&D input changes slowly over time and is highly correlated with firms' individual effects (Hausman et al., 1984; Pakes and Griliches, 1984; Blundell et al., 1995; Zhou, 2001; Hall et al., 2007; Noel and Schankerman, 2013). Moreover, small variation in within-firm may result in large measurement errors (Griliches and Hausman, 1986; Jennings et al., 2024).

Nevertheless, as we are well aware of heterogeneity in firm-level unobservables and associated endogeneity concerns, it is unrealistic to simply ignore firm FE models in empirical analyses. Thus, a more appropriate econometric procedure for identifying the explanatory power for R&D input (as well as other important factors that are persistent in time) is needed.

## 3. Data and Empirical Methods

In this section, we discuss how we construct our sample for our empirical analysis, how we measure patent output, how we measure R&D input, and how we examine the R&D-patent relation with and without firm fixed effects.

### *3.1. Sample formation*

To measure firms' patent output, we collect patent and citation data from the PatentsView database maintained by the US Patent and Trademark Office (USPTO). The PatentsView database provides detailed information on all patents granted by the USPTO since 1976. We then link the PatentsView data to publicly listed firms in the Center for Research in Security Prices ("CRSP" henceforth) database and the Compustat Industrial Annual files ("Compustat" hereafter) that provide firms' accounting and financial information using the patent assignee information of Kogan

[11] Similar to the prior figure, Panels (a) and (c) of this figure are based on the article-based counting method; and Panels (b) and (d) are based on the regression-based counting method. As the high-dimensional FEs Poisson regression has not been available until recently, we also include the following studies that use the pre-sample mean of patent output as a control variable to capture between-firm heterogeneity: Aghion et al. (2013); Bena et al. (2017); Blanco and Wehrheim (2017); Bloom et al. (2013); Custódio and Metzger (2014); Galasso and Simcoe (2011).

et al. (2017). We exclude financial and utility firms with four-digit standard industrial classification (SIC) codes in 6000-6999 and 4900-4999. We only consider the ordinary shares traded on NYSE, AMEX, and NASDAQ. Firms with negative and missing total assets are excluded. In addition, we collect institutional ownership data from the Thomson Reuters Institutional Holdings (13F) database.

We consider the following three common measures to capture firm-level innovation output: Patent denotes the number of new patents filed by a firm to the USPTO per year (and is granted later), Citation denotes the number of forward citations received by these patents, and Adjcitation denotes the number of adjusted forward citations received by these patents.[12] The first measure Patent is simple yet widely used in the economics and finance literature. The two citation measures offer quality-adjusted proxies for firms' innovation output because patents that are more technologically important are likely to receive more forward citations (Trajtenberg, 1990; Hall et al., 2005; Aghion et al., 2013).

Two issues are worth discussion before we proceed. First, we use a patent's application year rather than its grant year to construct the aforementioned measures because the former time placer is closer to the occurrence of firms' innovation output (Hall et al., 2005) and facilitates our analysis for the input-output relation between R&D and patents. Second, for a firm that does not have any patent filing record in a given year, we enter zeros for its Patent, Citation, and Adjcitation.

Our first sample includes 86,341 firm-year observations of 11,544 unique firms from 1975 to 2000. We intentionally end our main sample in 2000 to be consistent with most prior studies' samples – they are based on the first version of the NBER patent database that ends in 2000. We consider an extended sample period from 1976 to 2010 and find consistent results. Given that not all firms file for patents, we also construct our second sample, which includes 45,913 firm-year observations of 4,312 unique firms that have at least one patent filled during the same period, because some prior studies only consider patenting firms in their samples (e.g., Bloom et al., 2013; Aghion et al., 2013).

### *3.2. Patent production function estimation*

As discussed earlier, the economics literature has suggested a Cobb-Douglas production function for the relation between R&D input and patent output (e.g., Pakes and Griliches, 1984; Hall et al.,

[12]For each patent, we calculate its number of adjusted forward citations as its number of forward citations scaled by the average number of forward citations of all patents that are assigned in the same subsection and are granted in the same year (Seru, 2014).

1986; Kortum, 1993) To empirically examine the R&D-patent relation, we use the OLS regression to estimate the following model:

$$Innov_{i,t+1} = \gamma\, R\&D_{i,t} + \mathbf{x}_{i,t}^{\top}\boldsymbol{\beta} + \alpha_i + \epsilon_{i,t}, \tag{1}$$

in which the dependent variable $Innov_{i,t+1}$ is ln(1+Patent), ln(1+Citation), or ln(1+Adjcitation) of firm $i$ in year $t+1$ for OLS regressions. We also consider the Poisson regression, in which $Innov_{i,t+1}$ is specified to be Poisson-distributed, with:

$$\mathbb{E}\left(Innov_{i,t+1}\middle|\, R\&D_{i,t}, \mathbf{x}_{i,t}\right) = \exp\left(\gamma\, R\&D_{i,t} + \mathbf{x}_{i,t}^{\top}\boldsymbol{\beta} + \alpha_i\right), \tag{2}$$

in which the dependent variable $Innov_{i,t+1}$ is Patent or Citation of firm $i$ in year $t+1$.

The primary variable of interest, $R\&D$, denotes firm $i$'s R&D input in year $t$. Following the literature, we consider both R&D intensity and R&D stock. Since firms' R&D input highly correlates with firm size, we also include the logarithmic value of a firm's market equity, ln(ME), at calendar year-end in our main results.

Our primary proxy for R&D input in Equations (1) and (2) is R&D/Asset (R&D intensity), which is defined as firm $i$'s five-year accumulated R&D expenses divided by total assets in the fiscal year-end of year $t$, as total assets appear to be the most common scaling variable for R&D input in prior studies. Nevertheless, we also use market equity to scale five-year accumulated R&D expenses in our robustness checks (i.e., R&D/ME). Since $R\&D$ defined in this way has been scaled, we include firm size in our regressions. Our second proxy for R&D input is R&D stock, which is measured by ln(1+R&D) as the logarithmic value of firm $i$'s five-year accumulated R&D expenses in the fiscal year-end of year $t$ plus one. When we use this R&D input variable, we do not include variables related to firm size in regressions to avoid estimation biases due to collinearity.

We acknowledge that some firms may choose not to report their R&D expenses (Koh and Reeb, 2015); thus, we also include an indicator variable (R&D missing) that equals one for firms without R&D expenses and zero otherwise. In addition, $\mathbf{x}$ denotes a set of firm characteristics that previous studies have shown as explanatory variables of firms' innovation output.[13] All explanatory

[13]This set includes the following: ln(1+Age) is the natural logarithmic value of one plus the number of years since a firm's first appearance in Compustat. ln(K/L) is the natural logarithmic value of net property, plant, and equipment (PPENT) divided by the number of employees in Compustat. Tobin Q proxies a firm's value and is defined as the market value of equity plus the book value of assets minus the book value of equity minus balance sheet deferred taxes, divided by the book value of assets. ROA, the return on asset, is the profitability measure, which is calculated as the operating income before depreciation divided by the book value of total assets. Leverage

variables are lagged for one year and winsorized at the 1st and 99th percentiles.

Table 2 reports the summary statistics and correlation coefficients of the innovation measures and explanatory variables. Panel A lists the pooled mean, median, standard deviation (Stddev), minimum (Min), 25th percentile (Q1), 75th percentile (Q3), and maximum (Max) for the entire sample. The distribution of patent measures is similar to that of prior studies' summary statistics. We find that 43% of firm-year observations missing R&D reporting. Five-year R&D input amounts to 13% and 15% of total assets and market equity, respectively. Panel B reports the pairwise correlation coefficients of innovation measures and explanatory variables. We find that patent output is highly correlated with R&D input.

## 4. Solution 1: Without vs. With Firm Fixed Effects and Between vs. Within R-squared

We first implement the reduced-form OLS regression estimation as specified in Equation (1) and Section 3.2.[14] In Table 3, we present the regression results when the dependent variables are patents, forward citations, and adjusted-forward citations in Panels A, B, and C, respectively.

In our first set of analyses, we use R&D intensity (R&D/Assets) to capture R&D input (and include ln(ME) for the size effect) in Equation (1). Columns (1) and (2) of Panel A report the estimation results when we measure a firm's innovation output using patents. For brevity, we omit the estimates of control variables in the main text but provide them in Internet Appendix Table IA.1. Column (1) presents the estimation result using firm and year fixed effects. The coefficient on R&D/Assets is 0.043 andnd insignificant. In contrast, when we exclude firm fixed effects but retain year fixed effects in Column (2), the coefficient increases to 0.593 and becomes statistically significant. This stark contrast supports our argument that firm fixed effects absorb the impact of R&D on innovation output and lead to a "missing R&D effect".

controls for the financial leverage behavior in the innovation process, defined as the long-term debt plus current debt, divided by total assets. Cash/Asset is the liquidity of firms' cash flow measures and is the ratio of cash to total asset. KZ index, following Kaplan and Zingales (1997), is the financial constraint index, which is calculated as -1.002×(Cash flow)+0.283×(Tobin Q)+3.139×(Leverage)-39.368×(Dividends)-1.315×(Cash), in which Cash flow is the gross income before extraordinary items, and Dividends is calculated as the sum of common and preferred stocks dividends. Cash flow, Dividend, and Cash are all scaled by the lag net PPENT. InstOwn represents institutional ownership and is defined as the total institutional ownership from 13F filings divided by the total number of outstanding shares. (1-HHI) is one minus the Herfindahl-Hirschman index, and (1-HHI) square captures the nonlinear relation of market competition and innovation activities. Herfindahl-Hirschman index is the sum of squared sales-based market shares of all firms in the same industry. The industry is defined using the 3-digit SIC code.

[14]We implement the fixed effects estimation using the `reghdfe` package of Correia (2016) in `STATA` that is designed to deal with OLS regression with high dimensional fixed effects.

To further assess the link between the missing R&D effect and firm fixed effects, we report the between and within R-squared in all regressions in Table 3.[15] The between R-squared reflects how much the cross-sectional variation of firms' patent output can be explained by explanatory variables ($R\&D$ and $\mathbf{x}$). For each sample firm, we first calculate its time-series average of patents and $\hat{\gamma}\,\overline{R\&D_i}+\bar{\mathbf{x}}_i{}^{\top}\hat{\boldsymbol{\beta}}$ that captures the cross-sectional explanatory power of all explanatory variables other than firm fixed effects ($\alpha$). Then the squared, cross-firm correlation coefficient of those average patents and $\hat{\gamma}\,\overline{R\&D_i}+\bar{\mathbf{x}}_i{}^{\top}\hat{\boldsymbol{\beta}}$ is the between R-squared.

On the other hand, the within R-squared captures how much the time-series variation of a firm's patent output can be explained by regression predictions in the same dimension. It can be calculated by a "demeaned" regression: it is as the R-squared from regressing patents minus their time-series averages on the explanatory variables ($R\&D$ and $\mathbf{x}$) minus their time-series averages. Reporting between and within R-squared illustrates that firms' patent output is explained along cross-sectional heterogeneity among firms (high between R-squared) or within-firm temporal dynamics (high within R-squared). All detail of these two statistics is provided in Internet Appendix Section A.

In Panel A Column (2) without firm fixed effects, the between R-squared of 0.310 is much higher than the within R-squared of 0.020. When we add firm fixed effects to regressions, the between R-square drops to 0.209 but the within R-squared increases to 0.035. This comparison offers two implications: first, the fact that the between R-squared decreases from 0.310 to 0.209 once firm fixed effects exist highlights that the cross-sectional explanatory power of R&D (and other time-persistent explanatory variables) can be "absorbed" by firm fixed effects. Second, in the data structure of the R&D-patent relation, the heterogeneity across firms is more explainable (and thus empirically important) than that within firms.

Our empirical evidence is consistent with concerns raised by Hall et al. (2005) and many other economic studies: the insignificant and negligible explanatory power of R&D input for patent output can be attributed to the fact that both R&D and patents are persistent across years (i.e., small within variation) and mainly vary across firms (i.e., large between variation). In addition, the neglected dominance of the between variation may result in biases in statistical inferences as

[15] These two statistics are common in the econometrics literature, see Cameron et al. (2010, 2022), and are reported in many regression functions in modern statistical packages. For example, both `reghdfe` and `xtreg` report the within R-squared, but only `xtreg` also produces the between R-squared. However, it is a pity that this conveniently available information is not reported in most prior studies. To fill this gap we provide a companion ado-file, `panelr2.ado`, in our GitHub repository. After estimating a model, running this script computes the corresponding overall, within, and between R-squared for the identical specification.

pointed out in Griliches and Hausman (1986); Jennings et al. (2024); Breuer and DeHaan (2024).

Columns (3) and (4) of Table 3 Panel A present our results when R&D intensity is defined as the five-year accumulated R&D expense scaled by market equity (R&D/ME) to explain patents. In Column (3) including firm and year fixed effects, the coefficient on R&D/ME is 0.026 and statistically insignificant. In contrast, when we omit firm fixed effects in Column (4), the coefficient on R&D/ME increases to 0.502, and becomes statistically significant, restoring the positive R&D-patent relation. Moreover, the existence of firm fixed effects decreases the between R-squared from 0.310 to 0.206 and increases the within R-squared from 0.019 to 0.035.

In our third set of analyses, we consider the R&D stock (ln(1+R&D)) as R&D input (and no longer include ln(ME) in Equation (1) to avoid collinearity due to firm size). Panel A shows that the coefficient on ln(1+R&D) is 0.023 in Column (5). When firm fixed effects are dropped in Column (6), the coefficient on ln(1+R&D) increases sharply to 0.140. Again, we find that fixed effects models reduce the between R-squared but increase the within R-squared.

In Panels B and C of Table 3, we consider two other measures of innovation output: the number of forward citations and the number of adjusted forward citations, respectively. The results are fairly consistent with Panel A based on patent counts.

As some prior studies focus on patenting firms only, we also consider a sample of firms that have at least one patent filled during our sample period. This reduced yet more focused sample includes 45,913 firm-year observations of 4,312 unique firms. Internet Appendix Table IA.2 presents similar patterns: once firm fixed effects are added into our regressions, the coefficients on R&D input become either statistically insignificant or much smaller in economic magnitude. Furthermore, the between R-squared is always much higher than the within R-squared but is reduced by the existence of firm fixed effects.

Table 3 and Internet Appendix Table IA.2 thus suggest that the absence of an R&D input effect is driven by firm fixed effects. We thus recommend researchers to report models without firm fixed effects. If the coefficient estimates (and statistical significance) of explanatory variables of interest substantially increase in these models, researchers can highlight those models' cross-sectional explanatory power by reporting between and within R-squared. These two statistics are easily available and will help readers understand the source of regression models' explanatory ability as well as the relative importance of between and within variations.

## 5. Solution 2: Adjusted Hausman-Taylor estimation

We also develop a novel identification strategy inspired by the Hausman-Taylor estimator (Hausman and Taylor, 1981) for the coefficients of time-invariant regressors. This approach allows us to quantitatively assess the effect of R&D input on innovation output. We start with the following empirical model:

$$Innov_{i,t+1} = \gamma\, R\&D_{i,t} + \mathbf{x}_{i,t}^{\top}\boldsymbol{\beta} + \alpha_i + \epsilon_{i,t}, \tag{3}$$

where $Innov_{i,t+1}$ denotes the innovation output of firm $i$ at year $t+1$, $R\&D_{i,t}$ denotes the R&D input of firm $i$ at year $t$, and $\mathbf{x}_{it}$ is a $k$-dimensional vector of time-varying exogenous control variables, with $t = 1, 2, \ldots, T_i$ for $i = 1, 2, \ldots, N$. $\alpha_i$ denotes firm fixed effects. Because of the persistent nature of R&D input, accurately identifying $\gamma$ using the fixed effects estimator is challenging.

Hausman and Taylor (1981) discusses the identification of the coefficient of a time-invariant variable ($z_i$) using the following model:

$$y_{i,t+1} = z_i\gamma + \mathbf{x}_{it}^{\top}\boldsymbol{\beta} + \alpha_i + \epsilon_{it}. \tag{4}$$

In Equation (4), $y_{i,t+1}$ and $z_i$ respectively correspond to $Innov_{i,t+1}$ and $R\&D_{i,t}$ in Equation (3). However, Equation (4) imposes an even stricter assumption by treating $z_i$ as completely time-invariant.[16] Assume that both $\mathbf{x}_{it}$ and $z_i$ are uncorrelated with the idiosyncratic error term $\{\epsilon_{it}\}$ across all time horizons. Additionally, following Hausman and Taylor (1981), we assume that $\mathbf{x}_{it}$ is exogenous to firm fixed effects ($\alpha_i$); that is, for all $s, t = 1, 2, \ldots, T_i$ and $i = 1, 2, \ldots, N$, $\mathbb{E}(\mathbf{x}_{it}\epsilon_{is}) = \mathbf{0}$, $\mathbb{E}(\mathbf{x}_{it}\alpha_i) = \mathbf{0}$, and $\mathbb{E}(z_i\epsilon_{it}) = 0$.[17] Hausman and Taylor (1981) propose to identify $\gamma$ and $\boldsymbol{\beta}$ and using the following moment conditions without specifically estimating $\alpha_i$:

$$\mathbb{E}\left[\tilde{\mathbf{x}}_{it}^{\top}\left(y_{i,t+1} - z_i\gamma - \mathbf{x}_{it}^{\top}\boldsymbol{\beta}\right)\right] = \mathbf{0}, \tag{5}$$

$$\mathbb{E}\left[\mathbf{x}_{it}^{\top}\left(y_{i,t+1} - z_i\gamma - \mathbf{x}_{it}^{\top}\boldsymbol{\beta}\right)\right] = \mathbf{0}, \tag{6}$$

[16] Therefore, after applying the within transformation, $z_i$ entirely vanishes, making it impossible to identify $\gamma$ with the fixed effects estimator.

[17] To maintain relevance, this paper focuses on a simplified version of the original model, considering only the case where $\mathbf{x}_{it}$ is exogenous. The original model also allows at least a part of $\mathbf{x}_{it}$ is endogenous. For a comprehensive discussion, see Hansen (2022).

where $\tilde{\mathbf{x}}_{it} = \mathbf{x}_{it} - \bar{\mathbf{x}}_i$ is the de-meaned version of $\{\mathbf{x}_{it}\}$, in which $\bar{\mathbf{x}}_i = T_i^{-1} \sum_{t=1}^{T_i} \mathbf{x}_{it}$ is the time-series mean of $\{\mathbf{x}_{it}\}$. Given the moment conditions, $\gamma$ and $\boldsymbol{\beta}$ can be consistently estimated by the 2SLS (Wooldridge, 2002; Hansen, 2022) using $\tilde{\mathbf{x}}_{it}$ as internal instrumental variables.[18] Our generalized method of moments (GMM) estimators for $\gamma$ and $\boldsymbol{\beta}$ can be consistently estimated as follows: we start with the two-stage least squares (2SLS) estimators, use the residual $(y_{i,t+1} - z_i\hat{\gamma}^{2SLS} - \mathbf{x}_{it}^\top \hat{\boldsymbol{\beta}}^{2SLS})$ for the covariance of the moments, and then use its inverse as the weighting matrix to re-estimate Equation (4) without $\alpha_i$ to obtain GMM estimators $\hat{\gamma}^{GMM}$ and $\hat{\boldsymbol{\beta}}^{GMM}$.

Back to our research question, the population mean of R&D (for which we use $\overline{R\&D}_i$ as an estimate) may correlate with firm fixed effects ($\alpha_i$) by nature. Therefore, although $R\&D_{i,t}$ itself cannot be used for moment conditions, we can use the de-meaned version of R&D, $\widetilde{R\&D}_{i,t}$=$R\&D_{i,t} - \overline{R\&D}_i$, as moment conditions because $\alpha_i$ will be differenced away and, like $\tilde{\mathbf{x}}_{i,t}$, $\widetilde{R\&D}_{i,t}$ are uncorrelated with the idiosyncratic error term $\{\epsilon_{i,t}\}$. Thus, we have the following moment conditions for Equation (3):

$$\mathbb{E}\left[\widetilde{R\&D}_{it}\left(Innov_{i,t+1} - \hat{\gamma} R\&D_{i,t} - \mathbf{x}_{it}^\top \hat{\boldsymbol{\beta}}\right)\right] = 0; \tag{7}$$

$$\mathbb{E}\left[\tilde{\mathbf{x}}_{it}^\top\left(Innov_{i,t+1} - \hat{\gamma} R\&D_{i,t} - \mathbf{x}_{it}^\top \hat{\boldsymbol{\beta}}\right)\right] = \mathbf{0}; \tag{8}$$

$$\mathbb{E}\left[\mathbf{x}_{it}^\top\left(Innov_{i,t+1} - \hat{\gamma} R\&D_{i,t} - \mathbf{x}_{it}^\top \hat{\boldsymbol{\beta}}\right)\right] = \mathbf{0}. \tag{9}$$

As a result, the adjusted Hausman-Taylor estimates for $\gamma$ (the loading on R&D input) in Equation (3) can be estimated as follows: in the first stage, we regress $R\&D_{i,t}$ on $\tilde{\mathbf{x}}_{it}$ and $\widetilde{R\&D}_{i,t}$ together with control variables $\mathbf{x}_{it}$ and year fixed effects. In the second stage, we regress $Innov_{i,t+1}$ on predicted $R\&D_{i,t}$, $\mathbf{x}_{it}$, and year fixed effects for $\hat{\gamma}^{2SLS}$.

For our GMM estimation for $\gamma$, we start with the 2SLS estimators, use the residuals $(Innov_{i,t+1} - \hat{\gamma}^{2SLS} R\&D_{i,t} - \mathbf{x}_{it}^\top \hat{\boldsymbol{\beta}}^{2SLS})$ for the covariance of the moments, and then use its inverse as the weighting matrix to re-estimate Equation (3) without $\alpha_i$ to obtain GMM estimators $\hat{\gamma}^{GMM}$.[19] These estimated $\gamma$s are our adjusted Hausman-Taylor estimator. The efficacy and efficiency of the Hausman-Taylor estimator will be discussed in Section 7.

We apply the adjusted Hausman-Taylor (HT) method to our full sample using R&D/Asset as

[18] $\mathbf{x}_{it}$ will be included in the 2SLS estimation by default. Hausman and Taylor (1981) also propose a feasible generalized least squares (FGLS) type procedure. Under the assumption that the idiosyncratic errors $\epsilon_{it}$ and the fixed effects $\alpha_i$ are strictly mean independent and homoskedastic, one can consistently estimate $\sigma_\epsilon^2 = \text{var}(\epsilon_{it})$ and $\sigma_\alpha^2 = \text{var}(\alpha_i)$. These estimates can then be utilized to estimate $\gamma$ and $\boldsymbol{\beta}$.

[19] It is easy to implement in statistical package. For instance, the STATA code will be: `ivregress gmm y control (rd = demean_rd demean_control), wmatrix(cluster firmID)`

our R&D input and present our main results in Column (1) of Table 4 (as well as the full table in Internet Appendix Table IA.1 ). Panels A, B, and C are estimation results for patents, citations, and adjusted citations, respectively.

First, the coefficients on R&D input are consistently positive and significant across all specifications and dependent variables. The coefficient estimates are 0.220, 0.551, and 0.231 for patents, citations, and adjusted citations, respectively. The magnitude of the R&D/Asset coefficients using the adjusted Hausman-Taylor method is lower than those obtained via OLS without firm fixed effects in Column (2) in Table 3.

More importantly, the R&D coefficients under the adjusted Hausman-Taylor method are closer to those from OLS without firm fixed effects rather than firm FE model. For example, in patent regression, the estimate from firm FE model is 0.041, compared to 0.220 from the adjusted Hausman-Taylor method and 0.593 from OLS without firm fixed effects. This suggests that including firm fixed effects may significantly underestimate the impact of R&D input on innovation output. Conversely, OLS without firm fixed effects fails to account for firm-specific unobserved factors, potentially biasing the R&D effect by ignoring persistency in R&D activity within each firms.

In line with our previous analysis, we use alternative R&D input measures to assess the robustness of the R&D effect in Table 5. Consistent with the results using R&D/Assets, all coefficients in Column (1) for R&D/ME and ln(1+R&D) are positive and highly significant. The adjusted Hausman-Taylor estimators generally exhibit smaller magnitudes compared to the OLS estimates without firm fixed effects. However, when compared to the firm FE model, the adjusted Hausman-Taylor estimators are larger in magnitude.

Lastly, we apply the adjusted Hausman-Taylor method to a subsample of firms that have filed at least one patent during the sample period. The results are consistent with our full-sample analysis. (Detailed estimates of the patenting firms sample can be found in the Internet Appendix Table IA.3.)

## 6. Solution 3: Machine Learning Methods

Some prior literature argues that not controlling for firm fixed effects may result in some non-negligible, omitted-variable bias for some firms or some industries. However, if we control for *all* firm dummies (i.e., firm fixed effects models), we may underestimate the effect of R&D input on patent output as shown in prior sections. Given that machine learning methods are able to facilitate the selection of predictors and control variables (Chinco et al., 2019; Feng et al., 2020; Gu et al.,

2020; Erel et al., 2021; Reeb and Zhao, 2021) and individual dummies (Kock and Tang, 2019; Chan and Mátyás, 2022; Semenova et al., 2023), we use this technique to select some "informative" firm dummies, so we may draw a more appropriate statistical inference for the R&D-patent relation. Let us elaborate on this idea as follows: suppose innovation culture is the only fixed effect in the panel and only some firms have innovation culture (and all the rest do not), our machine learning methods aim to select those with such culture (which affects both R&D and innovation output) and thus suggest us to only add those firms' dummies in regression estimations. In other words, these methods also identify firms *without* such culture and advise us not to include their dummies in estimation.

In particular, we propose the following two methods: the post-regularization LASSO regression (PRL) and double machine learning (DML).

### *6.1. Post-regularization LASSO regression (PRL)*

The first technique is the post-regularization LASSO (PRL) estimator (Chernozhukov et al., 2015). Similar to the Frisch-Waugh-Lovell estimator (FWL, Frisch and Waugh, 1933; Lovell, 1963), the PRL estimator partials out nuisance variables before the estimation and inference of the parameters of interest. However, different from FWL, the PRL estimator selects predictors and control variables using LASSO, one of the state-of-the-art machine learning algorithms.

Based on the observation that $Innov$ has a rather small within variation compared to its between variation, we consider a variation of Equation (1), which only controls for a few important firm dummies:

$$Innov_{i,t+1} = \beta_0 + \beta_1 R\&D_{i,t} + \mathbf{x}_{i,t}^{\top}\boldsymbol{\beta}_2 + \sum_{s\in\mathcal{S}} \alpha_s \text{dummy}_{s,i} + u_{i,t}, \tag{10}$$

in which $\mathcal{S}$ is a nonempty subset of $\{1, 2, \dots N\}$ that contains a few important firm dummies, and $\text{dummy}_{s,i}$ is the dummy variable such that $\text{dummy}_{s,i} = 1$ if $s = i$, and 0 otherwise.

Without loss of generality, $R\&D_{i,t}$ and $\mathbf{x}_{i,t}$ can also be written as:

$$R\&D_{i,t} = \gamma_{1,0} + \sum_{s\in\mathcal{S}} \gamma_{1,s}\text{dummy}_{s,i} + v_{1,i,t}, \text{ and } \mathbf{x}_{i,t} = \boldsymbol{\gamma}_{2,0} + \sum_{s\in\mathcal{S}} \boldsymbol{\gamma}_{2,s}\text{dummy}_{s,i} + \mathbf{v}_{2,i,t}, \tag{11}$$

Equations (10) and (11) lead to the following moment conditions:

$$\mathbb{E}\left[\left(\mathbf{x}_{i,t}-\boldsymbol{\gamma}_{2,0}-\sum_{s\in\mathcal{S}}\boldsymbol{\gamma}_{2,s}\text{dummy}_{s,i}\right)\left(Innov_{i,t+1}-\beta_0-\beta_1\,R\&D_{i,t}-\mathbf{x}_{i,t}^{\top}\boldsymbol{\beta}_2-\sum_{s\in\mathcal{S}}\alpha_s\text{dummy}_{s,i}\right)\right]=\mathbf{0},$$

$$\mathbb{E}\left[\left(R\&D_{i,t}-\gamma_{1,0}-\sum_{s\in\mathcal{S}}\gamma_{1,s}\text{dummy}_{s,i}\right)\left(Innov_{i,t+1}-\beta_0-\beta_1\,R\&D_{i,t}-\mathbf{x}_{i,t}^{\top}\boldsymbol{\beta}_2-\sum_{s\in\mathcal{S}}\alpha_s\text{dummy}_{s,i}\right)\right]=0.$$

We note that when $\mathcal{S}=\{1,2,\ldots,N\}$ (i.e., when all firm dummies are non-zero), the moment conditions are identical to the firm FE model estimation. In this sense, firm FE models can be viewed as a special case. While $\mathcal{S}$ is known, the parameters of interest can be estimated by GMM. However, in practice, $\mathcal{S}$ is usually unknown and must be selected by researchers. In this paper, we follow Chernozhukov et al. (2015) and use LASSO.

The PRL method is a three-step procedure. First, we regress all of the variables of interest, including the patent output $Innov_{i,t+1}$, the R&D input $R\&D_{i,t}$, and other controls $\mathbf{x}_{i,t}$ on all $N$ dummies using LASSO:

$$\min_{\{\alpha_j\}_{j=0}^{N}}\quad\sum_{i=1}^{N}\sum_{t=1}^{T}\left(z_{it}-\alpha_0-\sum_{j=1}^{N}\alpha_j\text{dummy}_{j,i}\right)^2+\lambda\sum_{j=1}^{N}|\alpha_j|. \tag{12}$$

In Equation (12), $z_{it}$ denotes the variables of interest, and $\lambda$ is the tuning parameter that controls the extent of shrinkage and selection. Given a non-zero tuning parameter $\lambda$, the shrinkage and selection operator would *shrink* the estimated coefficients toward zero. Furthermore, among all coefficients, the ones of dummies that are *not important* in predicting the values of $z_{it}$ will be shrunk to zero, and those dummies with non-zero estimated coefficients are thus *selected* by LASSO. The value of $\lambda$ is determined using the Bayesian information criterion (BIC). Second, we regress the variables of interest on the LASSO-selected dummies using the post-LASSO ordinary least squares to obtain the residuals. Third, we regress the residuals from the equation of $Innov_{i,t+1}$ (Equation (10)) on the residuals from the equations of $R\&D_{i,t}$ and $\mathbf{x}_{i,t}$ (Equation (11)).[20]

In the Internet Appendix B, we show that, under regularity conditions and the observation that the variables of interest depend only on a nonempty subset $\mathcal{S}$, the PRL estimator is asymptotically normally distributed. Technically, as long as the *sparsity* condition holds (i.e., the number of strong

[20]This method is straightforward to implement in statistical software. For example, the STATA code is: `poregress y rd control, controls(i.firmID) vce(cluster firmID)`.

dummies is bounded from above by an order of $\sqrt{NT}/\ln N$), the PRL estimator has a conventional asymptotic distribution, which allows a conventional inference with respect to the coefficients of interest. Intuitively, since important dummies have been controlled for at the first stage, we are able to prevent the omitted-variable bias. On the other hand, since unimportant dummies are not selected, we are able to identify the coefficient of the persistent R&D input without potential underestimation.

### *6.2. Double Machine Learning*

In addition to the PRL method, we also consider the double machine learning (DML) approach (DML, Chernozhukov et al., 2018), which is an extension of the PRL method. Before the estimation, the DML method partitions the sample into two independent folds: the main fold and the auxiliary fold. As in the PRL method, first we regress all of the variables of interest, including the patent output $Innov_{i,t+1}$, the R&D input $R\&D_{i,t}$, and other controls $\mathbf{x}_{i,t}$ on all $N$ dummies using LASSO as in Equation (12), and then we regress the variables of interest on the LASSO-selected dummies using the post-LASSO ordinary least squares. However, instead of using the full sample as in the PRL method, we only use the auxiliary fold for the partialing-out regression. Finally, we plug in the main fold of the sample into the estimated equations, obtain the residuals, and regress the residuals from the equation of $Innov_{i,t+1}$ (Equation (10)) on the residuals from the equations of $R\&D_{i,t}$ and $\mathbf{x}_{i,t}$ (Equation (11)).

To further improve efficiency, Chernozhukov et al. (2018) propose the use of *cross-fitting*. Thus, after we obtaining our estimates, we reverse the procedure, using the main fold for the first stage of variable-selection and the auxiliary fold for the estimation of parameters of interest, and take the average of the two estimates.[21] In general, the sample-splitting step in DML may split the sample into $K$ folds with a finite $K \geq 2$. In our empirical studies, we split the sample into 5 folds.

Compared to the PRL method, Chernozhukov et al. (2018) argue that sample splitting can improve the performance in inference. Intuitively, because of the independence of the main fold and the auxiliary fold, the dependence between two estimation stages is reduced. In the Internet Appendix B, we show that the DML estimator has a smaller deviation from the asymptotic approximation than the PRL method.

Notably, Semenova et al. (2023) also employ LASSO for selecting individual dummies within the DML framework. However, our objectives differ markedly: Semenova et al. (2023) focus on

[21]This method is straightforward to implement in statistical software. For example, the STATA code is: `xporegress y rd control, controls(i.firmID) vce(cluster firmID) xfolds(#fold).`

debiasing the Nickell (1981) bias in dynamic panel models, and our primary goal is to estimate the coefficients of time-persistent variables.

*6.3. Results from the PRL and DML methods*

We apply the aforementioned estimation methods to our full sample using R&D/Asset as our R&D input measure and present the main results in Table 4 (as well as the full table in the Internet Appendix Table IA.1. Panels A, B, and C are estimation results for patents, citations, and adjusted citations, respectively. Table 4 Columns (2) and (3) are PRL and DML estimators, respectively, with selected firm and year dummies.

In Panel A of Table 4 for patent output, we find that the explanatory power of R&D input is highly significantly positive. More importantly, the coefficients on R&D input are closer to the OLS estimates without firm fixed effects (Column (2) in Table 3) than to firm FE estimates (Column (1) in Table 3). For example, we find that the PRL estimates are 0.199, while the DML estimates are 0.213. These values are smaller than the estimates of 0.593 reported in Column (2) in Table 3, which do not account for firm fixed effects. However, they are significantly larger than the FE estimates of 0.041 in Columns (1) in Table 3. The same patterns are found in Panels B and C for citations and adjusted citations, respectively. Results presented in Table 4 suggest that selecting important firm dummies restores the positive R&D-patent relation. Furthermore, the observation that both PRL and DML estimates deliver R&D-elasticity that is closer to an OLS model without firm fixed effects suggests that simply including dummies for all firms may not be the best practice in empirical analysis.

To further understand the size of "optimal firm fixed effects" based on our two methods, we also report the numbers of dummies for firms and years selected by the PRL and DML methods in Table 4. Before the selection, there exist 11,570 firms and year dummies (11,544+26) in Columns (2) and (3). Column (2) of Panel A in Table 4 shows that the PRL method selects 1,241 dummies out of 11,570 firm-year dummies, corresponding to a ratio of 10.73% dummies selected in the patent regression. In Column (3), the DML method selects 15.01% of the dummies. For the citation (adjusted citation) regression, the selected ratios are 4.54% for PRL and 8.18% for DML (10.32% for PRL and 16.27% for DML). Internet Appendix Section C provides a detailed analysis of the characteristics of selected versus non-selected firms. Internet Appendix Table IA.4 lists the top 100 selected firms, while Table IA.5 examines the within-firm variation in various R&D measures for selected versus non-selected firms.

We also perform several robustness checks and find consistent results. First, we use alternative

R&D measures to examine the robustness of the R&D effect. Table 5 provides the coefficient estimates and the corresponding selected ratio for alternative R&D intensity, R&D/ME. We also use ln(1+R&D) as the proxy for R&D input and exclude ln(ME) from regression models. In the Internet Appendix Tables IA.3, we implement the same estimation as in Tables 4 and 5 using a sample of firms with at least one patent in our sample period.

We find that about 10% to 20% dummies are selected by two machine learning methods, supporting our proposal that it is inappropriate to simply include dummies for all firms in the sample. Our evidence also offers an important insight: most firm dummies are not crucial for identifying the effect of R&D input on patent output. In addition, the R&D coefficient estimates based on these two methods are closer to our OLS estimates without firm fixed effects, suggesting that the bias from adding firm fixed effects overpowers the bias from not adding any of them.

In this section, we present two feasible solutions: post-regularization LASSO regression and double machine learning, both of which are easy for empirical researchers to implement (our codes and example data are provided in footnotes and the link on the title page). These methods not only resolve the debate for adding firm fixed effects or not but also enable researchers to decide exactly which firm dummies should be added into models for better identification.

## 7. Simulation study on the within- and between-variation

### *7.1. Set-up*

In this section, we conduct simulation experiments to investigate how varying levels of between- and within-firm R&D effects affect the efficacy and efficiency of different estimators. Specifically, we examine both discrete and continuous outcomes, embedding a within-variation design into the data generation process (DGP) outlined by Cohn et al. (2022).

We simulate panel data observations $\{y_{i,t}, z_{i,t}, x_{i,t}\}$, where $i$ indexes the firm and $t$ indexes the year. $y_{i,t}$ is the discrete or the continuous dependent variable, and $z_{i,t}$ and $x_{i,t}$ proxy for R&D and control variables, respectively. Our primary interest is to understand how the between-firm and within-firm variations in $z_{i,t}$ affect different estimators. For this purpose, we define $z_{i,t} = 0.5\eta_i + 0.5\nu_{i,t}$, where $\eta_i$ and $\nu_{i,t}$ are independently drawn from normal distributions truncated at the 1st and 99th percentiles, with standard deviations $\sigma_\eta$ and $\sigma_\nu$, respectively. $\eta_i$ represents time-invariant firm fixed effects, and $\nu_{i,t}$ is the firm-and-time varying component. Consequently,

the ratio of between variation to the total variation is given by:

$$\text{Between variation ratio} = \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_\nu^2},$$

We set $\sigma_\eta = 1$, and varying the between variation ratio from 0.71 to 0.91 to analyze its impact on estimation results. A higher value in the between variation ratio reflects an increase in the proportion of between variation relative to total variation, with a corresponding decrease in within variation. We hypothesize that the fixed effects estimators will perform worse as the proportion of between variation increases.

To generate the discrete or continuous $y_{i,t}$, we adopt the DGP described by Cohn et al. (2022). For discrete outcomes, $y_{i,t}$ is drawn from a negative binomial distribution with conditional mean: $E(y_{i,t}|z_{i,t}, x_{i,t}) = \exp(\gamma z_{i,t} + x_{i,t})$, where we set the true value of $\gamma$ as 0.2. The overdispersion parameter of negative binominal distribution is set as constant $\alpha$. A larger value of $\alpha$ corresponds to a greater dispersion of $y_{i,t}$. For continuous outcome, $y_{i,t}$ is generated using a mixture model. Each mixture component follows a $\chi^2(1)$ distribution. The number of mixture components is determined by the product of the conditional mean (as above) and a log-normal random variable with mean one and variance controlled by a parameter $\alpha$.

For both count and continuous outcomes, $\alpha$ is set to 0.001, 0.5, and 2, representing cases of limited overdispersion, moderate overdispersion, and extreme overdispersion, respectively. In addition, $x_{i,t}$ is sampled from a normal distribution with zero mean and standard deviation of 2. The data is generated as a balanced panel, with 500 firms observed over 10 years each, and the Monte Carlo replicate number is 10,000.[22]

We first calculate the rejection rate for each simulated panel, defined as the percentage of the 10,000 simulated panels in which the hypothesis of $\gamma = 0$ is rejected at the 5% significant level. The higher rejection rate implies that we have more confidence in identifying the significant R&D-Patent relation. Our second and the third metrics concern the precision and variability of $\gamma$ estimates: the mean square error (MSE) is the mean of the sum of squares of the estimated deviation from the actual value, and the mean absolute error (MAE) uses the absolute distance instead of the square distance.

[22]Our simulation design is a modification of the code provided in Cohn et al. (2022), available at `https://data.mendeley.com/datasets/nc37vsf2bp/1`.

*7.2. OLS, firm fixed effects model, and adjusted Hausman-Taylor method*

Figure 2 compares the performance of firm FE models ("FE", black triangle line), OLS without firm fixed effects ("OLS", blue circle line), and adjusted Hausman-Taylor estimators ("adjHT", brown diamond line) for discrete outcomes. FE consistently shows the lowest rejection rate and the highest MSE and MAE across all between-variation ratios and overdispersion levels. In low-overdispersion cases (subplot a-(i)), FE's rejection rate declines from 13.1% to 6.6% as the between-variation ratio increases. The drop is even steeper in high-overdispersion cases (subplot a-(iii)), reaching the lowest rejection rate as 4.7%. FE also demonstrates the highest MSE, which worsens with increasing between-variation ratios: in low-overdispersion cases (subplot b-(i)), the MSE is modest but peaks at 53.8 in high-overdispersion settings (subplot b-(iii)). MAE results follow the same trend as MSE, confirming the inefficiency of FE estimator.

The adjHT estimator's rejection rate outperforms that of FE estimators, with average increases ranging from 0.4% to 1.5%. The adjHT estimators also have lower MSE and MAE compared to FE, with MSE values ranging from 3.1 to 20.9, approximately 52% to 64% of the MSE for FE estimators. A similar reduction is observed in MAE results. The MAE values of adjHT account only for 81% to 85% of the MAE of FE. OLS estimators demonstrate robust performance across all settings, consistently achieving the highest rejection rate, lowest MSE, and lowest MAE. This underscores its reliability in this simulation design.

We find similar results for continuous outcomes in Internet Appendix Figure IA.2, mirroring the patterns in Figure 2. Both discrete and continuous designs underscore the inefficiency of FE estimators, consistent with empirical R&D studies where R&D's limited time-series variation and being highly correlated with firm fixed effects hinder the ability of firm FE estimators to capture the genuine R&D-patent relation.

*7.3. PRL*

Figure 2 also shows that PRL (PRL, red square line) achieves the highest rejection rate for discrete outcomes.[23] In the low between-variation ratio and low-overdispersion scenario (subplot a-(i)), PRL achieves the highest rejection rate at 43.3%, outperforming OLS (39.0%), adjHT (14.6%), and FE (13.1%). PRL consistently demonstrates superior rejection rates which help to identify the non-zero link between $z_{i,t}$ variables and outcomes across all levels of between-variation ratios and overdispersion.

[23]Since the key distinction between PRL and DML lies only in sample splitting, we only present the simulations for PRL estimates.

In terms of parameter efficiency, PRL also achieves the lowest MSE and MAE among all estimators. For example, in the low-overdispersion scenario ($\alpha = 0.001$, subplot b-(i)), PRL achieves an MSE of 2.04 to 2.16, remaining low in the high-overdispersion scenario ($\alpha = 2$, subplot b-(iii)) at 2.44 to 2.74. By comparison, FE estimators exhibit substantially higher MSE values, ranging from 8.06 to 32.69 in subplot b-(i) and 14.81 to 53.86 in subplot b-(iii). Unlike FE, PRL maintains stable MSE and MAE values as between-group variation increases. Additionally, the distinction between PRL and OLS becomes more pronounced in MAE, where the MAE of OLS averages 1.28 times larger than that of PRL.

The high rejection rate, low error levels, and stability of PRL are not limited to discrete outcomes but extend to continuous outcomes, as shown in Figure IA.2. of the Internet Appendix. Our simulation exercise thus highlights PRL's robustness and efficiency in parameter inference and estimation across various outcome types, levels of outcome overdispersion, and degrees of between-group variation in the variable of interest.

## 8. Poisson Estimation

### *8.1. Poisson regressions without and with firm fixed effects*

To account for the discrete nature of patent and citation counts, we also examine Poisson regression models in this section. Similar to our earlier design for OLS regressions, we estimate Poisson regressions in Equation (2) using the Quasi-Maximum Likelihood of (Silva and Tenreyro, 2006).[24] All explanatory variables have been defined earlier and the standard errors are also clustered by firm. Table 6 presents our results when we use R&D/Asset as the proxy for R&D input and the full sample. Panel A (B) presents main results when the dependent variable is patent counts (citation counts). Column (1) is for Poisson regressions including firm and year fixed effects, and Column (2) is Poisson regressions without firm fixed effects. (Internet Appendix Table IA.6 provides a full set of estimates.)

Panels A and B of Table 6 indicate that the R&D coefficients are negative when firm fixed effects are included in Column (1). Specifically, the estimates for patent counts are –0.248, while for citation counts they are –0.125, respectively. However, once we remove firm fixed effects, the R&D input regains its significance and positive association with patent counts in Column (2). The coefficients increase substantially to 2.305, for patent counts, and to 2.094 for citation counts,

[24] We use `ppmlhdfe` package of Correia et al. (2020b) in `STATA` that is designed to deal with Poisson regressions with high dimensional fixed effects.

all statistically significant. Overall, Poisson regression results are consistent with our earlier OLS regression results in the following way: a strong positive R&D-patent relation exists without firm fixed effects; however, such a relation is seriously reduced or eliminated once we start to include firm fixed effects in regressions.

We also consider the following robustness checks in Table 7. First, we use alternative R&D measures to examine the robustness of our results in the count models. Panels A.1 and B.1 present results of R&D/ME in explaining patent counts and citation counts, respectively. We find that the same patterns as R&D/Assets in the Table 6 above. In addition, we also use ln(1+R&D) as the proxy for R&D input and drop ln(ME) in Poisson regressions. Panels A.2 and B.2 show that the coefficients on R&D input are significantly positive in models without firm fixed effects. When we introduce firm fixed effects to regressions, the coefficients on ln(1+R&D) drop by more than 90%. For example, in the patent count model, the coefficient is 0.054 in Column (1) of Panel A.2 when firm fixed effects are included, but it increases to 0.790 when firm fixed effects are excluded. Moreover, we find a consistent pattern when we focus on a sample of firms that have at least one patent granted during the sample period in Internet Appendix Table IA.7.

All results presented in this section suggest that the biases driven by firm fixed effects are not specific to OLS regressions. In fact, such biases appear to be a prevailing phenomenon that deserves researchers' attention and treatment.

*8.2. Machine learning in selecting firm dummies in Poisson regressions*

To select important firm dummies, we use the post-regularization LASSO Poisson regression (PRL Poisson) (Belloni et al., 2016). Specifically, we consider the variation of Equation (2):

$$\mu_{i,t} := \mathbb{E}\left(Innov_{i,t+1} \middle| R\&D_{i,t}, \mathbf{x}_{i,t}\right) = \exp\left(\alpha_0 + \sum_{s\in\mathcal{S}} \alpha_s \text{dummy}_{s,i} + \beta_1 R\&D_{i,t} + \mathbf{x}_{i,t}^{\top}\boldsymbol{\beta}_2\right), \quad (13)$$

in which $\mathcal{S}$ is a nonempty subset of $\{1, 2, \ldots N\}$ and contains a few important firm dummies, and $\text{dummy}_{s,i}$ is the dummy variable such that $\text{dummy}_{s,i} = 1$ if $s = i$, and 0 otherwise. Again, $R\&D_{i,t}$ and $\mathbf{x}_{i,t}$ can be written as:

$$R\&D_{i,t} = \gamma_{1,0} + \sum_{s\in\mathcal{S}} \gamma_{1,s}\text{dummy}_{s,i} + v_{1,i,t}, \text{ and } \mathbf{x}_{i,t} = \boldsymbol{\gamma}_{2,0} + \sum_{s\in\mathcal{S}} \boldsymbol{\gamma}_{2,s}\text{dummy}_{s,i} + \mathbf{v}_{2,i,t}, \quad (14)$$

Equations (13) and (14) lead to the following moment conditions:

$$\mathbb{E}\left[\left(\mathbf{x}_{i,t}-\boldsymbol{\gamma}_{2,0}-\sum_{s\in\mathcal{S}}\boldsymbol{\gamma}_{2,s}\text{dummy}_{s,i}\right)\left(Innov_{i,t+1}-\mu_{i,t}\right)\right]=\mathbf{0},$$

$$\mathbb{E}\left[\left(R\&D_{i,t}-\boldsymbol{\gamma}_{1,0}-\sum_{s\in\mathcal{S}}\boldsymbol{\gamma}_{1,s}\text{dummy}_{s,i}\right)\left(Innov_{i,t+1}-\mu_{i,t}\right)\right]=0.$$

Again, when $\mathcal{S}$ is known, the parameters can be estimated using the moment conditions above by GMM. When $\mathcal{S}$ is unknown, we use Poisson LASSO and LASSO to select dummy variables. Specifically, we perform Poisson LASSO of $Innov_{i,t+1}$ on $R\&D_{i,t}$, $\mathbf{x}_{i,t}$, and all dummies to select the dummies, and fit a Poisson regression of $Innov_{i,t+1}$ on $R\&D_{i,t}$, $\mathbf{x}_{i,t}$, and the selected dummies. We denote the coefficients of the selected dummies as $\tilde{\alpha}_s$. We then perform LASSO of $R\&D_{i,t}$ and $\mathbf{x}_{i,t}$ on all dummies, and fit linear regressions of $R\&D_{i,t}$ and $\mathbf{x}_{i,t}$ on the selected dummies again. Internet Appendix D provides more detailed on obtaining the PRL Poisson estimations.[25] In Internet Appendix E, we show that under regularity conditions and the observation that the variables of interest depend only on a nonempty subset $\mathcal{S}$, the PRL Poisson estimator is asymptotically normally distributed.

*8.3. Results from PRL and DML methods in Poisson regressions*

Table 6 also displays our results based on R&D/Asset for patent counts (Panel A) and citation counts (Panel B). Columns (3) and (4) are estimates of the PRL Poisson and DML Poisson, respectively. (The full tables of all estimates are provided the Table IA.6 in the Internet Appendix.)

First, we find that the PRL and DML Poisson estimates of the R&D coefficients are significantly positive. The PRL and DML Poisson estimates are closer to the Poisson estimates without any firm fixed effects. For example, in Panel A of Table 6, the PRL Poisson estimate is 2.407, which is close to 2.305–the estimate from Poisson regressions without firm fixed effects in Column (2). Additionally, we define the selected ratio as the number of selected dummies divided by the total number of dummies, as in earlier PRL and DML in OLS. The PRL Poisson and DML Poisson methods' selected ratios are again 11% to 21% for models with firm and year fixed effects. Panel B for citation counts shows similar results.

[25]The STATA codes are easy to implement as: `popoisson y rd control, controls(i.firmID) vce(cluster firmID) coef` for PRL Poisson; and `xpoisson y rd control, controls(i.firmID) vce(cluster firmID) coef xfolds(#fold)` for DML Poisson.

We also use alternative R&D measures to examine the robustness of the R&D effect in the Poisson count models. Table 7 provides the coefficient estimates and the corresponding selection ratio for alternative R&D intensity, R&D/ME, and R&D stock, ln(1+R&D). We implement the same estimation as in Table 6 using a sample of firms with at least one patent in our sample period in Internet Appendix Table IA.7. All these findings suggest that while Poisson regressions with firm fixed effects may underestimate the impact of R&D on innovation, PRL and DML methods in the Poisson framework consistently deliver a positive relation between R&D and innovation outputs by effectively accounting for firm-specific effects without entirely absorbing the variables of interest.

*8.4. Simulations in Poisson regressions*

This section compares the rejection rate, MSE, and MAE of Poisson with firm fixed effects, Poisson without firm fixed effects, and PRL Poisson methods. The data-generating process follows the design described in Section 7. Figure 3 and the Internet Appendix Figure IA.3 illustrate the performance of Poisson with firm fixed effects ("FE Poisson", black triangle line), Poisson without firm fixed effecs ("Poisson", blue circle line), and PRL Poisson ("PRL Poisson", red square line) for discrete and continuous outcomes, respectively.

Subplot (a) of Figure 3 and Figure IA.3 display the rejection rates for discrete and continuous outcomes, respectively. Across the three estimators, PRL Poisson demonstrates the highest rejection rates in medium- and high-overdispersion scenarios, and matching the 100% rejection rate achieved by Poisson for both outcome types.

In contrast, FE Poisson consistently delivers the lowest rejection rates, particularly as the between-group variation increases. In low-overdispersion scenarios (subplot a-(i)), its rejection rate declines to 95.6% for discrete outcomes and drops sharply to 58.6% for continuous outcomes. This performance gap becomes even more pronounced in medium-overdispersion scenarios (subplot a-(ii)) and high-overdispersion scenarios (subplot a-(iii)), where the rejection rate of FE Poisson deteriorates further. The disparity is especially evident for continuous outcomes, highlighting the limited ability of FE Poisson to maintain robust rejection rates under higher overdispersion or between-group variation.

The MSE and MAE of FE Poisson increase when the between variation increases, and more so in the high overdispersion cases. For example, subplot b-(iii) of Figure 3 shows that the MSE of FE Poisson increases from 3.95% to 15.99%, compared to the low overdispersion subplot b-(i) in the range between 0.07% and 0.30%. The same pattern applies to MAE, as subplot c-(iii) shows

that the MAE of FE Poisson increases from 15.66% to 31.49%, compared to the low overdispersion subplot c-(i) in the range between 2.14% and 4.35%.

The MSE of Poisson and PRL Poisson depends on the dispersion levels of the outcomes. In low dispersion scenario for discrete outcome case (subplot b-(i) and c-(i) in Figure 3), both approaches maintain low and stable error rates, with MSE ranging from 0.01% to 0.02% and MAE between 0.83 and 1.02%. In median overdispersion case (subplot b-(ii) and c-(ii)), both Poisson and PRL Poisson continue to outperform FE Poisson. Among the three methods, the PRL Poisson method achieves the smallest MAE.

In extreme-overdispersion scenarios (subplot b-(iii) and c-(iii)), trade-offs emerge between FE Poisson and PRL Poisson. At lower levels of between-group variation, FE Poisson performs better, but as between-group variation increases, PRL Poisson becomes the preferred method due to its ability to handle higher levels of variability effectively. Throughout all scenarios, Poisson consistently maintains the lowest error levels.

A similar pattern is observed in Figure IA.3 for the simulations based on continuous outcomes. Poisson consistently achieves the lowest error rates across all scenarios, while PRL Poisson demonstrates strong performance, particularly under high overdispersion or significant between-group variation. In contrast, FE Poisson shows limited robustness, with its error rates increasing sharply as overdispersion or between-group variation rises.

Overall, Poisson regressions with fixed effects are associated with lower rejection rates and higher error rates in comparison with PRL Poisson and Poisson regressions without fixed effects, especially in high-overdispersion and high between-group variation scenarios. These findings align with the results from the simulations for linear estimators in Section 7, and highlight the advantage of the machine learning methods in handling persistent explanatory variables.

## 9. Conclusion

In this paper, we examine an intriguing and puzzling phenomenon that R&D input cannot explain patent output in the emerging literature of corporate innovation. Our literature review suggests that such a missing link can be attributed to firm fixed effects in regression models. As many recent studies aim to discover new explanatory factors for firm-level patent outcome, the absence of positive R&D coefficients requires us to be cautious in interpreting the explanatory power of these driving forces.

We first examine the R&D-patent relation using regression models both without and with firm

fixed effects. By comparing the changes in both between and within R-squared across models, we show that it is indeed the existence of firm fixed effects that eliminates the explanatory power of R&D input for patent output. We then propose an adjusted Hausman-Taylor estimator to separate the R&D effect from firm-specific unobservables, which delivers coefficients on R&D input that are much closer to the point estimates of regression models without firm fixed effects than to those of fixed effects models. All these findings confirm our proposition that firm fixed effects regressions underestimate the role of R&D input (and likely other persistent variables as well).

We further propose two advanced machine learning methods, the post-regularization LASSO (PRL) estimator and its extension based on the double machine learning (DML) method, to solve the firm-specific unobservable effects and to select informative firm dummies. These advanced methods select 10% to 20% of individual firms dummies, suggesting that many firm dummies do not have distinct explanatory power for patent output. More importantly, these two methods support a substantial R&D effect with point estimates that are much closer to regressions without firm fixed effects than to those fixed effects models. Thus, adding all firm dummies in models may sometimes bias statistical inferences more than entirely ignoring firm fixed effects.

These empirical results are also supported in our simulations that highlight between- and within-firm variations in panels for our analyses of the efficacy and efficiency of different estimators. As between-firm variation increases relative to within-firm variation, PRL performs the best and fixed effects estimators perform the worst in rejection rates and error rates. These simulation results confirm the advantage of machine learning in handling persistent explanatory variables.

We encourage researchers to use caution in interpreting the results from fixed effects models in their empirical analyses. In addition, researchers may consider (i) reporting both between and within R-squared of fixed effects models as well as estimating models without individual fixed effects; (ii) implementing the adjusted Hausman-Taylor estimator we propose; and (iii) utilizing the advanced machine learning techniques we demonstrate to be more selective in using firm dummies. These approaches can be easily implemented using the codes we prepare, which hopefully facilitate future exploration of important yet persistent factors in finance and economics.

## References

Acharya, V.V., Baghai, R.P., Subramanian, K.V., 2014. Wrongful discharge laws and innovation. The Review of Financial Studies 27, 301–346.

Aghion, P., Van Reenen, J., Zingales, L., 2013. Innovation and institutional ownership. American Economic Review 103, 277–304.

Amore, M.D., Schneider, C., Žaldokas, A., 2013. Credit supply and corporate innovation. Journal of Financial Economics 109, 835–855.

Angrist, J.D., Pischke, J.S., 2009. Mostly harmless econometrics: An empiricist's companion. Princeton University Press.

Arora, A., Belenzon, S., Sheer, L., 2017. Back to basics: Why do firms invest in research? NBER Working Paper .

Atanassov, J., Liu, X., 2020. Can corporate income tax cuts stimulate innovation? Journal of Financial and Quantitative Analysis 55, 1415–1465.

Balsmeier, B., Fleming, L., Manso, G., 2017. Independent boards and innovation. Journal of Financial Economics 123, 536–557.

Belloni, A., Chernozhukov, V., Wei, Y., 2016. Post-selection inference for generalized linear models with many controls. Journal of Business & Economic Statistics 34, 606–619.

Bellstam, G., Bhagat, S., Cookson, J.A., 2021. A text-based analysis of corporate innovation. Management Science 67, 4004–4031.

Bena, J., Ferreira, M.A., Matos, P., Pires, P., 2017. Are foreign investors locusts? The long-term effects of foreign institutional ownership. Journal of Financial Economics 126, 122–146.

Blanco, I., Wehrheim, D., 2017. The bright side of financial derivatives: Options trading and firm innovation. Journal of Financial Economics 125, 99–119.

Bloom, N., Schankerman, M., Van Reenen, J., 2013. Identifying technology spillovers and product market rivalry. Econometrica 81, 1347–1393.

Blundell, R., Griffith, R., Reenen, J.V., 1995. Dynamic count data models of technological innovation. The Economic Journal 105, 333–344.

Blundell, R., Griffith, R., Van Reenen, J., 1999. Market share, market value and innovation in a panel of British manufacturing firms. The Review of Economic Studies 66, 529–554.

Breuer, M., DeHaan, E., 2024. Using and interpreting fixed effects models. Journal of Accounting Research 62, 1183–1226.

Cameron, A.C., Trivedi, P.K., et al., 2010. Microeconometrics using stata. Stata press College Station, TX.

Cameron, A.C., Trivedi, P.K., et al., 2022. Microeconometrics using stata. Second edition. Stata press College Station, TX.

Celikyurt, U., Sevilir, M., Shivdasani, A., 2014. Venture capitalists on boards of mature public firms. The Review of Financial Studies 27, 56–101.

Chan, F., Mátyás, L., 2022. Linear econometric models with machine learning, in: Econometrics with Machine Learning. Springer Cham, pp. 1–39.

Chang, X., Chen, Y., Wang, S.Q., Zhang, K., Zhang, W., 2019. Credit default swaps and corporate innovation. Journal of Financial Economics 134, 474–500.

Chang, X., Fu, K., Low, A., Zhang, W., 2015. Non-executive employee stock options and corporate innovation. Journal of Financial Economics 115, 168–188.

Chemmanur, T.J., Kong, L., Krishnan, K., Yu, Q., 2019. Top management human capital, inventor mobility, and corporate innovation. Journal of Financial and Quantitative Analysis 54, 2383–2422.

Chemmanur, T.J., Loutskina, E., Tian, X., 2014. Corporate venture capital, value creation, and innovation. The Review of Financial Studies 27, 2434–2473.

Chemmanur, T.J., Tian, X., 2018. Do antitakeover provisions spur corporate innovation? A regression discontinuity analysis. Journal of Financial and Quantitative Analysis 53, 1163–1194.

Chen, M.A., Wu, Q., Yang, B., 2019. How valuable is FinTech innovation? The Review of Financial Studies 32, 2062–2106.

Chen, Y., Podolski, E.J., Rhee, S.G., Veeraraghavan, M., 2014. Local gambling preferences and corporate innovative success. Journal of Financial and Quantitative Analysis 49, 77–106.

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C.B., Newey, W., Robins, J., 2018. Double/debiased machine learning for treatment and structural parameters. The Econometrics Journal 21, C1–C68.

Chernozhukov, V., Hansen, C.B., Spindler, M., 2015. Post-selection and post-regularization inference in linear models with many controls and instruments. American Economic Review Papers and Proceedings 105, 486–490.

Chinco, A., Clark-Joseph, A.D., Ye, M., 2019. Sparse signals in the cross-section of returns. The Journal of Finance 74, 449–492.

Chu, Y., Tian, X., Wang, W., 2019. Corporate innovation along the supply chain. Management Science 65, 2445–2466.

Cohen, L., Diether, K., Malloy, C., 2013. Misvaluing innovation. The Review of Financial Studies 26, 635–666.

Cohen, W.M., Levinthal, D.A., 1989. Innovation and learning: the two faces of R&D. The Economic Journal 99, 569–596.

Cohn, J.B., Liu, Z., Wardlaw, M.I., 2022. Count (and count-like) data in finance. Journal of Financial Economics 146, 529–551.

Coles, J.L., Lemmon, M.L., Meschke, J.F., 2012. Structural models and endogeneity in corporate finance: The link between managerial ownership and corporate performance. Journal of Financial Economics 103, 149–168.

Correia, S., 2016. Linear models with high-dimensional fixed effects: An efficient and feasible estimator. Working Paper.

Correia, S., Guimarães, P., Zylkin, T., 2020a. Fast poisson estimation with high-dimensional fixed effects. The Stata Journal 20, 95–115.

Correia, S., Guimarães, P., Zylkin, T., 2020b. Fast Poisson estimation with high-dimensional fixed effects. The Stata Journal 20, 95–115.

Custódio, C., Ferreira, M.A., Matos, P., 2019. Do general managerial skills spur innovation? Management Science 65, 459–476.

Custódio, C., Metzger, D., 2014. Financial expert CEOs: CEOs work experience and firm s financial policies. Journal of Financial Economics 114, 125–154.

Ederer, F., Manso, G., 2011. Incentives for innovation: Bankruptcy, corporate governance, and compensation systems. Handbook of Law, Innovation, and Growth , 90–111.

Erel, I., Stern, L.H., Tan, C., Weisbach, M.S., 2021. Selecting directors using machine learning. The Review of Financial Studies 34, 3226–3264.

Faleye, O., Hoitash, R., Hoitash, U., 2011. The costs of intense board monitoring. Journal of Financial Economics 101, 160–181.

Faleye, O., Kovacs, T., Venkateswaran, A., 2014. Do better-connected CEOs innovate more? Journal of Financial and Quantitative Analysis 49, 1201–1225.

Fang, V.W., Tian, X., Tice, S., 2014. Does stock liquidity enhance or impede firm innovation? The Journal of Finance 69, 2085–2125.

Feng, G., Giglio, S., Xiu, D., 2020. Taming the factor zoo: A test of new factors. The Journal of Finance 75, 1327–1370.

Flammer, C., Kacperczyk, A., 2016. The impact of stakeholder orientation on innovation: Evidence from a natural experiment. Management Science 62, 1982–2001.

Frisch, R., Waugh, F.V., 1933. Partial time regressions as compared with individual trends. Econometrica 1, 387–401.

Fu, R., Kraft, A., Tian, X., Zhang, H., Zuo, L., 2020. Financial reporting frequency and corporate innovation. The Journal of Law and Economics 63, 501–530.

Galasso, A., Simcoe, T.S., 2011. CEO overconfidence and innovation. Management Science 57, 1469–1484.

Gao, H., Zhang, W., 2017. Employment nondiscrimination acts and corporate innovation. Management Science 63, 2982–2999.

Gomes-Casseres, B., Hagedoorn, J., Jaffe, A.B., 2006. Do alliances promote knowledge flows? Journal of Financial Economics 80, 5–33.

Griffin, D., Li, K., Xu, T., 2021. Board gender diversity and corporate innovation: International evidence. Journal of Financial and Quantitative Analysis 56, 123–154.

Griliches, Z., 1990. Patent statistics as economic indicators: A survey. Journal of Economic Literature 28, 1661–1707.

Griliches, Z., 1998. Patent statistics as economic indicators: A survey, in: R&D and productivity: The econometric evidence. University of Chicago Press, pp. 287–343.

Griliches, Z., Hausman, J.A., 1986. Errors in variables in panel data. Journal of Econometrics 31, 93–118.

Gu, S., Kelly, B., Xiu, D., 2020. Empirical asset pricing via machine learning. The Review of Financial Studies 33, 2223–2273.

Hall, B.H., Griliches, Z., Hausman, J.A., 1986. Patents and R and D: Is there a lag? International Economic Review 27, 265–283.

Hall, B.H., Jaffe, A., Trajtenberg, M., 2005. Market value and patent citations. RAND Journal of Economics 36, 16–38.

Hall, B.H., Thoma, G., Torrisi, S., 2007. The market value of patents and R&D: Evidence from European firms., in: Academy of Management Proceedings, Academy of Management Briarcliff Manor, NY 10510. pp. 1–6.

Hansen, B., 2022. Econometrics. Princeton University Press.

Hausman, J., Hall, B.H., Griliches, Z., 1984. Econometric models for count data with an application to the patents-R&D relationship. Econometrica 52, 909–938.

Hausman, J.A., Taylor, W.E., 1981. Panel data and unobservable individual effects. Econometrica: Journal of the Econometric society , 1377–1398.

He, J., Tian, X., 2018. Finance and corporate innovation: A survey. Asia-Pacific Journal of Financial Studies 47, 165–212.

He, J.J., Tian, X., 2013. The dark side of analyst coverage: The case of innovation. Journal of Financial Economics 109, 856–878.

Hirshleifer, D., Low, A., Teoh, S.H., 2012. Are overconfident CEOs better innovators? The Journal of Finance 67, 1457–1498.

Huang, Q., Yuan, T., 2021. Does political corruption impede firm innovation? Evidence from the United States. Journal of Financial and Quantitative Analysis 56, 213–248.

Imbens, G.W., Wooldridge, J.M., 2009. Recent developments in the econometrics of program evaluation. Journal of

economic literature 47, 5–86.

Islam, E., Zein, J., 2020. Inventor CEOs. Journal of Financial Economics 135, 505–527.

Jennings, J., Kim, J.M., Lee, J., Taylor, D., 2024. Measurement error, fixed effects, and false positives in accounting research. Review of Accounting Studies 29, 959–995.

Kamien, M.I., Schwartz, N.L., 1975. Market structure and innovation: A survey. Journal of Economic Literature 13, 1–37.

Kaplan, S.N., Zingales, L., 1997. Do investment-cash flow sensitivities provide useful measures of financing constraints? The Quarterly Journal of Economics 112, 169–215.

Kock, A.B., Tang, H., 2019. Uniform inference in high-dimensional dynamic panel data models with approximately sparse fixed effects. Econometric Theory 35, 295–359.

Kogan, L., Papanikolaou, D., Seru, A., Stoffman, N., 2017. Technological innovation, resource allocation, and growth. The Quarterly Journal of Economics 132, 665–712.

Koh, P.S., Reeb, D.M., 2015. Missing R&D. Journal of Accounting and Economics 60, 73–94.

Kong, L., 2020. Government spending and corporate innovation. Management Science 66, 1584–1604.

Kortum, S., 1993. Equilibrium R&D and the patent–R&R ratio: US evidence. The American Economic Review 83, 450–457.

Lerner, J., Seru, A., 2022. The use and misuse of patent data: Issues for finance and beyond. The Review of Financial Studies 35, 2667–2704.

Lerner, J., Wulf, J., 2007. Innovation and incentives: Evidence from corporate R&D. The Review of Economics and Statistics 89, 634–644.

Lovell, M.C., 1963. Seasonal adjustment of economic time series and multiple regression analysis. Journal of the American Statistical Association 58, 993–1010.

Luong, H., Moshirian, F., Nguyen, L., Tian, X., Zhang, B., 2017. How do foreign institutional investors enhance firm innovation? Journal of Financial and Quantitative Analysis 52, 1449–1490.

Nickell, S., 1981. Biases in dynamic models with fixed effects. Econometrica 49, 1824–1851.

Noel, M., Schankerman, M., 2013. Strategic patenting and software innovation. The Journal of Industrial Economics 61, 481–520.

Ovtchinnikov, A.V., Reza, S.W., Wu, Y., 2020. Political activism and firm innovation. Journal of Financial and Quantitative Analysis 55, 989–1024.

Pakes, A., Griliches, Z., 1984. Patents and R&D at the firm level: A first look, in: R&D, Patents, and Productivity. University of Chicago Press, pp. 55–72.

Reeb, D.M., Zhao, W., 2021. Disregarding the shoulders of giants: Inferences from innovation research. David M. Reeb, and Wanli Zhao .

Roberts, M.R., Whited, T.M., 2013. Endogeneity in empirical corporate finance, in: Handbook of the Economics of Finance. volume 2, pp. 493–572.

Semenova, V., Goldman, M., Chernozhukov, V., Taddy, M., 2023. Inference on heterogeneous treatment effects in high-dimensional dynamic panels under weak dependence. Quantitative Economics 14, 471–510.

Seru, A., 2014. Firm boundaries matter: Evidence from conglomerates and R&D activity. Journal of Financial Economics 111, 381–405.

Silva, J.S., Tenreyro, S., 2006. The log of gravity. The Review of Economics and Statistics 88, 641–658.

Sunder, J., Sunder, S.V., Zhang, J., 2017. Pilot CEOs and corporate innovation. Journal of Financial Economics 123, 209–224.

Tian, X., Wang, T.Y., 2014. Tolerance for failure and corporate innovation. The Review of Financial Studies 27, 211–255.

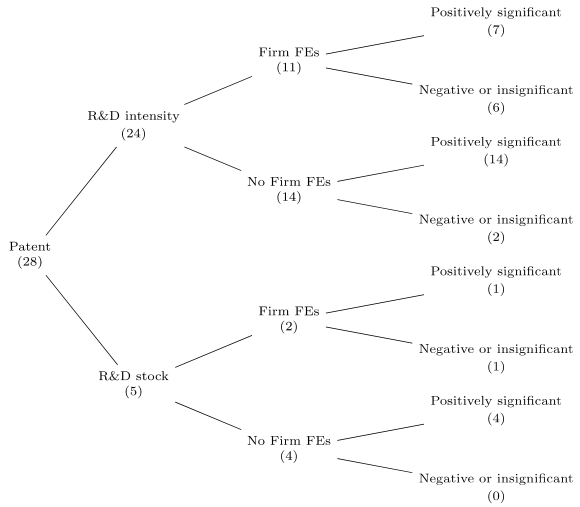
Tibshirani, R., 1996. Regression shrinkage and selection via the LASSO. Journal of the Royal Statistical Society. Series B (Methodological) 58, 267–288.

Trajtenberg, M., 1990. A penny for your quotes: Patent citations and the value of innovations. The Rand Journal of Economics 21, 172–187.

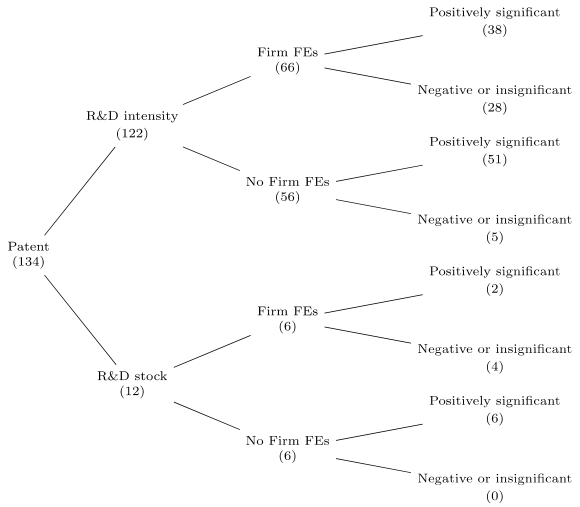
Wooldridge, J.M., 2002. Econometric analysis of cross section and panel data mit press. Cambridge, ma 108, 245–254.

Zhong, R.I., 2018. Transparency and firm innovation. Journal of Accounting and Economics 66, 67–93.

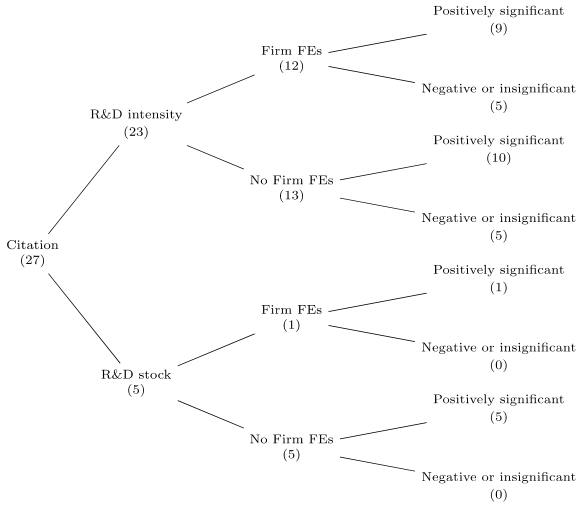
Zhou, X., 2001. Understanding the determinants of managerial ownership and the link between ownership and performance: Comment. Journal of Financial Economics 62, 559–571.



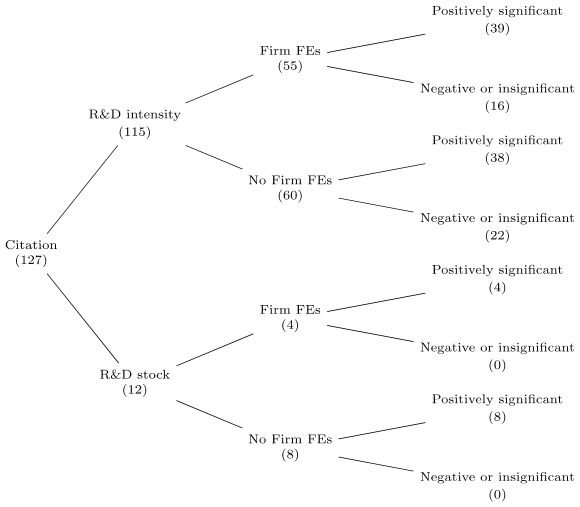

(a) Patent OLS model: article number




(b) Patent OLS model: regression number

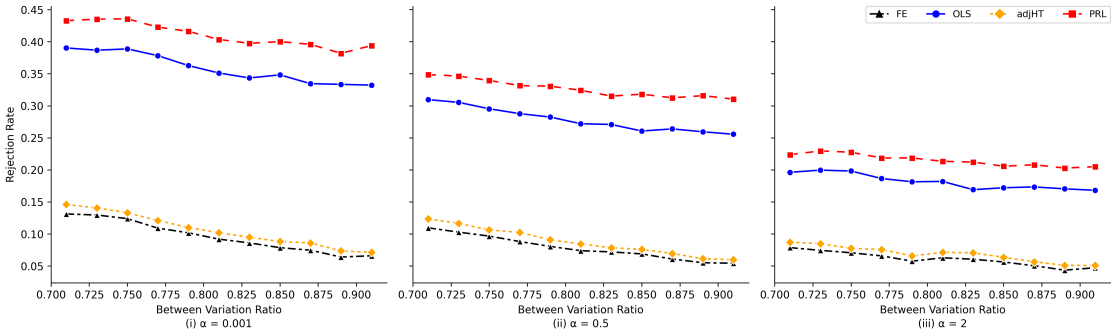



(c) Citation OLS model: article number

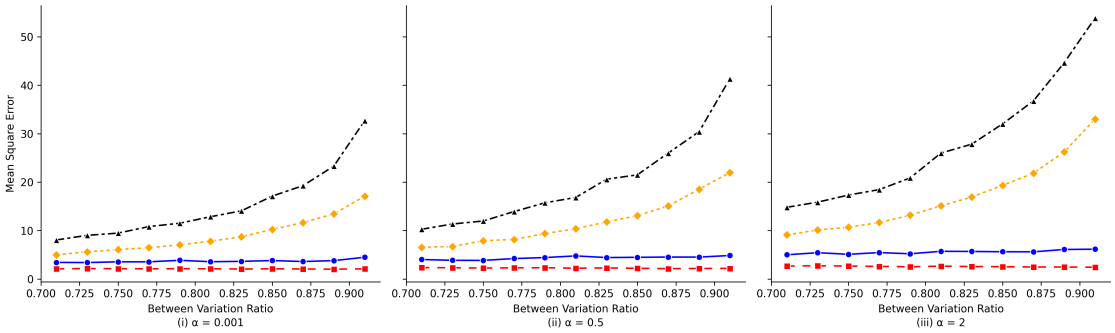



(d) Citation OLS model: regression number

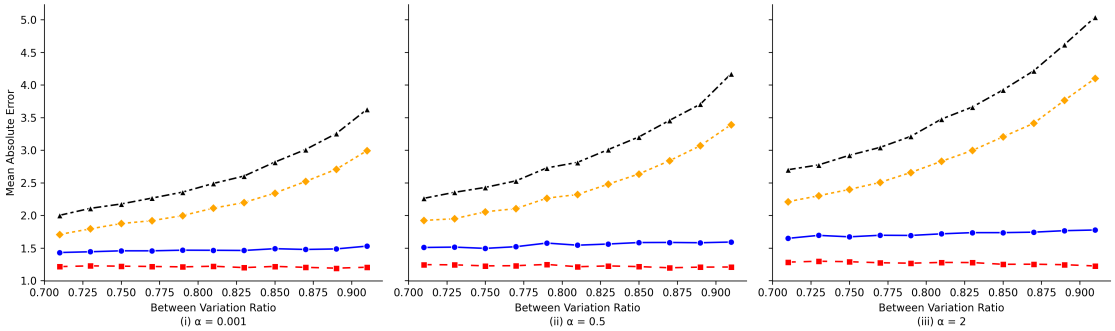
Figure 1: Patent and citation OLS studies




(a) Rejection rate

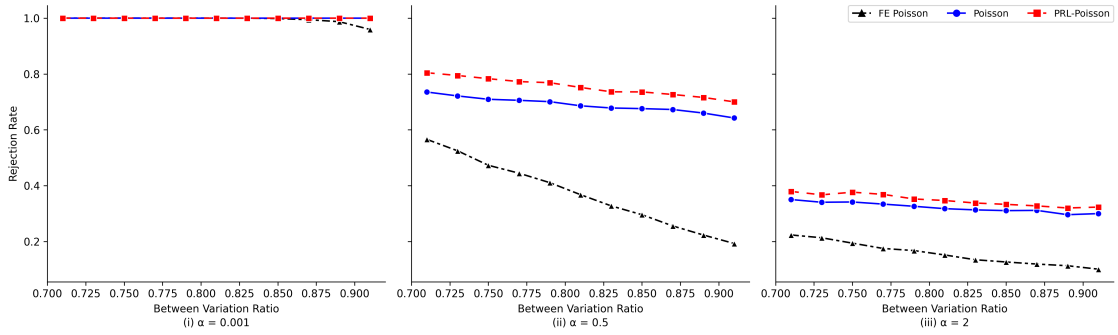



(b) Mean square error

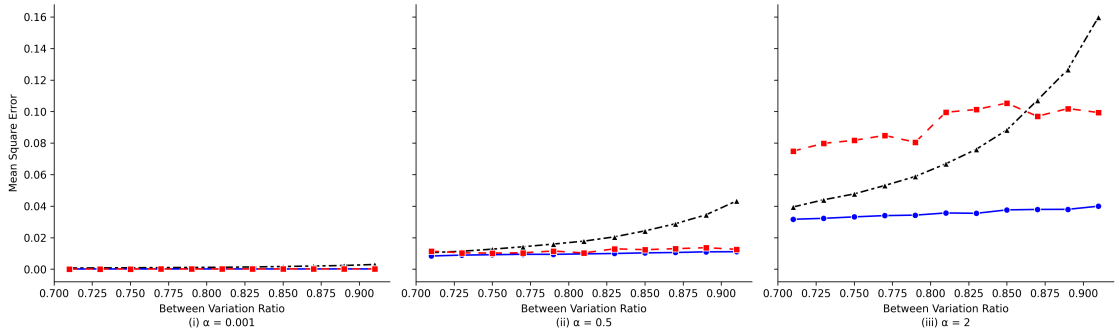



(c) Mean absolute error

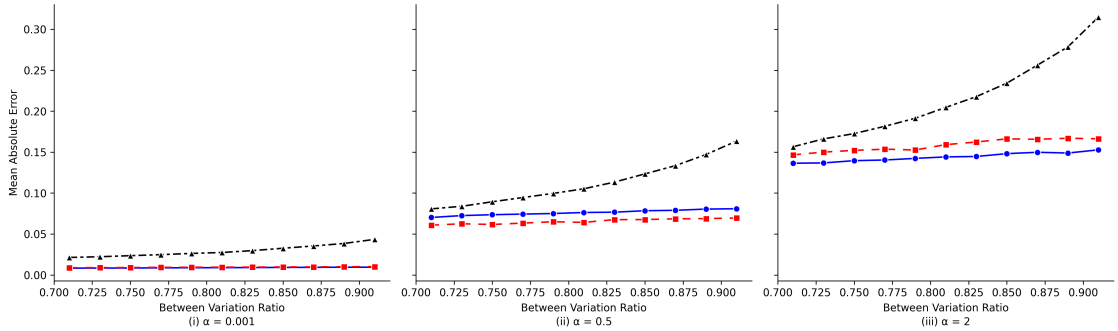
Figure 2: Simulation rejection rates and error rates for discrete outcomes: FE, OLS, adjHT, and PRL. This figure compares the rejection and error rates for four estimators: FE (regression with full set of firm dummies), OLS (regression without any firm dummies), adjHT (adjusted Hausman-Taylor), and PRL (post-regularization LASSO). The discrete outcome $y_{i,t}$ is generated from the negative binominal with conditional mean $\exp(0.2z_{i,t} + x_{i,t})$, and $z_{i,t} = 0.5\eta_i + 0.5\nu_{i,t}$. $\eta_i$ and $\nu_{i,t}$ are independently drawn from normal distributions truncated at the 1st and 99th percentiles, with standard deviations $\sigma_\eta$ and $\sigma_\nu$. The between variation ratio is defined as $\sigma_\eta^2/(\sigma_\eta^2+\sigma_\nu^2)$. Subplots (i), (ii), and (iii) represent low ($\alpha = 0.001$), moderate ($\alpha = 0.5$), and high overdispersion ($\alpha = 2$) levels of the negative binominal outcomes, respectively.




(a) Rejection rate




(b) Mean square error




(c) Mean absolute error

Figure 3: Simulation rejection rates and error rates for discrete outcomes: FE Poisson, Poisson, and PRL Poisson. This figure compares the rejection and error rates for three estimators: FE Poisson (Poisson regression with full set of firm dummies), Poisson (Poisson regression without any firm dummies), PRL Poisson (post-regularization LASSO Poisson regression). The discrete outcome $y_{i,t}$ is generated from the negative binominal with conditional mean $\exp(0.2z_{i,t} + x_{i,t})$, and $z_{i,t} = 0.5\eta_i + 0.5\nu_{i,t}$. $\eta_i$ and $\nu_{i,t}$ are independently drawn from normal distributions truncated at the 1st and 99th percentiles, with standard deviations $\sigma_\eta$ and $\sigma_\nu$. The between variation ratio is defined as $\sigma_\eta^2/(\sigma_\eta^2 + \sigma_\nu^2)$. Subplots (i), (ii), and (iii) represent low ($\alpha = 0.001$), moderate ($\alpha = 0.5$), and high overdispersion ($\alpha = 2$) levels of the negative binominal outcomes, respectively.

Table 1: R&D-Innovation literature overview

| Article | Journal | Estimation | Innovation | R&D | Firm FEs | No Firm FEs | Pos-Sig | Neg-Insig |
|---|---|---|---|---|---|---|---|---|
| Acharya et al. (2014) | RFS | OLS | Patent/Citation | Intensity | V | | V | |
| Aghion et al. (2013) | AER | OLS/Poisson/NB | Patent/Citation | Stock | V* | V | V | V |
| Amore et al. (2013) | JFE | Poisson | Patent/Citation | Stock | V | | V | V |
| Atanassov and Liu (2020) | JFQA | OLS | Patent/Citation | Intensity | V | | V | |
| Balsmeier et al. (2017) | JFE | OLS | Patent/Citation | Stock | V | V | V | V |
| Bellstam et al. (2021) | MS | OLS | Citation | Intensity | V | V | | V |
| Bena et al. (2017) | JFE | OLS/Poisson | Patent | Stock | V* | | V | |
| Blanco and Wehrheim (2017) | JFE | OLS/NB | Patent/Citation | Stock | V* | V | V | |
| Bloom et al. (2013) | ECTA | NB | Citation | Stock | V* | V | V | |
| Chang et al. (2015) | JFE | OLS | Patent/Citation | Intensity | | V | V | |
| Chang et al. (2019) | JFE | OLS | Patent/Citation | Intensity | V | | | V |
| Chemmanur et al. (2014) | RFS | OLS | Patent/Citation | Intensity | | V | V | V |
| Chemmanur and Tian (2018) | JFQA | OLS | Patent/Citation | Intensity | V | | V | |
| Chemmanur et al. (2019) | JFQA | OLS | Patent/Citation | Intensity | | V | V | V |
| Chen et al. (2014) | JFQA | OLS | Patent/Citation | Stock | | V | V | |
| Chen et al. (2019) | RFS | Poisson | Patent | Stock | V | | V | V |
| Chu et al. (2019) | MS | OLS | Patent/Citation | Intensity | | V | V | V |
| Custódio and Metzger (2014) | JFE | NB | Patent/Citation | Intensity | V* | | V | |
| Custódio et al. (2019) | MS | OLS | Patent/Citation | Intensity/Stock | | V | V | |
| Faleye et al. (2014) | JFQA | OLS | Patent/Citation | Intensity | | V | V | |
| Fang et al. (2014) | JF | OLS | Patent/Citation | Intensity | V | | V | V |
| Flammer and Kacperczyk (2016) | MS | OLS | Patent/Citation | Intensity | V | | V | |
| Fu et al. (2020) | JLE | OLS | Patent/Citation | Intensity | V | | V | |
| Galasso and Simcoe (2011) | MS | Poisson | Patent/Citation | Stock | V* | V | V | V |
| Gao and Zhang (2017) | MS | OLS | Patent/Citation | Intensity | V | | V | V |
| He and Tian (2013) | JFE | OLS | Patent/Citation | Intensity | V | | V | V |
| Hirshleifer et al. (2012) | JF | OLS | Patent/Citation | Intensity | | V | V | |
| Huang and Yuan (2021) | JFQA | OLS | Patent/Citation | Intensity | | V | V | |
| Islam and Zein (2020) | JFE | OLS | Patent/Citation | Intensity | | V | V | |
| Kong (2020) | MS | OLS | Patent/Citation | Intensity | V | | V | V |
| Lerner and Wulf (2007) | REStat | OLS | Patent | Intensity | | V | V | |
| Luong et al. (2017) | JFQA | OLS | Patent/Citation | Intensity | V | V | V | V |
| Ovtchinnikov et al. (2020) | JFQA | OLS | Patent/Citation | Intensity | | V | V | |
| Sunder et al. (2017) | JFE | Poisson | Patent/Citation | Intensity | | V | V | V |
| Tian and Wang (2014) | RFS | OLS | Patent/Citation | Intensity | | V | V | V |
| Zhong (2018) | JAE | OLS | Patent | Intensity | | V | V | |

This table summarizes the R&D and Patent/Citation research. Each column indicates at least one estimation result in tables (including tables in the main text and appendix) has the marked properties. Therefore, some columns are not mutually exclusive. The journal includes Econometrica (ECTA), Journal of Accounting and Economics (JAE), Journal of Financial Economics (JFE), Journal of Financial and Quantitative Analysis (JFQA), Journal of Law and Economics (JLE), Management Science (MS), Review of Financial Studies (RFS), The American Economic Review (AER), The Journal of Finance (JF), and The Review of Economics and Statistics (REStat). Estimation approaches include: OLS (pooled least square and panel regressions), Poisson (pooled Poisson and inflated Poisson model), and NB stand for negative binomial models. The dependent variable includes patent-type and citation-type innovation measures or both of them. The Patent includes: patent count, patent with truncated-bias adjusted, patents weighted by forward citations, logarithm values of patents, and others; and Citation includes: forward citation counts, truncation-bias adjusted citation, technology-time adjusted citation, logarithm values of citation, and others. Two forms of R&D measures are studied. R&D Intensity includes: R&D scaled by the total asset or sales, the logarithm of the scaled R&D values; and R&D stock have R&D level or logarithm of the R&D values with different weighting schemes on annual R&D expenses. Firm fixed effect include the within transformation and firm dummies and the asterisk marks the research uses the Blundell et al. (1999) presample mean scaling estimator. Pos-Sig indicates that at least one column of the related R&D-innovation estimates is positive and significant at a 5% (or less) significance level. Neg-Insig indicates that the coefficient is equal or less than zero or positively insignificant at the 5% level.

Table 2: Summary statistics and correlation

Panel A: Summary statistics

| | Mean | Stddev | Min | Q1 | Median | Q3 | Max |
|---|---|---|---|---|---|---|---|
| Patent | 7.72 | 59.63 | 0.00 | 0.00 | 0.00 | 1.00 | 4,387 |
| Citation | 207.10 | 1988.81 | 0.00 | 0.00 | 0.00 | 8.00 | 165,728 |
| Adjcitation | 8.77 | 71.22 | 0.00 | 0.00 | 0.00 | 0.40 | 5527.87 |
| ln(1+Patent) | 0.53 | 1.11 | 0.00 | 0.00 | 0.00 | 0.69 | 8.39 |
| ln(1+Citation) | 1.25 | 2.27 | 0.00 | 0.00 | 0.00 | 2.20 | 12.02 |
| ln(1+Adjcitation) | 0.54 | 1.16 | 0.00 | 0.00 | 0.00 | 0.34 | 8.62 |
| R&D/Asset | 0.13 | 0.26 | 0.00 | 0.00 | 0.00 | 0.14 | 1.64 |
| R&D/ME | 0.15 | 0.50 | 0.00 | 0.00 | 0.00 | 0.14 | 28.05 |
| ln(1+R&D) | 4.61 | 4.86 | 0.00 | 0.00 | 2.56 | 9.18 | 14.02 |
| ln(ME) | 11.13 | 2.07 | 6.99 | 9.60 | 10.95 | 12.51 | 16.41 |
| R&D missing | 0.43 | 0.50 | 0.00 | 0.00 | 0.00 | 1.00 | 1.00 |
| ln(1+Age) | 2.48 | 0.75 | 0.69 | 1.95 | 2.48 | 3.09 | 3.85 |
| ln(K/L) | 10.00 | 1.29 | 6.89 | 9.18 | 9.85 | 10.64 | 14.10 |
| Tobin Q | 1.76 | 1.66 | 0.53 | 0.94 | 1.22 | 1.85 | 12.64 |
| ROA | 0.10 | 0.18 | -0.88 | 0.06 | 0.13 | 0.19 | 0.40 |
| Leverage | 0.23 | 0.18 | 0.00 | 0.07 | 0.21 | 0.35 | 0.74 |
| Cash/Asset | 0.14 | 0.17 | 0.00 | 0.02 | 0.07 | 0.18 | 0.88 |
| KZ index | -3.42 | 10.77 | -79.54 | -3.48 | -0.54 | 1.03 | 6.79 |
| InstOwn | 0.23 | 0.24 | 0.00 | 0.01 | 0.15 | 0.40 | 0.84 |
| (1-HHI) | 0.75 | 0.20 | 0.00 | 0.70 | 0.80 | 0.89 | 0.99 |
| (1-HHI) square | 0.61 | 0.23 | 0.00 | 0.49 | 0.65 | 0.79 | 0.98 |

Panel B: Correlations

| | Patent | Citation | Adjcitation | ln(1+Patent) | ln(1+Citation) | ln(1+Adjcitation) |
|---|---|---|---|---|---|---|
| R&D/Asset | 0.05 | 0.05 | 0.05 | 0.17 | 0.22 | 0.17 |
| R&D/ME | 0.05 | 0.04 | 0.05 | 0.15 | 0.17 | 0.15 |
| ln(1+R&D) | 0.20 | 0.17 | 0.20 | 0.55 | 0.57 | 0.53 |
| ln(ME) | 0.24 | 0.20 | 0.24 | 0.48 | 0.44 | 0.47 |
| R&D missing | -0.10 | -0.08 | -0.10 | -0.31 | -0.34 | -0.30 |
| ln(1+Age) | 0.14 | 0.10 | 0.13 | 0.30 | 0.25 | 0.27 |
| ln(K/L) | 0.07 | 0.06 | 0.07 | 0.11 | 0.09 | 0.10 |
| Tobin Q | 0.03 | 0.05 | 0.04 | 0.07 | 0.11 | 0.09 |
| ROA | 0.05 | 0.04 | 0.05 | 0.09 | 0.07 | 0.09 |
| Leverage | -0.01 | -0.02 | -0.02 | -0.08 | -0.11 | -0.09 |
| Cash/Asset | -0.02 | 0.00 | -0.01 | 0.01 | 0.06 | 0.02 |
| KZ index | 0.00 | 0.00 | 0.00 | -0.01 | -0.03 | -0.01 |
| InstOwn | 0.11 | 0.10 | 0.11 | 0.26 | 0.26 | 0.26 |
| (1-HHI) | -0.02 | 0.00 | -0.01 | 0.01 | 0.02 | 0.01 |
| (1-HHI) square | -0.02 | -0.01 | -0.02 | 0.00 | 0.01 | 0.00 |

Panel A reports the pooled mean, median, standard deviation(Stddev), minimum (Min), 25th percentile (Q1), 75th percentile (Q3), and maximum (Max) for the entire sample. All variables except innovation measures (i.e., patent, citation, and adjusted citation) are winsorized at the 1st and 99th percentiles. ln(1+Patent) denotes the natural logarithmic value of 1 plus the patent count of firms filling in year $t+1$, and ln(1+Citation) (ln(1+Adjcitation)) denotes the natural logarithmic value of 1 plus (adjusted) the citation count of firm in year $t+1$. R&D/Asset is the last five years of accumulated R&D expenses divided by total assets in the fiscal year ending in year $t$. ln(ME) is the natural logarithmic value of market equity at the end of year $t$. R&D missing is a dummy variable that equals one for firms with no R&D expenses. ln(1+Age) is the natural logarithmic value of one plus the number of years since a firm's first appearance in Compustat. ln(K/L) is the natural logarithmic value of net property, plant, and equipment divided by the number of employees in Compustat. Tobin Q is the market value of equity plus the book value of assets minus the book value of equity minus balance sheet deferred taxes, divided by the book value of assets. ROA is the operating income before depreciation divided by the book value of total assets. Leverage is the long-term debt plus current debt, divided by total assets. Cash/Asset is the ratio of cash to total assets. KZ index is calculated as -1.002×(cash flow)+ 0.28×(Tobin Q)+ 3.139×(leverage)- 39.368×(Dividends)- 1.315×(Cash holdings). This calculation follows Kaplan and Zingales (1997). InstOwn is the percentage of institutional ownership defined as total institutional ownership from 13F filings divided by the total number of shares outstanding. (1-HHI) and (1-HHI) square are one minus the Herfindahl index and square of one minus the Herfindahl index. Herfindahl index is the sum of squared sales-based market shares of all firms in the same industry where industry is defined using the 3-digit SIC code. Panel B reports the pooled correlations between innovation measures and firm characteristics.

Table 3: Innovation to R&D Regression: OLS and Fixed Effects

| R&D is defined as | R&D/Asset | | R&D/ME | | ln(1+R&D) | |
|---|---|---|---|---|---|---|
| | FE | OLS | FE | OLS | FE | OLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: Patent regression** | | | | | | |
| R&D | 0.041 | 0.593*** | 0.026 | 0.502*** | 0.023*** | 0.140*** |
| | (0.028) | (0.042) | (0.018) | (0.035) | (0.003) | (0.004) |
| $R^2$ | 0.853 | 0.362 | 0.853 | 0.364 | 0.851 | 0.402 |
| Between $R^2$ | 0.209 | 0.310 | 0.206 | 0.310 | 0.257 | 0.359 |
| Within $R^2$ | 0.035 | 0.020 | 0.035 | 0.019 | 0.021 | 0.014 |
| Control variables | Y | Y | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | N | Y | N |
| Year FEs | Y | Y | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 84,620 | 86,341 | 84,620 | 86,341 |
| **Panel B: Citation regression** | | | | | | |
| R&D | -0.051 | 1.396*** | -0.024 | 1.040*** | 0.036*** | 0.286*** |
| | (0.068) | (0.084) | (0.040) | (0.064) | (0.007) | (0.006) |
| $R^2$ | 0.772 | 0.334 | 0.772 | 0.332 | 0.770 | 0.396 |
| Between $R^2$ | 0.169 | 0.325 | 0.172 | 0.321 | 0.228 | 0.395 |
| Within $R^2$ | 0.020 | 0.010 | 0.020 | 0.009 | 0.013 | 0.007 |
| Control variables | Y | Y | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | N | Y | N |
| Year FEs | Y | Y | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 84,620 | 86,341 | 84,620 | 86,341 |
| **Panel C: Adjusted citation regression** | | | | | | |
| R&D | 0.033 | 0.590*** | 0.021 | 0.506*** | 0.022*** | 0.143*** |
| | (0.031) | (0.045) | (0.019) | (0.037) | (0.003) | (0.004) |
| $R^2$ | 0.829 | 0.338 | 0.829 | 0.339 | 0.827 | 0.376 |
| Between $R^2$ | 0.190 | 0.290 | 0.188 | 0.293 | 0.223 | 0.339 |
| Within $R^2$ | 0.024 | 0.014 | 0.024 | 0.013 | 0.014 | 0.009 |
| Control variables | Y | Y | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | N | Y | N |
| Year FEs | Y | Y | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 84,620 | 86,341 | 84,620 | 86,341 |

This table presents regression results of innovation outcomes on R&D using firm fixed effects (FE) and OLS models. Columns are grouped by the R&D intensity measures: R&D/Asset, R&D/ME, and ln(1+R&D). Standard errors clustered at the firm level are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Innovation to R&D Regression: AdjHT, PRL, and DML

| | (1) adjHT (Year) | (2) PRL (Firm, Year) | (3) DML (Firm, Year) |
|---|---|---|---|
| **Panel A: Patent regression** | | | |
| R&D/Asset | 0.220*** | 0.199*** | 0.213*** |
| | (0.027) | (0.018) | (0.014) |
| Number of FEs | | 11,570 | 11,570 |
| Number of Selected FEs | | 1,241 | 1,737 |
| Selected ratio | | 10.73% | 15.01% |
| Control variables | Y | Y | Y |
| Firm FEs | N | Y | Y |
| Year FEs | Y | Y | Y |
| Observations | 86,341 | 86,341 | 86,341 |
| **Panel B: Citation regression** | | | |
| R&D/Asset | 0.551*** | 1.397*** | 1.364*** |
| | (0.065) | (0.083) | (0.050) |
| Number of FEs | | 11,570 | 11,570 |
| Number of Selected FEs | | 525 | 947 |
| Selected ratio | | 4.54% | 8.18% |
| Control variables | Y | Y | Y |
| Firm FEs | N | Y | Y |
| Year FEs | Y | Y | Y |
| Observations | 86,341 | 86,341 | 86,341 |
| **Panel C: Adjusted citation regression** | | | |
| R&D/Asset | 0.231*** | 0.210*** | 0.198*** |
| | (0.030) | (0.019) | (0.015) |
| Number of FEs | | 11,570 | 11,570 |
| Number of Selected FEs | | 1,194 | 1,882 |
| Selected ratio | | 10.32% | 16.27% |
| Control variables | Y | Y | Y |
| Firm FEs | N | Y | Y |
| Year FEs | Y | Y | Y |
| Observations | 86,341 | 86,341 | 86,341 |

This table presents results of innovation on R&D intensity using different estimation methods. Column (1) reports adjusted Hausman-Taylor (adjHT) estimates with year fixed effects. Columns (2) and (3) present Post-Regularization LASSO (PRL) and Double Machine Learning (DML) estimates with firm and year fixed effects, respectively. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Innovation to alternative R&D measures regression: AdjHT, PRL, and DML

| | (1) adjHT (Year) | (2) PRL (Firm, Year) | (3) DML (Firm, Year) |
|---|---|---|---|
| **Panel A: Patent regression** | | | |
| **A.1 R&D scaled by market equity** | | | |
| R&D/ME | 0.139*** | 0.112*** | 0.123*** |
| | (0.018) | (0.015) | (0.012) |
| Selected ratio | | 10.73% | 15.01% |
| **A.2 R&D stock** | | | |
| ln(1+R&D) | 0.071*** | 0.032*** | 0.035*** |
| | (0.003) | (0.001) | (0.001) |
| Selected ratio | | 10.73% | 15.00% |
| **Panel B: Citation regression** | | | |
| **B.1 R&D scaled by market equity** | | | |
| R&D/ME | 0.286*** | 1.015*** | 1.001*** |
| | (0.040) | (0.064) | (0.038) |
| Selected ratio | | 4.54% | 8.18% |
| **B.2 R&D Stock** | | | |
| ln(1+R&D) | 0.176*** | 0.285*** | 0.285*** |
| | (0.006) | (0.006) | (0.003) |
| Selected ratio | | 4.54% | 8.18% |
| **Panel C: Adjusted Citation Regression** | | | |
| **C.1 R&D scaled by market equity** | | | |
| R&D/ME | 0.135*** | 0.119*** | 0.117*** |
| | (0.019) | (0.016) | (0.012) |
| Selected ratio | | 10.32% | 16.27% |
| **C.2 R&D stock** | | | |
| ln(1+R&D) | 0.071*** | 0.035*** | 0.035*** |
| | (0.003) | (0.001) | (0.001) |
| Selected ratio | | 10.32% | 16.26% |
| Control variables | Y | Y | Y |
| Firm FEs | N | Y | Y |
| Year FEs | Y | Y | Y |
| Observations | 86,341 | 86,341 | 86,341 |

This table presents the results of innovation on alternative R&D measures using different estimation methods. Column (1) reports adjusted Hausman-Taylor (adjHT) estimates with year fixed effects. Columns (2) and (3) present Post-Regularization LASSO (PRL) and Double Machine Learning (DML) estimates with firm and year fixed effects, respectively. The standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Innovation to R&D intensity Poisson regression

| | (1) FE Poisson (Firm, Year) | (2) Poisson (Year) | (3) PRL Poisson (Firm, Year) | (4) DML Poisson (Firm, Year) |
|---|---|---|---|---|
| **Panel A: Patent count model** | | | | |
| R&D/Asset | −0.248 | 2.305*** | 2.407*** | 2.312*** |
| | (0.255) | (0.187) | (0.161) | (0.120) |
| Number of FEs | | | 11,570 | 11,570 |
| Number of Selected FEs | | | 1,218 | 2,484 |
| Selected ratio | | | 10.53% | 21.47% |
| Control variables | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | Y |
| Year FEs | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 86,341 | 86,341 |
| **Panel B: Citation count model** | | | | |
| R&D/Asset | −0.125 | 2.094*** | 2.299*** | 2.262*** |
| | (0.252) | (0.219) | (0.256) | (0.113) |
| Number of FEs | | | 11,570 | 11,570 |
| Number of Selected FEs | | | 1,216 | 2,426 |
| Selected ratio | | | 10.51% | 20.97% |
| Control variables | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | Y |
| Year FEs | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 86,341 | 86,341 |

This table presents the Poisson regression results of innovation on R&D intensity using different estimation methods. Column (1) reports fixed effects (FE) Poisson estimates with firm and year fixed effects. Column (2) presents Poisson estimates with year fixed effects. Columns (3) and (4) present Post-Regularization LASSO (PRL) Poisson and Double Machine Learning (DML) Poisson estimates with firm and year fixed effects, respectively. The standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The selected ratio is the number of selected year and firm dummies divided by the total number of year and firm dummies.

Table 7: Innovation to alternative R&D measure Poisson regression

| | (1) FE Poisson (Firm, Year) | (2) Poisson (Year) | (3) PRL Poisson (Firm, Year) | (4) DML Poisson (Firm, Year) |
|---|---|---|---|---|
| **Panel A: Patent count model** | | | | |
| **A.1 R&D scaled by market equity** | | | | |
| R&D/ME | 0.177 | 1.547*** | 1.742*** | 1.723*** |
| | (0.148) | (0.179) | (0.105) | (0.081) |
| Selected ratio | | | 9.89% | 20.21% |
| **A.2 R&D stock** | | | | |
| ln(1+R&D) | 0.054* | 0.790*** | 0.775*** | 0.779*** |
| | (0.029) | (0.080) | (0.085) | (0.040) |
| Selected ratio | | | 9.27% | 20.48% |
| Control variables | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | Y |
| Year FEs | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 86,341 | 86,341 |
| **Panel B: Citation count model** | | | | |
| **B.1 R&D scaled by market equity** | | | | |
| R&D/ME | 0.209 | 1.622*** | 1.872*** | 1.886*** |
| | (0.161) | (0.173) | (0.151) | (0.103) |
| Selected ratio | | | 10.35% | 21.58% |
| **B.2 R&D stock** | | | | |
| ln(1+R&D) | 0.090** | 0.784*** | 0.711 | 0.779*** |
| | (0.043) | (0.115) | (1.225) | (0.056) |
| Selected ratio | | | 9.91% | 21.14% |
| Control variables | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | Y |
| Year FEs | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 86,341 | 86,341 |

This table presents the Poisson regression results of innovation on alternative R&D measures using different estimation methods. Column (1) reports fixed effects (FE) Poisson estimates with firm and year fixed effects. Column (2) presents Poisson estimates with year fixed effects. Columns (3) and (4) present Post-Regularization LASSO (PRL) Poisson and Double Machine Learning (DML) Poisson estimates with firm and year fixed effects, respectively. The standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The selected ratio is the number of selected year and firm dummies divided by the total number of year and firm dummies.

# Internet Appendix for "Revisiting the Missing R&D-Patent Relation: Challenges and Solutions for Firm Fixed Effects Models"

## Internet Appendix A: Overall, Between, and Within $R^2$

In this section, we discuss different types of $R^2$ measures used in the fixed regression (see also Cameron and Trivedi, 2010, 2022). We specify an empirical model for $i = 1, \cdots, N$, and firm $i$ has $T_i$ observations. The regression with firm dummies is:

$$y_{i,t} = \mathbf{x}_{i,t}^{\top}\boldsymbol{\beta} + \alpha_i + \epsilon_{i,t}, \tag{IA.1}$$

The R-squared reported in the `reghdfe` command is the common coefficient of determination from the above dummy variables regression. Specifically, $\mathbf{x}_{i,t} \in \mathbb{R}^{K+1}$ includes intercept, and we only include $(N-1)$ firm dummies to avoid the perfect multicollinearity. Total sample size is $n = \sum_i T_i$. Define the predicted value of $y_{it}$ as

$$\hat{y}_{it} = \mathbf{x}_{i,t}^{\top}\hat{\boldsymbol{\beta}} + \hat{\alpha}_i$$

The variations of $y_{it}$ can be decomposed as:

$$\begin{aligned} \text{total sum of squares (TSS)} &= \sum_{i,t}\big(y_{it} - \bar{y}\big)^2, \\ \text{explained sum of squares (ESS)} &= \sum_{i,t}\big(\hat{y}_{it} - \bar{\hat{y}}\big)^2, \\ \text{residual sum of squares (RSS)} &= \sum_{i,t}\big(y_{it} - \hat{y}_{it}\big)^2 \end{aligned} \tag{IA.2}$$

where $\bar{y} := (\sum_{i,t} y_{it})/n$, and $\bar{\hat{y}} := (\sum_{i,t} \hat{y}_{it})/n$. Thus:

$$R^2 = \frac{\text{ESS}}{\text{TSS}} = 1 - \frac{\text{RSS}}{\text{TSS}}.$$

The Between R-squared reports the square of the correlation coefficient between the within-individual means of the original $y$ and the fitted value for the within-individual means of the independent variable. We define the within-individual mean of $y_{it}$ and $\mathbf{x}_{it}$ as $\bar{y}_i = T_i^{-1}\sum_t y_{it}$ and $\bar{\mathbf{x}}_i = T_i^{-1}\sum_t \mathbf{x}_{it}$. Given the estimated coefficients from Equation (IA.1), we form the predicted value for the within-individual means as $\bar{\mathbf{x}}_i^{\top}\hat{\boldsymbol{\beta}}$. The Between R-squared is thus the square of the correlation coefficient of $\bar{y}_i$ and $\bar{\mathbf{x}}_i^{\top}\hat{\boldsymbol{\beta}}$.

The Within R-squared reported is defined as the coefficient of determination for the within

transformation regression. First, we eliminated the firm dummies from Equation (IA.1) by subtraction of the corresponding firm (entity)'s time series means, i.e., $\tilde{y}_{it} := y_{it} - \bar{y}_i$, and the regression model is

$$\tilde{y}_{it} = \tilde{\mathbf{x}}_{i,t}^{\top}\boldsymbol{\beta} + \tilde{\varepsilon}_{it}$$

$\tilde{\mathbf{x}}_{it} := \mathbf{x}_{it} - \bar{\mathbf{x}}_i$. $\tilde{\varepsilon}_{it} = \varepsilon_{it} - \bar{\varepsilon}_i$. The within estimator (FE estimator), $\hat{\boldsymbol{\beta}}_{FE}$, is the OLS estimator of this model. We can define the TSS, ESS, and RSS for the decomposition of variance for the $\tilde{y}_{it}$ analogically:

$$\begin{aligned}
\text{TSS}_{\text{within}} &= \sum_{i,t}\left(\tilde{y}_{it} - \bar{\tilde{y}}\right)^2; \\
\text{ESS}_{\text{within}} &= \sum_{i,t}\left(\hat{\tilde{y}}_{it} - \bar{\hat{\tilde{y}}}\right)^2; \\
\text{RSS}_{\text{within}} &= \sum_{i,t}\left(\tilde{y}_{it} - \hat{\tilde{y}}_{it}\right)^2,
\end{aligned} \tag{IA.3}$$

where $\hat{\tilde{y}}_{it} := \tilde{\mathbf{x}}_{it}^{\top}\hat{\beta}_{\text{FE}}$, and $\bar{\hat{\tilde{y}}} := \sum_{i,t}\hat{\tilde{y}}_{it}/n$. Thus,

$$R^2_{\text{within}} = \frac{\text{ESS}_{\text{within}}}{\text{TSS}_{\text{within}}} = 1 - \frac{\text{RSS}_{\text{within}}}{\text{TSS}_{\text{within}}}.$$

**Internet Appendix B: Asymptotic Normality of PRL and DML**

In this Appendix, we show the asymptotic normality of the post-regularization LASSO estimator (PRL, Chernozhukov et al., 2015) the double machine learning estimator (DML,Chernozhukov et al., 2018) used in our paper.

Consider the linear specification as in Models (10) and (11) of our paper. To simplify notation, we use $y_{i,t}$ to denote $Innov_{i,t+1}$, $\mathbf{X}_{i,t}$ to denote the $(k+1)\times 1$ vector $\left[R\&D_{i,t}, \mathbf{x}_{i,t}^{\top}\right]^{\top}$, $\mathbf{D}_{i,t}$ to denote $\left[\sqrt{N}\text{dummy}_{1,i}, \sqrt{N}\text{dummy}_{2,i}, \ldots, \sqrt{N}\text{dummy}_{N,i}\right]^{\top}$, and $\mathbf{v}_{i,t}$ to denote $\left[v_{1,i,t}, \mathbf{v}_{2,i,t}^{\top}\right]^{\top}$. We also use $\boldsymbol{\beta}$ to denote $\left[\beta_1, \boldsymbol{\beta}_2^{\top}\right]^{\top}$, $\boldsymbol{\alpha}$ to denote $[\alpha_1, \alpha_2, \ldots, \alpha_N]$, $\boldsymbol{\gamma}_0$ to denote $\left[\gamma_{1,0}, \boldsymbol{\gamma}_{2,0}^{\top}\right]^{\top}$, and $\boldsymbol{\Gamma}$ to denote the $N \times (k+1)$ matrix of $\left\{\gamma_{1,s}\right\}$ and $\left\{\boldsymbol{\gamma}_{2,s}\right\}$. Model (10) can be written as:

$$y_{i,t} = \beta_0 + \mathbf{X}_{i,t}^{\top}\boldsymbol{\beta} + \mathbf{D}_{i,t}^{\top}\boldsymbol{\alpha} + u_{i,t}, \quad \text{where} \quad \mathbb{E}\left(u_{i,t}\left|\mathbf{X}_{i,t}, \mathbf{D}_{i,t}\right.\right) = 0. \tag{IA.4}$$

And Model (11) can be written as:

$$\mathbf{X}_{i,t} = \boldsymbol{\gamma}_0 + \boldsymbol{\Gamma}\mathbf{D}_{i,t} + \mathbf{v}_{i,t}, \quad \text{where} \quad \mathbb{E}\left(\mathbf{v}_{i,t}\left|\mathbf{D}_{i,t}\right.\right) = \mathbf{0}. \tag{IA.5}$$

In models IA.4 and IA.5 we consider not only the important firm dummies in $\mathcal{S}$, which is the set

of important firm dummies, but also consider all the firm dummies, since the set of important firm dummies are unknown to econometricians. Also, the firm dummies are standardized by pre-multiplying $\sqrt{N}$.

Let $\mathbf{\Gamma}^\top = \left[\boldsymbol{\gamma}_1, \boldsymbol{\gamma}_2, \ldots, \boldsymbol{\gamma}_{k+1}\right]$, i.e., let $\boldsymbol{\gamma}_r^\top$ denote the $r$th row of $\mathbf{\Gamma}$. Let $s_{NT} = \left\| \boldsymbol{\alpha} + \sum_{r=1}^{k+1} \boldsymbol{\gamma}_r \right\|_0$ denote the number of important firm dummies (the number of dummies with non-zero coefficients).

**Condition B.1** As $N, T \to \infty$, $s_{NT}^2 \left(\ln N\right)^2 \Big/ (NT) = o(1)$.

Condition B.1 is the same as the corresponding assumption in Belloni et al. (2016) when the number of nuisance variables equals to $N$, and the sample size equals to $NT$. While allowing for the number of coefficients to grow as $N \to \infty$, Condition B.1 requires that the coefficients $\boldsymbol{\alpha}$ and $\mathbf{\Gamma}$ are sparse in the sense that the number of non-zero coefficients grows more slowly than $\sqrt{NT}$.

Substituting equation IA.5 into the rewritten equation IA.4 gives a system for $y_{i,t}$ and $\mathbf{X}_{i,t}$ that depends only on $\mathbf{D}_{i,t}$:

$$\begin{aligned} y_{i,t} &= \theta_0 + \mathbf{D}_{i,t}^\top \boldsymbol{\theta} + e_{i,t}, \text{ and} \\ \mathbf{X}_{i,t} &= \boldsymbol{\gamma}_0 + \mathbf{\Gamma} \mathbf{D}_{i,t} + \mathbf{v}_{i,t}, \end{aligned}$$

in which $\theta_0 = \beta_0 + \boldsymbol{\gamma}_0^\top \boldsymbol{\beta}$, $\quad \boldsymbol{\theta} = \boldsymbol{\alpha} + \mathbf{\Gamma}^\top \boldsymbol{\beta}$, and $e_{i,t} = u_{i,t} + \mathbf{v}_{i,t}^\top \boldsymbol{\beta}$.

Let $\widetilde{\boldsymbol{\beta}}$ denote the infeasible estimator:

$$\widetilde{\boldsymbol{\beta}} = \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbf{v}_{i,t} \mathbf{v}_{i,t}^\top \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbf{v}_{i,t} e_{i,t}.$$

$\widetilde{\boldsymbol{\beta}}$ satisfies that:

$$\sqrt{NT} \left( \widetilde{\boldsymbol{\beta}} - \boldsymbol{\beta} \right) = \left( \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbf{v}_{i,t} \mathbf{v}_{i,t}^\top \right)^{-1} \frac{1}{\sqrt{NT}} \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbf{v}_{i,t} u_{i,t},$$

which is asymptotic Gaussian distributed under regularity conditions.

$\widetilde{\boldsymbol{\beta}}$ is infeasible because $\theta_0$, $\boldsymbol{\theta}$, $\boldsymbol{\gamma}_0$, and $\mathbf{\Gamma}$ are unknown to econometricians. We let $\widehat{e}_{i,t} = y_{i,t} - \widehat{\theta}_0 - \mathbf{D}_{i,t}^\top \widehat{\boldsymbol{\theta}}$, and $\widehat{\mathbf{v}}_{i,t} = \mathbf{X}_{i,t} - \widehat{\boldsymbol{\gamma}}_0 - \widehat{\mathbf{\Gamma}} \mathbf{D}_{i,t}$, in which $\widehat{\theta}_0$, $\widehat{\boldsymbol{\theta}}$, $\widehat{\boldsymbol{\gamma}}_0$, and $\widehat{\mathbf{\Gamma}}$ are post-LASSO estimates for $\theta_0$, $\boldsymbol{\theta}$, $\boldsymbol{\gamma}_0$, and $\mathbf{\Gamma}$. We then let:

$$\widehat{\boldsymbol{\beta}} = \left( \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{\mathbf{v}}_{i,t} \widehat{\mathbf{v}}_{i,t}^\top \right)^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{\mathbf{v}}_{i,t} \widehat{e}_{i,t}.$$

**Condition B.2** With a probability approaching one as $N, T \to \infty$, the post-LASSO estimates

$\widehat{\boldsymbol{\theta}}$ and $\widehat{\boldsymbol{\gamma}}_r$ with $r = 1, 2, \ldots, k+1$ satisfy the following standard performance bounds:

$$\left\|\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right\|_1 = O_p\left(\sqrt{\frac{s_{NT}^2}{NT}\ln N}\right), \quad \|\widehat{\boldsymbol{\gamma}}_r - \boldsymbol{\gamma}_r\|_1 = O_p\left(\sqrt{\frac{s_{NT}^2}{NT}\ln N}\right), \text{ and}$$
$$\left\|\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right\|_2 = O_p\left(\sqrt{\frac{s_{NT}}{NT}\ln N}\right), \quad \|\widehat{\boldsymbol{\gamma}}_r - \boldsymbol{\gamma}_r\|_2 = O_p\left(\sqrt{\frac{s_{NT}}{NT}\ln N}\right).$$

Condition B.2 is the same as the corresponding assumption in Chernozhukov et al. (2015) with the number of variable $N$ and the sample size $NT$. We note that Condition B.2 only regulates $\widehat{\boldsymbol{\theta}}$ and $\widehat{\boldsymbol{\Gamma}}$, the estimated coefficients of the firm dummies. For the intercepts, the estimates have the standard $\sqrt{NT}$ rate, i.e., $\widehat{\theta}_0 - \theta_0 = O_p\left(1 \Big/ \sqrt{NT}\right)$, and $\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0 = O_p\left(1 \Big/ \sqrt{NT}\right)$. Condition B.2 is standard in sparsity-based estimators. One key requirement for Condition B.2 is the restricted eigenvalue condition. After standardization: $(NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}\mathbf{D}_{i,t}^{\top} = \mathbf{I}_N$, and the eigenvalues are 1, such that the restricted eigenvalue condition is satisfied.

**Proposition B.1** Suppose equations IA.4 and IA.5, and Conditions B.1 and B.2 hold. Then

$$\sqrt{NT}\left(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}\right) = \sqrt{NT}\left(\widetilde{\boldsymbol{\beta}} - \boldsymbol{\beta}\right) + o_p(1).$$

**Proof.** Since

$$\widehat{\mathbf{v}}_{i,t} = \mathbf{X}_{i,t} - \widehat{\boldsymbol{\gamma}}_0 - \widehat{\boldsymbol{\Gamma}}\mathbf{D}_{i,t} = \mathbf{v}_{i,t} - (\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0) - \left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)\mathbf{D}_{i,t}, \text{ and}$$
$$\widehat{e}_{i,t} = y_{i,t} - \widehat{\theta}_0 - \mathbf{D}_{i,t}^{\top}\widehat{\boldsymbol{\theta}} = e_{i,t} - \left(\widehat{\theta}_0 - \theta_0\right) - \mathbf{D}_{i,t}^{\top}\left(\widehat{\boldsymbol{\theta}} - \boldsymbol{\theta}\right),$$

we have

$$\begin{aligned}
\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\mathbf{v}}_{i,t}\widehat{\mathbf{v}}_{i,t}^{\top} &= \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\mathbf{v}_{i,t}^{\top} - \left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\right)(\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0)^{\top} - \frac{\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}^{\top} \\
&- \left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\mathbf{D}_{i,t}^{\top}\right)\left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)^{\top} - \left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}\mathbf{v}_{i,t}^{\top} \\
&+ (\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0)(\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0)^{\top} - (\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0)\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}^{\top}\right)\left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)^{\top} \\
&- \left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}\right)(\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0)^{\top} + \left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}\mathbf{D}_{i,t}^{\top}\right)\left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)^{\top},
\end{aligned}$$

and

$$\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\mathbf{v}}_{i,t}\widehat{e}_{i,t}=\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}e_{i,t}-\left(\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\right)\left(\widehat{\theta}_0-\theta_0\right)-\frac{\widehat{\boldsymbol{\gamma}}_0-\boldsymbol{\gamma}_0}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}e_{i,t}$$
$$-\left(\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\mathbf{D}_{i,t}^{\top}\right)\left(\widehat{\boldsymbol{\theta}}-\boldsymbol{\theta}\right)-\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)\left(\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}e_{i,t}\right)$$
$$+\sqrt{NT}\left(\widehat{\boldsymbol{\gamma}}_0-\boldsymbol{\gamma}_0\right)\left(\widehat{\theta}_0-\theta_0\right)-\left(\widehat{\boldsymbol{\gamma}}_0-\boldsymbol{\gamma}_0\right)\left(\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}^{\top}\right)\left(\widehat{\boldsymbol{\theta}}-\boldsymbol{\theta}\right)$$
$$-\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)\left(\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}\right)\left(\widehat{\theta}_0-\theta_0\right)+\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)\left(\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}\mathbf{D}_{i,t}^{\top}\right)\left(\widehat{\boldsymbol{\theta}}-\boldsymbol{\theta}\right).$$

Then for $(NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\mathbf{v}}_{i,t}\widehat{\mathbf{v}}_{i,t}^{\top}$,

$$\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\mathbf{D}_{i,t}^{\top}\right)\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)^{\top}=o_p\left(1\right)\cdot O_p\left(\sqrt{\frac{s_{NT}^2}{NT}\ln N}\right)=o_p\left(\frac{1}{\sqrt{\ln N}}\right)=o_p\left(1\right),$$
$$\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)\left(\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}\mathbf{D}_{i,t}^{\top}\right)\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)^{\top}=\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)^{\top}.$$

By the Cauchy-Schwarz inequality, for any $q$ and $r=1,2,\ldots,k+1$:

$$\left(\widehat{\boldsymbol{\gamma}}_q-\boldsymbol{\gamma}_q\right)^{\top}\left(\widehat{\boldsymbol{\gamma}}_r-\boldsymbol{\gamma}_r\right)\leq\left\|\widehat{\boldsymbol{\gamma}}_q-\boldsymbol{\gamma}_q\right\|_2\left\|\widehat{\boldsymbol{\gamma}}_r-\boldsymbol{\gamma}_r\right\|_2=O_p\left(\frac{s_{NT}}{NT}\ln N\right)=o_p\left(\frac{1}{\sqrt{NT}}\right).$$

Since all the other terms except for the first term clearly have an even smaller order, we have:

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\mathbf{v}}_{i,t}\widehat{\mathbf{v}}_{i,t}^{\top}=\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\mathbf{v}_{i,t}^{\top}+o_p\left(1\right).$$

For $(NT)^{-1/2}\sum_{i=1}^{N}\sum_{t=1}^{T}\widehat{\mathbf{v}}_{i,t}\widehat{e}_{i,t}$,

$$\left(\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\mathbf{D}_{i,t}^{\top}\right)\left(\widehat{\boldsymbol{\theta}}-\boldsymbol{\theta}\right)=O_p\left(1\right)\cdot O_p\left(\sqrt{\frac{s_{NT}^2}{NT}\ln N}\right)=o_p\left(\frac{1}{\sqrt{\ln N}}\right)=o_p\left(1\right),$$
$$\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)\left(\frac{1}{\sqrt{NT}}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}e_{i,t}\right)=O_p\left(1\right)\cdot O_p\left(\sqrt{\frac{s_{NT}^2}{NT}\ln N}\right)=o_p\left(\frac{1}{\sqrt{\ln N}}\right)=o_p\left(1\right),$$

and by the Cauchy-Schwarz inequality, for $r = 1, 2, \ldots, k+1$,

$$\begin{aligned} & (\widehat{\boldsymbol{\gamma}}_r - \boldsymbol{\gamma}_r)^\top \left( \frac{1}{\sqrt{NT}} \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbf{D}_{i,t} \mathbf{D}_{i,t}^\top \right) \left( \widehat{\boldsymbol{\theta}} - \boldsymbol{\theta} \right) \\ = \; & \sqrt{NT} \left( \widehat{\boldsymbol{\gamma}}_r - \boldsymbol{\gamma}_r \right)^\top \left( \widehat{\boldsymbol{\theta}} - \boldsymbol{\theta} \right) \leq \sqrt{NT} \left\| \widehat{\boldsymbol{\gamma}}_r - \boldsymbol{\gamma}_r \right\|_2 \left\| \widehat{\boldsymbol{\theta}} - \boldsymbol{\theta} \right\|_2 = \sqrt{NT} O_p \left( \frac{s_{NT}}{NT} \ln N \right) = o_p(1). \end{aligned}$$

Since all other terms except for the first term clearly have an even smaller order, we have:

$$\frac{1}{\sqrt{NT}} \sum_{i=1}^{N} \sum_{t=1}^{T} \widehat{\mathbf{v}}_{i,t} \widehat{e}_{i,t} = \frac{1}{\sqrt{NT}} \sum_{i=1}^{N} \sum_{t=1}^{T} \mathbf{v}_{i,t} e_{i,t} + o_p(1). \; \square$$

For the DML estimator, since $\widehat{\boldsymbol{\theta}}$ is computed using the auxiliary fold, and $\mathbf{v}_{i,t}$ and $\mathbf{D}_{i,t}$ are from the main fold, $\widehat{\boldsymbol{\theta}}$ is independent from $\mathbf{v}_{i,t}\mathbf{D}_{i,t}$, and $\left[ (NT/2)^{-1/2} \sum_i \sum_t \mathbf{v}_{i,t} \mathbf{D}_{i,t}^\top \right] \left( \widehat{\boldsymbol{\theta}} - \boldsymbol{\theta} \right)$ has a zero mean and a variance:

$$\mathbb{E}\left[ \left( \widehat{\boldsymbol{\theta}} - \boldsymbol{\theta} \right)^\top \left( \frac{2}{NT} \sum_i \sum_t \mathbf{D}_{i,t} \mathbf{v}_{i,t}^\top \mathbf{v}_{i,t} \mathbf{D}_{i,t}^\top \right) \left( \widehat{\boldsymbol{\theta}} - \boldsymbol{\theta} \right) \right] = O(1) \cdot \left\| \widehat{\boldsymbol{\theta}} - \boldsymbol{\theta} \right\|_2^2 = O\left( \frac{s_{NT}}{NT} \ln N \right).$$

Therefore:

$$\left( \frac{1}{\sqrt{NT/2}} \sum_i \sum_t \mathbf{v}_{i,t} \mathbf{D}_{i,t}^\top \right) \left( \widehat{\boldsymbol{\theta}} - \boldsymbol{\theta} \right) = O_p\left( \sqrt{\frac{s_{NT}}{NT} \ln N} \right),$$

which is smaller than the one for PRL. We can also show that $\left( \widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma} \right) (NT/2)^{-1/2} \sum_i \sum_t \mathbf{D}_{i,t} e_{i,t} = O_p\left( \sqrt{s_{NT} \ln N / NT} \right)$. That is, the deviation of the asymptotic distribution of the DML estimator from the Gaussian approximation is smaller in magnitude than the deviation of the PRL estimator.

## Internet Appendix C: Characteristics of the Selected Firms

We analyze the properties of the selected firms in greater detail. We use the PRL method with R&D scaled by total assets (R&D/Asset) as the illustration example. Previous results show that the PRL method selects 1,241 dummies out of 11,570 firm and year dummies, corresponding to a selection rate of 10.73% in the patent regression. Among these, 1,215 are firm dummies and 26 are year dummies.

To better understand which firms the PRL selects, we rank the estimated firm fixed effects from the patent LASSO regression. Specifically, the estimates of $\alpha_j$ in Equation (12), where $z$ is $\ln(1 + \text{Patent})$. The top 100 firms are reported in Internet Appendix Table IA.4. Intel, Lucent Technologies, General Electric Co., APTIV, and Eastman Kodak Co. are among the top-ranked

companies. This result is consistent with our selection criterion, which aims to identify the most influential firms that drive innovation output.

We also examine the difference in within-firm variation between the selected and non-selected firms across various R&D measures. We begin with the R&D measure is defined as R&D scaled by total assets (R&D/Asset). For each of the 11,544 firms in the sample, we compute the within-firm standard deviation of R&D/Asset over time as $\text{std}_i(\text{R\&D}) := (\frac{1}{T_i}\sum_t(\text{R\&D}_{i,t} - \bar{\text{R\&D}}_i)^2)^{1/2}$, where $T_i$ is the number of firm-year observations for firm $i$, and $\bar{\text{R\&D}}_i$ is the firm-level (time-series) average of R&D/Asset. This measure captures the degree of temporal variation in R&D activity within each firm.

We then estimate a cross-sectional regression of $\text{std}_i(\text{R\&D})$ on the selected dummy (*D_selected*), which equals one if the firm is selected by the PRL approach and zero otherwise. Results are presented in Column (1) of Internet Appendix Table IA.5. We find that the within-firm standard deviation for selected firms exceeds that of non-selected firms by 0.051 (0.106 vs. 0.055), which is statistically significant. The findings are consistent across alternative R&D measures. When R&D is scaled by market equity (R&D/ME), or transformed via the natural logarithm $\ln(1+\text{R\&D})$, the within-firm variation remains significantly higher for selected firms, as shown in Columns (2) and (3) of Table IA.5.

## Internet Appendix D: Estimation of PRL Poisson

The post-regularization LASSO Poisson regression (PRL Possion) algorithm is based on the section 2.1 in Belloni et al. (2016). Consider the conditional mean function as: $E(y_{i,t+1}|d_{i,t-1}, \mathbf{x}_{i,t-1}) = G\left(\beta_{1,0}d_{i,t-1} + \mathbf{x}'_{i,t-1}\boldsymbol{\beta}_2\right)$, in which $G(\cdot) = \exp(\cdot)$, and $d_{i,t-1}$ is the policy variable or a treatment variable. The PRL Poisson method proceeds in three main steps:

1. Perform the Post-LASSO-Poisson of $y_{i,t}$ on $d_{i,t-1}$ and $\mathbf{x}_{i,t-1}$ to estimate the nuisance function $\mathbf{x}'_{i,t-1}\boldsymbol{\beta}_2$.
   (a) Run the LASSO-Poisson of $y_{i,t}$ on $d_{i,t-1}$ and $\mathbf{x}_{i,t-1}$. $\tilde{\mathbf{x}}_{i,t-1}$ denote the selected control.
   (b) Run the Poisson regression of $y_{i,t}$ on $d_{i,t-1}$ and $\tilde{\mathbf{x}}_{i,t-1}$. Denote estimates as $\tilde{\beta}_1$, and $\tilde{\boldsymbol{\beta}}_2$, and keep the observation-level weights $w_i = G'\left(\tilde{\beta}_1 d_{i,t-1} + \tilde{\mathbf{x}}'_{i,t-1}\tilde{\boldsymbol{\beta}}_2\right)$, in which $G'(t) = \partial G(t)/\partial t$.
2. Perform Post-LASSO-OLS of $\sqrt{w_i}d_{i,t-1}$ on $\sqrt{w_i}\mathbf{x}_{i,t-1}$ to estimate the instrument $z_{0,i}$.
   (a) Perform a linear LASSO of $\sqrt{w_i}d_{i,t-1}$ on $\sqrt{w_i}\mathbf{x}_{i,t-1}$. $\check{\mathbf{x}}_{i,t-1}$ denote the selected control.
   (b) Perform the linear regression of $\sqrt{w_i}d_{i,t-1}$ on $\sqrt{w_i}\check{\mathbf{x}}_{i,t-1}$. Denote the estimates as $\check{\boldsymbol{\theta}}$. and use the unweighted residual $z_{i,t-1} := d_{i,t-1} - \check{\mathbf{x}}'_{i,t-1}\check{\boldsymbol{\theta}}$ as the instrument variable.
3. Combine the previous two steps to estimate $\beta_{1,0}$ using the instrumental Poisson regression with estimates of $\mathbf{x}'_{i,t-1}\boldsymbol{\beta}_2$ from step 1 and the instrument variable $z_{i,t-1}$ from step 2.

(a) Compute $\hat{\beta}_1$ by solving the following sample moment equations:

$$\frac{1}{NT}\sum_i\sum_t\left\{\left[y_{i,t+1}-G\left(\beta_1 d_{i,t-1}+\tilde{\mathbf{x}}_{i,t-1}'\tilde{\boldsymbol{\beta}}_2\right)\right]z_{i,t-1}\right\}=0.$$

In our empirical analysis, we perform the cross-validation with 10-folds in step 1 and 2 to select the optimal penalty parameters on the LASSO methods and use the cluster by firm standard errors to account for the within-firm heterogeneity in step 3.

## Internet Appendix E: Asymptotic Normality of PRL Poisson

In this Appendix, we show the asymptotic normality of the post-regularization LASSO Poisson estimator in Belloni et al. (2016). We consider the Poisson setting in Models (13) and (14) of our paper, and to simplify the notation, we write these models as:

$$\begin{aligned}\mu_{i,t}&=\mathbb{E}\left(y_{i,t}\left|\mathbf{X}_{i,t},\mathbf{D}_{i,t}\right.\right)=\exp\left(\beta_0+\mathbf{X}_{i,t}^\top\boldsymbol{\beta}+\mathbf{D}_{i,t}^\top\boldsymbol{\alpha}\right),\\ \mathbf{X}_{i,t}&=\boldsymbol{\gamma}_0+\boldsymbol{\Gamma}\mathbf{D}_{i,t}+\mathbf{v}_{i,t}.\end{aligned}$$

$\boldsymbol{\beta}$ is estimated by GMM using the following moment condition:

$$g\left(\boldsymbol{\beta}\right)=\frac{1}{NT}\sum_{i=1}^N\sum_{t=1}^T\left(\mathbf{X}_{i,t}-\widehat{\boldsymbol{\gamma}}_0-\widehat{\boldsymbol{\Gamma}}\mathbf{D}_{i,t}\right)\left[y_{i,t}-\exp\left(\widehat{\beta}_0+\mathbf{X}_{i,t}^\top\boldsymbol{\beta}+\mathbf{D}_{i,t}^\top\widehat{\boldsymbol{\alpha}}\right)\right]=\mathbf{0},$$

in which $\widehat{\beta}_0$, $\widehat{\boldsymbol{\alpha}}$, $\widehat{\boldsymbol{\gamma}}_0$, and $\widehat{\boldsymbol{\Gamma}}$ are post-Poisson-LASSO or post-LASSO estimates for $\beta_0$, $\boldsymbol{\alpha}$, $\boldsymbol{\gamma}_0$, and $\boldsymbol{\Gamma}$.

Let $\widetilde{\boldsymbol{\beta}}$ be the infeasible estimator using the moment condition:

$$\begin{aligned}h\left(\boldsymbol{\beta}\right)&=\frac{1}{NT}\sum_{i=1}^N\sum_{t=1}^T\left(\mathbf{X}_{i,t}-\boldsymbol{\gamma}_0-\boldsymbol{\Gamma}\mathbf{D}_{i,t}\right)\left[y_{i,t}-\exp\left(\beta_0+\mathbf{X}_{i,t}^\top\boldsymbol{\beta}+\mathbf{D}_{i,t}^\top\boldsymbol{\alpha}\right)\right]\\&=\frac{1}{NT}\sum_{i=1}^N\sum_{t=1}^T\mathbf{v}_{i,t}\left[y_{i,t}-\exp\left(\beta_0+\mathbf{X}_{i,t}^\top\boldsymbol{\beta}+\mathbf{D}_{i,t}^\top\boldsymbol{\alpha}\right)\right]=\mathbf{0}.\end{aligned}$$

The conditions are similar to the ones for the linear specification. Let $s_{NT}=\left\|\boldsymbol{\alpha}+\sum_{r=1}^{k+1}\boldsymbol{\gamma}_r\right\|_0$ denote the number of important firm dummies (i.e., the number of dummies with non-zero coefficients).

**Condition E.1** As $N,T\to\infty$, $s_{NT}^2\left(\ln N\right)^2\Big/\left(NT\right)=o(1)$.

**Condition E.2** With a probability approaching one as $N,T\to\infty$, the post-LASSO estimates

$\widehat{\boldsymbol{\theta}}$ and $\widehat{\boldsymbol{\gamma}}_r$ with $r = 1, 2, \ldots, k+1$ satisfy the following standard performance bounds:

$$\|\widehat{\boldsymbol{\alpha}} - \boldsymbol{\alpha}\|_1 = O_p\left(\sqrt{\frac{s_{NT}^2}{NT}\ln N}\right), \quad \|\widehat{\boldsymbol{\gamma}}_r - \boldsymbol{\gamma}_r\|_1 = O_p\left(\sqrt{\frac{s_{NT}^2}{NT}\ln N}\right),$$
$$\|\widehat{\boldsymbol{\alpha}} - \boldsymbol{\alpha}\|_2 = O_p\left(\sqrt{\frac{s_{NT}}{NT}\ln N}\right), \quad \|\widehat{\boldsymbol{\gamma}}_r - \boldsymbol{\gamma}_r\|_2 = O_p\left(\sqrt{\frac{s_{NT}}{NT}\ln N}\right).$$

**Proposition E.1** Suppose Conditions E.1 and E.2 hold. Then:

$$\sqrt{NT}\left(\widehat{\boldsymbol{\beta}} - \boldsymbol{\beta}\right) = \sqrt{NT}\left(\widetilde{\boldsymbol{\beta}} - \boldsymbol{\beta}\right) + o_p(1).$$

**Proof.** It suffices to show that $h(\boldsymbol{\beta}) = g(\boldsymbol{\beta}) + o_p\left((NT)^{-1/2}\right)$, i.e., the difference of $h(\boldsymbol{\beta})$, the moment condition for the infeasible estimator, and $g(\boldsymbol{\beta})$, the moment condition for the GMM, is $o_p\left((NT)^{-1/2}\right)$. $g(\boldsymbol{\beta})$ can be written as:

$$\begin{aligned}
g(\beta) &= \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\mathbf{X}_{i,t} - \widehat{\boldsymbol{\gamma}}_0 - \widehat{\boldsymbol{\Gamma}}\mathbf{D}_{i,t}\right)\left[y_{i,t} - \exp\left(\widehat{\beta}_0 + \mathbf{X}_{i,t}^{\top}\boldsymbol{\beta} + \mathbf{D}_{i,t}^{\top}\widehat{\boldsymbol{\alpha}}\right)\right] \\
&= \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[\mathbf{v}_{i,t} - (\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0) - \left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)\mathbf{D}_{i,t}\right] \\
&\quad \left\{y_{i,t} - \exp\left(\beta_0 + \mathbf{X}_{i,t}^{\top}\boldsymbol{\beta} + \mathbf{D}_{i,t}^{\top}\boldsymbol{\alpha}\right)\left[1 + \left(\widehat{\beta}_0 - \beta_0\right) + \mathbf{D}_{i,t}^{\top}(\widehat{\boldsymbol{\alpha}} - \boldsymbol{\alpha}) + (s.o.)\right]\right\} \\
&= h(\boldsymbol{\beta}) + A_1 + A_2 + A_3 + (s.o.),
\end{aligned}$$

in which

$$A_1 = -\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\left[\left(\widehat{\beta}_0 - \beta_0\right) + \mathbf{D}_{i,t}^{\top}(\widehat{\boldsymbol{\alpha}} - \boldsymbol{\alpha})\right]$$
$$A_2 = -\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[(\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0) + \left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)\mathbf{D}_{i,t}\right]\left[y_{i,t} - \exp\left(\beta_0 + \mathbf{X}_{i,t}^{\top}\boldsymbol{\beta} + \mathbf{D}_{i,t}^{\top}\boldsymbol{\alpha}\right)\right]$$
$$A_3 = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left[(\widehat{\boldsymbol{\gamma}}_0 - \boldsymbol{\gamma}_0) + \left(\widehat{\boldsymbol{\Gamma}} - \boldsymbol{\Gamma}\right)\mathbf{D}_{i,t}\right]\left[\left(\widehat{\beta}_0 - \beta_0\right) + \mathbf{D}_{i,t}^{\top}(\widehat{\boldsymbol{\alpha}} - \boldsymbol{\alpha})\right],$$

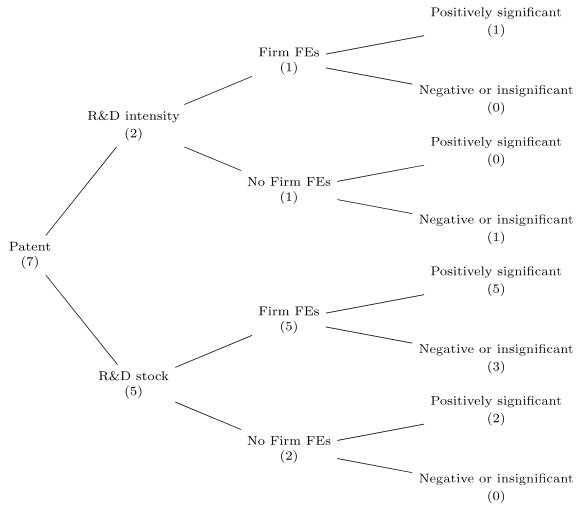
and $(s.o.)$ denotes terms with smaller order. Using Conditions E.1 and E.2,

$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{v}_{i,t}\mathbf{D}_{i,t}^{\top}\left(\widehat{\boldsymbol{\alpha}}-\boldsymbol{\alpha}\right)=O_p\left(\frac{1}{\sqrt{NT}}\right)\cdot O_p\left(\sqrt{\frac{s_{NT}^2}{NT}\ln N}\right)=o_p\left(\frac{1}{\sqrt{NT\ln N}}\right),$$
$$\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\widehat{\boldsymbol{\Gamma}}-\boldsymbol{\Gamma}\right)\mathbf{D}_{i,t}\left[y_{i,t}-\exp\left(\beta_0+\mathbf{X}_{i,t}^{\top}\boldsymbol{\beta}+\mathbf{D}_{i,t}^{\top}\boldsymbol{\alpha}\right)\right]=o_p\left(\frac{1}{\sqrt{NT\ln N}}\right),$$

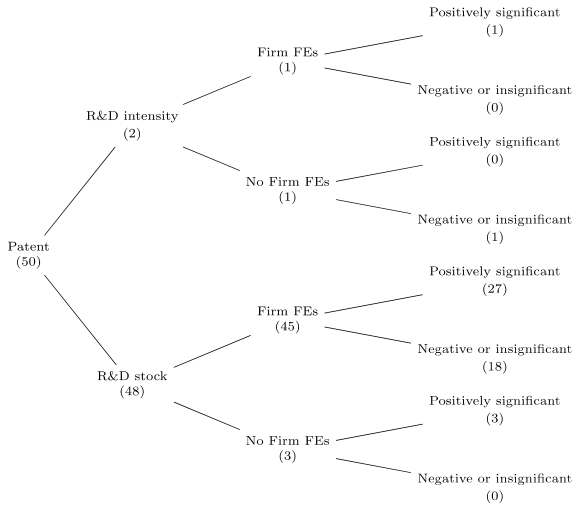
and for any $r=1,2,\ldots,k+1$, by the Cauchy-Schwarz inequality,

$$\begin{aligned}&\left(\widehat{\boldsymbol{\gamma}}_r-\boldsymbol{\gamma}_r\right)^{\top}\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\mathbf{D}_{i,t}\mathbf{D}_{i,t}^{\top}\left(\widehat{\boldsymbol{\alpha}}-\boldsymbol{\alpha}\right)\\ =\;&\left(\widehat{\boldsymbol{\gamma}}_r-\boldsymbol{\gamma}_r\right)^{\top}\left(\widehat{\boldsymbol{\alpha}}-\boldsymbol{\alpha}\right)\leq\left\|\widehat{\boldsymbol{\gamma}}_r-\boldsymbol{\gamma}_r\right\|_2\left\|\widehat{\boldsymbol{\alpha}}-\boldsymbol{\alpha}\right\|_2=O_p\left(\frac{s_{NT}}{NT}\ln N\right)=o_p\left(\frac{1}{\sqrt{NT}}\right).\end{aligned}$$

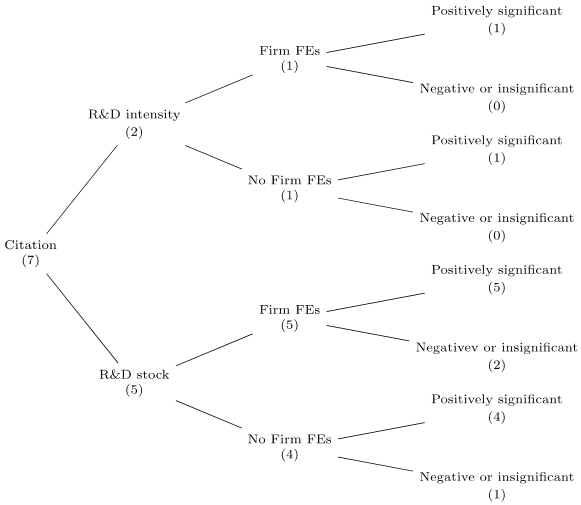
Since all the other terms except for the first term clearly have an even smaller order, we have: $h\left(\boldsymbol{\beta}\right)=g\left(\boldsymbol{\beta}\right)+o_p\left(\left(NT\right)^{-1/2}\right)$. $\square$



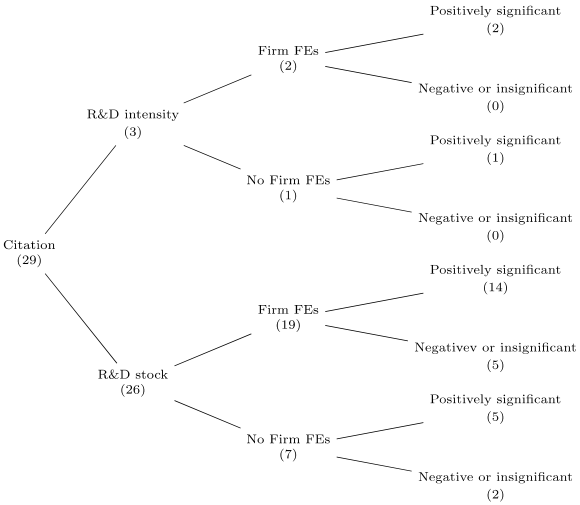

(a) Patent count model: article number




(b) Patent count model: regression number

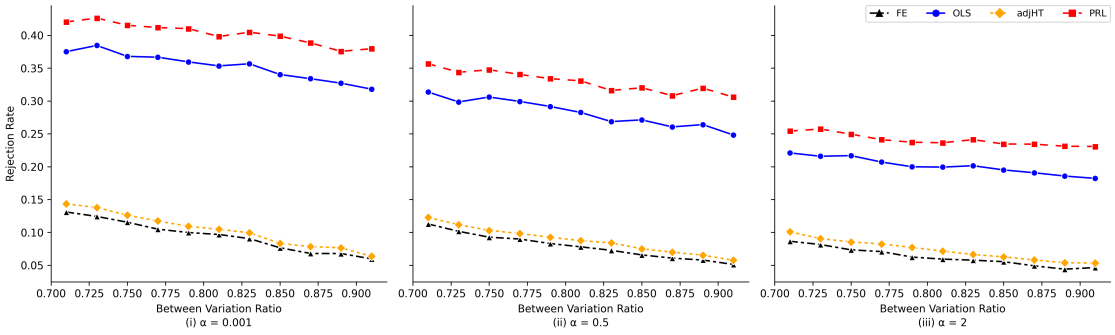



(c) Citation count model: article number

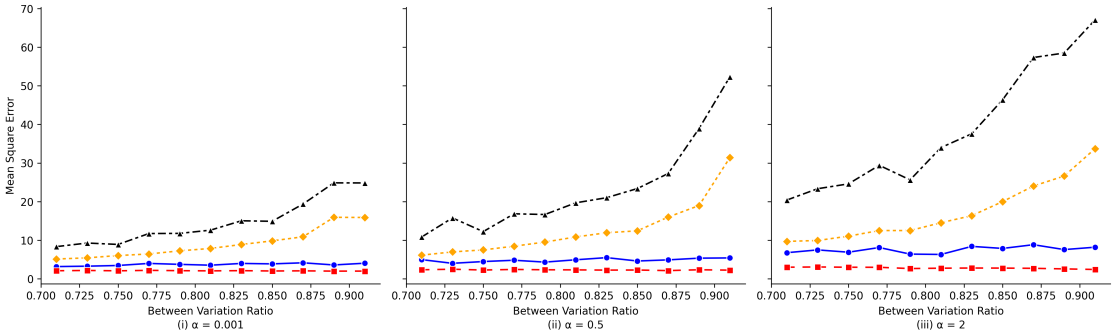



(d) Citation count model: regression number

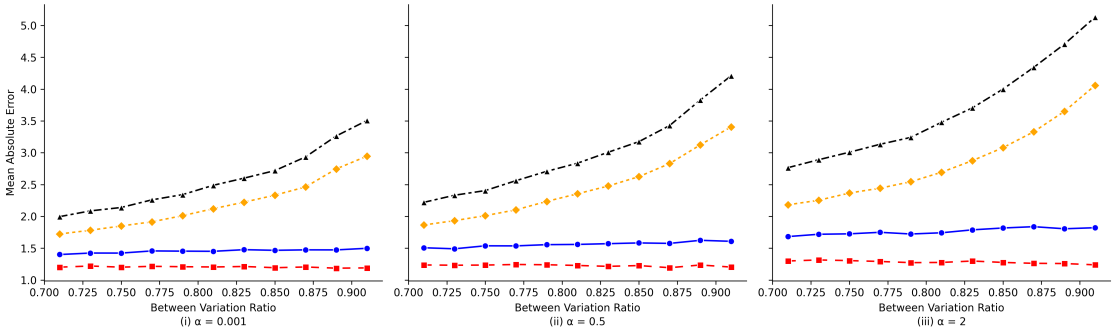
Figure IA.1: Patent and citation count-model studies




(a) Rejection rate

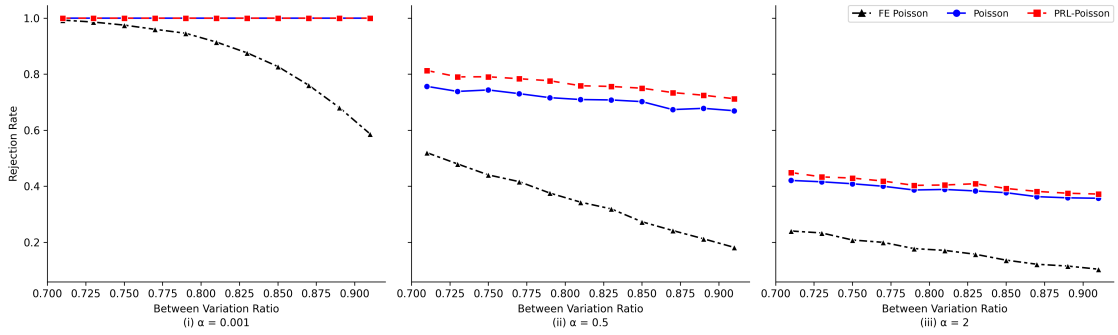



(b) Mean square error

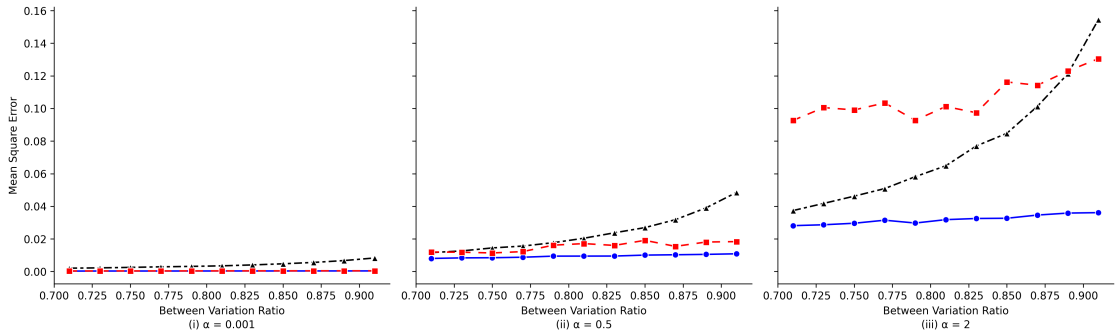



(c) Mean absolute error

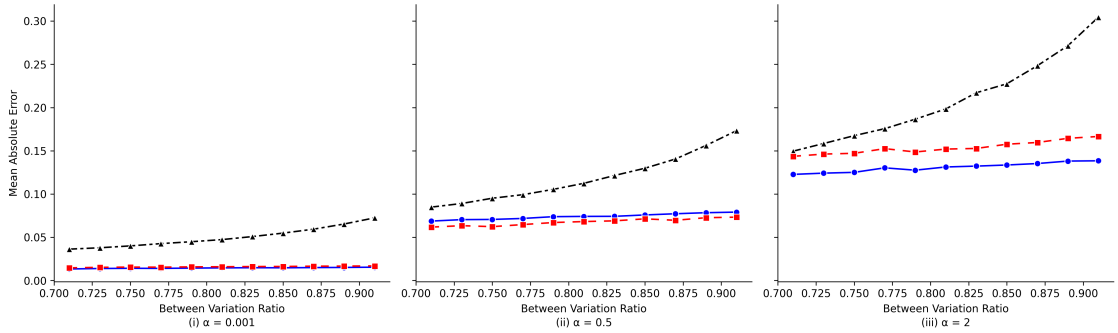
Figure IA.2: Simulation rejection rates and error rates for continuous outcomes: FE, OLS, adjHT, and PRL. This figure compares the rejection and error rates for four estimators: FE (regression with full set of firm dummies), OLS (regression without any firm dummies), adjHT (adjusted Hausman-Taylor), and PRL (post-regularization LASSO). The continuous outcome $y_{i,t}$ is generated from a mixture of $\chi^2(1)$ distributions. The number of mixture components is the product of $\exp(0.2z_{i,t} + x_{i,t})$, and a log-normal random variable with mean one and variance controlled by $\alpha$, where $z_{i,t} = 0.5\eta_i + 0.5\nu_{i,t}$. $\eta_i$ and $\nu_{i,t}$ are independently drawn from normal distributions truncated at the 1st and 99th percentiles, with standard deviations $\sigma_\eta$ and $\sigma_\nu$. The between variation ratio is defined as $\sigma_\eta^2/(\sigma_\eta^2 + \sigma_\nu^2)$. Subplots (i), (ii), and (iii) represent low ($\alpha = 0.001$), moderate ($\alpha = 0.5$), and high overdispersion ($\alpha = 2$) of the continuous outcomes, respectively.




(a) Rejection rate




(b) Mean square error




(c) Mean absolute error

Figure IA.3: Simulation rejection rates and error rates for continuous outcomes: FE Poisson, Poisson, and PRL Poisson. This figure compares the rejection and error rates for three estimators: FE Poisson (Poisson regression with full set of firm dummies), Poisson (Poisson regression without any firm dummies), PRL Poisson (post-regularization LASSO Poisson regression). The continuous outcome $y_{i,t}$ is generated from a mixture of $\chi^2(1)$ distributions. The number of mixture components is the product of $\exp(0.2z_{i,t} + x_{i,t})$, and a log-normal random variable with mean one and variance controlled by $\alpha$, where $z_{i,t} = 0.5\eta_i + 0.5\nu_{i,t}$. $\eta_i$ and $\nu_{i,t}$ are independently drawn from normal distributions truncated at the 1st and 99th percentiles, with standard deviations $\sigma_\eta$ and $\sigma_\nu$. The between variation ratio is defined as $\sigma_\eta^2/(\sigma_\eta^2 + \sigma_\nu^2)$. Subplots (i), (ii), and (iii) represent low ($\alpha = 0.001$), moderate ($\alpha = 0.5$), and high overdispersion ($\alpha = 2$) of the continuous outcomes, respectively.

Table IA.1: Innovation to R&D intensity regression (Full table)

| | (1) FE (Firm, Year) | (2) OLS (Year) | (3) adjHT (Year) | (4) PRL (Firm, Year) | (5) DML (Firm, Year) |
|---|---|---|---|---|---|
| **Panel A: Patent regression** | | | | | |
| R&D/Asset | 0.041 | 0.593*** | 0.220*** | 0.199*** | 0.213*** |
| | (0.028) | (0.042) | (0.027) | (0.018) | (0.014) |
| ln(ME) | 0.112*** | 0.275*** | 0.155*** | 0.034*** | 0.038*** |
| | (0.007) | (0.013) | (0.007) | (0.004) | (0.003) |
| ln(1+Age) | 0.108*** | 0.177*** | 0.085*** | 0.056*** | 0.055*** |
| | (0.019) | (0.012) | (0.009) | (0.006) | (0.004) |
| ln(K/L) | 0.023*** | 0.037*** | 0.028*** | 0.006** | 0.010*** |
| | (0.007) | (0.007) | (0.005) | (0.003) | (0.002) |
| R&D missing | −0.026* | −0.539*** | −0.359*** | −0.151*** | −0.162*** |
| | (0.014) | (0.020) | (0.014) | (0.009) | (0.006) |
| Tobin Q | −0.018*** | −0.049*** | −0.026*** | 0.004 | 0.001 |
| | (0.004) | (0.006) | (0.003) | (0.003) | (0.002) |
| ROA | −0.085*** | −0.131*** | −0.130*** | 0.029 | 0.010 |
| | (0.023) | (0.046) | (0.022) | (0.022) | (0.016) |
| Leverage | 0.003 | −0.065* | −0.078*** | −0.055*** | −0.065*** |
| | (0.025) | (0.038) | (0.023) | (0.018) | (0.013) |
| Cash/Asset | 0.050 | −0.008 | 0.149*** | 0.075*** | 0.051*** |
| | (0.031) | (0.048) | (0.027) | (0.024) | (0.018) |
| KZ index | 0.001** | 0.001 | 0.001*** | 0.000 | −0.001** |
| | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) |
| InstOwn | −0.052* | −0.329*** | −0.124*** | 0.005 | 0.007 |
| | (0.030) | (0.065) | (0.032) | (0.025) | (0.019) |
| (1-HHI) | −0.185** | 0.443*** | 0.093 | 0.289*** | 0.262*** |
| | (0.081) | (0.171) | (0.082) | (0.055) | (0.040) |
| $(1\text{-HHI})^2$ | 0.171** | −0.473*** | −0.060 | −0.250*** | −0.227*** |
| | (0.070) | (0.143) | (0.071) | (0.049) | (0.036) |
| Firm FEs | Y | N | N | Y | Y |
| Year FEs | Y | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 86,341 | 86,341 | 86,341 |
| **Panel B: Citation regression** | | | | | |
| R&D/Asset | −0.051 | 1.396*** | 0.551*** | 1.397*** | 1.364*** |
| | (0.068) | (0.084) | (0.065) | (0.083) | (0.050) |
| ln(ME) | 0.196*** | 0.486*** | 0.325*** | 0.478*** | 0.476*** |
| | (0.014) | (0.019) | (0.013) | (0.019) | (0.010) |
| ln(1+Age) | 0.190*** | 0.295*** | 0.157*** | 0.297*** | 0.300*** |
| | (0.036) | (0.023) | (0.019) | (0.024) | (0.013) |
| ln(K/L) | 0.040*** | 0.065*** | 0.055*** | 0.074*** | 0.075*** |
| | (0.014) | (0.013) | (0.010) | (0.012) | (0.007) |
| R&D missing | −0.090*** | −1.168*** | −0.937*** | −1.171*** | −1.175*** |
| | (0.031) | (0.037) | (0.032) | (0.037) | (0.020) |
| Tobin Q | −0.030*** | −0.057*** | −0.039*** | −0.063*** | −0.061*** |
| | (0.008) | (0.011) | (0.007) | (0.011) | (0.007) |
| ROA | −0.150*** | −0.071 | −0.309*** | −0.072 | −0.092* |
| | (0.058) | (0.090) | (0.056) | (0.089) | (0.056) |
| Leverage | −0.027 | −0.188** | −0.186*** | −0.181** | −0.179*** |
| | (0.058) | (0.076) | (0.053) | (0.075) | (0.047) |
| Cash/Asset | 0.215*** | 0.334*** | 0.566*** | 0.291*** | 0.251*** |
| | (0.074) | (0.101) | (0.067) | (0.096) | (0.061) |
| KZ index | 0.001 | 0.002 | 0.002** | −0.001 | −0.002** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| InstOwn | 0.052 | −0.271** | −0.081 | −0.227** | −0.228*** |

**Table IA.1 – continued from previous page**

| | (1) FE (Firm, Year) | (2) OLS (Year) | (3) adjHT (Year) | (4) PRL (Firm, Year) | (5) DML (Firm, Year) |
|---|---|---|---|---|---|
| | (0.063) | (0.112) | (0.065) | (0.112) | (0.064) |
| (1-HHI) | −0.247 | 1.334*** | 0.460*** | 1.451*** | 1.306*** |
| | (0.171) | (0.291) | (0.173) | (0.258) | (0.157) |
| $(1\text{-HHI})^2$ | 0.227 | −1.298*** | −0.399*** | −1.372*** | −1.227*** |
| | (0.155) | (0.250) | (0.153) | (0.223) | (0.136) |
| Firm FEs | Y | N | N | Y | Y |
| Year FEs | Y | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 86,341 | 86,341 | 86,341 |
| **Panel C: Adjusted citation regression** | | | | | |
| R&D/Asset | 0.033 | 0.590*** | 0.231*** | 0.210*** | 0.198*** |
| | (0.031) | (0.045) | (0.030) | (0.019) | (0.015) |
| ln(ME) | 0.109*** | 0.282*** | 0.156*** | 0.037*** | 0.040*** |
| | (0.008) | (0.013) | (0.007) | (0.004) | (0.003) |
| ln(1+Age) | 0.104*** | 0.158*** | 0.067*** | 0.049*** | 0.054*** |
| | (0.019) | (0.013) | (0.009) | (0.006) | (0.005) |
| ln(K/L) | 0.020*** | 0.035*** | 0.025*** | 0.007** | 0.010*** |
| | (0.007) | (0.007) | (0.005) | (0.003) | (0.002) |
| R&D missing | −0.027* | −0.555*** | −0.364*** | −0.168*** | −0.168*** |
| | (0.015) | (0.020) | (0.015) | (0.009) | (0.006) |
| Tobin Q | −0.018*** | −0.043*** | −0.026*** | 0.003 | 0.001 |
| | (0.004) | (0.006) | (0.004) | (0.003) | (0.002) |
| ROA | −0.089*** | −0.100** | −0.121*** | 0.047** | 0.010 |
| | (0.025) | (0.049) | (0.024) | (0.024) | (0.018) |
| Leverage | 0.006 | −0.062 | −0.055** | −0.061*** | −0.057*** |
| | (0.028) | (0.040) | (0.026) | (0.020) | (0.015) |
| Cash/Asset | 0.090** | 0.048 | 0.199*** | 0.084*** | 0.050** |
| | (0.035) | (0.052) | (0.031) | (0.026) | (0.020) |
| KZ index | 0.001 | 0.001** | 0.001*** | 0.000 | −0.001*** |
| | (0.000) | (0.001) | (0.000) | (0.000) | (0.000) |
| InstOwn | −0.048 | −0.318*** | −0.108*** | 0.035 | 0.016 |
| | (0.032) | (0.069) | (0.033) | (0.028) | (0.021) |
| (1-HHI) | −0.214** | 0.446** | 0.095 | 0.301*** | 0.268*** |
| | (0.085) | (0.175) | (0.086) | (0.059) | (0.044) |
| $(1\text{-HHI})^2$ | 0.194*** | −0.479*** | −0.071 | −0.259*** | −0.232*** |
| | (0.075) | (0.147) | (0.075) | (0.053) | (0.039) |
| Firm FEs | Y | N | N | Y | Y |
| Year FEs | Y | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 86,341 | 86,341 | 86,341 |

This table presents the full regression results of innovation on R&D intensity using different estimation methods. Column (1) reports fixed effects (FE) estimates with firm and year fixed effects. Column (2) presents OLS estimates with year fixed effects. Column (3) reports adjusted Hausman-Taylor (adjHT) estimates with year fixed effects. Columns (4) and (5) present Post-Regularization LASSO (PRL) and Double Machine Learning (DML) estimates with firm and year fixed effects, respectively. The standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table IA.2: Innovation to R&D Regression for Patenting Firms: FE and OLS

| | R&D/Asset | | R&D/ME | | ln(1+R&D) | |
|---|---|---|---|---|---|---|
| | FE | OLS | FE | OLS | FE | OLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: Patent regression** | | | | | | |
| R&D | 0.035 | 0.448*** | 0.102*** | 0.499*** | 0.032*** | 0.225*** |
| | (0.031) | (0.045) | (0.024) | (0.041) | (0.005) | (0.009) |
| $R^2$ | 0.822 | 0.424 | 0.822 | 0.429 | 0.817 | 0.417 |
| Between $R^2$ | 0.288 | 0.418 | 0.302 | 0.425 | 0.234 | 0.421 |
| Within $R^2$ | 0.063 | 0.042 | 0.064 | 0.043 | 0.036 | 0.022 |
| Control variables | Y | Y | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | N | Y | N |
| Year FEs | Y | Y | Y | Y | Y | Y |
| Observations | 45,679 | 45,913 | 45,679 | 45,913 | 45,679 | 45,913 |
| **Panel B: Citation regression** | | | | | | |
| R&D | -0.061 | 0.777*** | 0.120** | 0.818*** | 0.051*** | 0.390*** |
| | (0.079) | (0.087) | (0.054) | (0.073) | (0.010) | (0.013) |
| $R^2$ | 0.695 | 0.340 | 0.695 | 0.343 | 0.690 | 0.345 |
| Between $R^2$ | 0.193 | 0.382 | 0.212 | 0.389 | 0.152 | 0.391 |
| Within $R^2$ | 0.037 | 0.022 | 0.037 | 0.022 | 0.022 | 0.012 |
| Control variables | Y | Y | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | N | Y | N |
| Year FEs | Y | Y | Y | Y | Y | Y |
| Observations | 45,679 | 45,913 | 45,679 | 45,913 | 45,679 | 45,913 |
| **Panel C: Adjusted citation regression** | | | | | | |
| R&D | 0.033 | 0.419*** | 0.098*** | 0.508*** | 0.030*** | 0.231*** |
| | (0.036) | (0.049) | (0.026) | (0.044) | (0.005) | (0.010) |
| $R^2$ | 0.795 | 0.391 | 0.795 | 0.396 | 0.790 | 0.383 |
| Between $R^2$ | 0.253 | 0.388 | 0.267 | 0.398 | 0.190 | 0.387 |
| Within $R^2$ | 0.045 | 0.029 | 0.045 | 0.030 | 0.024 | 0.014 |
| Control variables | Y | Y | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | N | Y | N |
| Year FEs | Y | Y | Y | Y | Y | Y |
| Observations | 45,679 | 45,913 | 45,679 | 45,913 | 45,679 | 45,913 |

This table presents updated regression results of innovation outcomes on R&D using firm fixed effects (FE) and OLS models for patenting firms. Columns correspond to different R&D intensity measures. Standard errors clustered at the firm level are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table IA.3: Innovation to R&D regression for patenting firms: AdjHT, PRL, and DML

| | adjHT (Year) | PRL (Firm, Year) | DML (Firm, Year) |
|---|---|---|---|
| **Panel A: Patent regression** | | | |
| **A.1 R&D scaled by total asset** | | | |
| R&D/Asset | 0.161*** | 0.406*** | 0.399*** |
| | (0.030) | (0.044) | (0.025) |
| Selected ratio | | 3.34% | 6.32% |
| **A.2 R&D scaled by market equity** | | | |
| R&D/ME | 0.244*** | 0.468*** | 0.472*** |
| | (0.024) | (0.041) | (0.023) |
| Selected ratio | | 3.34% | 6.80% |
| **A.3 R&D stock** | | | |
| ln(1+R&D) | 0.090*** | 0.222*** | 0.221*** |
| | (0.005) | (0.009) | (0.005) |
| Selected ratio | | 3.34% | 6.32% |
| **Panel B: Citation regression** | | | |
| **B.1 R&D scaled by total asset** | | | |
| R&D/Asset | 0.317*** | 0.738*** | 0.740*** |
| | (0.075) | (0.084) | (0.054) |
| Selected ratio | | 3.34% | 6.32% |
| **B.2 R&D scaled by market equity** | | | |
| R&D/ME | 0.451*** | 0.779*** | 0.775*** |
| | (0.053) | (0.072) | (0.045) |
| Selected ratio | | 3.34% | 6.80% |
| **B.3 R&D stock** | | | |
| ln(1+R&D) | 0.193*** | 0.385*** | 0.384*** |
| | (0.009) | (0.013) | (0.007) |
| Selected ratio | | 3.34% | 6.32% |
| **Panel C: Adjusted citation regression** | | | |
| **C.1 R&D scaled by total asset** | | | |
| R&D/Asset | 0.175*** | 0.369*** | 0.377*** |
| | (0.034) | (0.047) | (0.028) |
| Selected ratio | | 3.34% | 6.32% |
| **C.2 R&D scaled by market equity** | | | |
| R&D/ME | 0.248*** | 0.471*** | 0.483*** |
| | (0.026) | (0.044) | (0.025) |
| Selected ratio | | 3.34% | 6.80% |
| **C.3 R&D stock** | | | |
| ln(1+R&D) | 0.089*** | 0.228*** | 0.227*** |
| | (0.005) | (0.009) | (0.005) |
| Selected ratio | | 3.34% | 6.32% |
| Control variables | Y | Y | Y |
| Firm FEs | N | Y | Y |
| Year FEs | Y | Y | Y |
| Observations | 45,913 | 45,913 | 45,913 |

This table presents the results of innovation on R&D measures for patenting firms using adjusted Hausman-Taylor (adjHT), Post-Regularization LASSO (PRL), and Double Machine Learning (DML). Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The selected ratio is the number of selected year and firm dummies divided by the total number of year and firm dummies.

Table IA.4: Selected 100 company list

| Rank | CONM | TIC | SIC | NAICS | CITY | STATE |
|---|---|---|---|---|---|---|
| 1 | INTL BUSINESS MACHINES CORP | IBM | 7370 | 519130 | Armonk | NY |
| 2 | LUCENT TECHNOLOGIES INC | LU.1 | 7373 | 541512 | Plano | TX |
| 3 | GENERAL ELECTRIC CO | GE | 9997 | 999977 | Boston | MA |
| 4 | APTIV PLC | APTV | 3714 | 336320 | Dublin | |
| 5 | EASTMAN KODAK CO | KODK | 3577 | 333316 | Rochester | NY |
| 6 | MOTOROLA SOLUTIONS INC | MSI | 3663 | 334220 | Chicago | IL |
| 7 | GENERAL MOTORS CO | GM | 3711 | 336110 | Detroit | MI |
| 8 | DU PONT (E I) DE NEMOURS | DD.2 | 2820 | 3252 | Indianapolis | IN |
| 9 | AT&T CORP | T.2 | 4813 | 517110 | Bedminster | NJ |
| 10 | DUPONT DE NEMOURS INC | DD | 2860 | 325199 | Wilmington | DE |
| 11 | XEROX HOLDINGS CORP | XRX | 3577 | 333316 | Norwalk | CT |
| 12 | AT&T INC | T | 4812 | 517312 | Dallas | TX |
| 13 | TEXAS INSTRUMENTS INC | TXN | 3674 | 334413 | Dallas | TX |
| 14 | 3M CO | MMM | 2670 | 322220 | Saint Paul | MN |
| 15 | RCA CORP | RCA.1 | 3600 | 335 | New York | NY |
| 16 | BROADCOM CORP | BRCM | 3674 | 334413 | San Jose | CA |
| 17 | NORTH AMERICAN PHILIPS CORP | PHG1 | 3640 | 3351 | Andover | MA |
| 18 | EXXON MOBIL CORP | XOM | 2911 | 324110 | Irving | TX |
| 19 | HP INC | HPQ | 3570 | 33411 | Palo Alto | CA |
| 20 | MERCK & CO | MRK | 2834 | 325412 | Kenilworth | NJ |
| 21 | FORD MOTOR CO | F | 3711 | 33611 | Dearborn | MI |
| 22 | HONEYWELL INTERNATIONAL INC | HON | 9997 | 336413 | Charlotte | NC |
| 23 | CBS CORP -OLD | CBS.2 | 4833 | 513120 | New York | NY |
| 24 | RAYTHEON TECHNOLOGIES CORP | RTX | 3724 | 336412 | Arlington | VA |
| 25 | PROCTER & GAMBLE CO | PG | 2840 | 325611 | Cincinnati | OH |
| 26 | SUN MICROSYSTEMS INC | JAVA.1 | 3571 | 334111 | Redwood City | CA |
| 27 | QUALCOMM INC | QCOM | 3674 | 334413 | San Diego | CA |
| 28 | MOBIL CORP | MOB.2 | 2911 | 324110 | Fairfax | VA |
| 29 | CONOCOPHILLIPS | COP | 1311 | 2111 | Houston | TX |
| 30 | MICRON TECHNOLOGY INC | MU | 3674 | 334413 | Boise | ID |
| 31 | JOHNSON & JOHNSON | JNJ | 2834 | 325412 | New Brunswick | NJ |
| 32 | BRISTOL-MYERS SQUIBB CO | BMY | 2834 | 325412 | New York | NY |
| 33 | BOEING CO | BA | 3721 | 336411 | Chicago | IL |
| 34 | CATERPILLAR INC | CAT | 3531 | 333120 | Irving | TX |
| 36 | SHELL OIL CO | 4108A | 1311 | 211112 | Houston | TX |
| 37 | LEXMARK INTL INC -CL A | LXK | 3577 | 334118 | Lexington | KY |
| 38 | HONEYWELL INC | HON.Z | 3822 | 334512 | Minneapolis | MN |
| 39 | MICROSOFT CORP | MSFT | 7372 | 513210 | Redmond | WA |
| 40 | PPG INDUSTRIES INC | PPG | 2851 | 325510 | Pittsburgh | PA |
| 41 | PHARMACIA CORP | PHA.1 | 2834 | 325412 | Kalamazoo | MI |
| 42 | PFIZER INC | PFE | 2834 | 325412 | New York | NY |
| 43 | SPERRY CORP | SY.2 | 3570 | 3341 | New York | NY |
| 44 | ROCKWELL AUTOMATION | ROK | 3620 | 335314 | Milwaukee | WI |
| 45 | LILLY (ELI) & CO | LLY | 2834 | 325412 | Indianapolis | IN |
| 46 | ITT INC | ITT | 3561 | 333914 | White Plains | NY |
| 47 | UNISYS CORP | UIS | 7373 | 541512 | Blue Bell | PA |
| 48 | JUNIPER NETWORKS INC | JNPR | 3576 | 334118 | Sunnyvale | CA |
| 49 | GOODYEAR TIRE & RUBBER CO | GT | 3011 | 326211 | Akron | OH |
| 50 | ABBOTT LABORATORIES | ABT | 3845 | 334510 | North Chicago | IL |
| 51 | AMERICAN CYANAMID CO | ACY.1 | 2800 | 325 | Madison | NJ |
| 52 | BAKER HUGHES INC | BHI | 1381 | 213111 | Houston | TX |
| 52 | BAKER HUGHES CO | BKR | 1389 | 213112 | Houston | TX |
| 53 | CORNING INC | GLW | 3679 | 334419 | Corning | NY |
| 54 | INTEL CORP | INTC | 3674 | 334413 | Santa Clara | CA |
| 55 | PITNEY BOWES INC | PBI | 3579 | 333318 | Stamford | CT |
| 56 | EASTMAN CHEMICAL CO | EMN | 2800 | 325 | Kingsport | TN |

Continued on next page

| Rank | CONM | TIC | SIC | NAICS | CITY | STATE |
|---|---|---|---|---|---|---|
| 57 | UNION CARBIDE CORP | DOW2 | 2860 | 325199 | Seadrift | TX |
| 58 | AMKOR TECHNOLOGY INC | AMKR | 3674 | 334413 | Tempe | AZ |
| 59 | PALM INC | PALM | 3571 | 334111 | Sunnyvale | CA |
| 60 | CHEVRON CORP | CVX | 2911 | 324110 | San Ramon | CA |
| 61 | TEXACO INC | TX.2 | 2911 | 324110 | White Plains | NY |
| 62 | TRW INC | TRW.1 | 3714 | 336330 | Cleveland | OH |
| 63 | AMOCO CORP | AN.2 | 2911 | 324110 | Houston | TX |
| 64 | DEERE & CO | DE | 3523 | 333111 | Moline | IL |
| 65 | MILLENNIUM PHARMACEUTICALS | MLNM | 2835 | 325413 | Cambridge | MA |
| 66 | NATIONAL SEMICONDUCTOR CORP | NSM.2 | 3674 | 334413 | Santa Clara | CA |
| 67 | NORTHROP GRUMMAN CORP | NOC | 3812 | 334511 | Falls Church | VA |
| 68 | RAYTHEON CO | RTN | 3812 | 334511 | Waltham | MA |
| 69 | VERIZON COMMUNICATIONS INC | VZ | 4812 | 517312 | New York | NY |
| 70 | EMERSON ELECTRIC CO | EMR | 3823 | 334513 | Saint Louis | MO |
| 71 | FMC CORP | FMC | 2870 | 325320 | Philadelphia | PA |
| 72 | BAXTER INTERNATIONAL INC | BAX | 2834 | 325412 | Deerfield | IL |
| 73 | ADVANCED MICRO DEVICES | AMD | 3674 | 334413 | Santa Clara | CA |
| 74 | AIR PRODUCTS & CHEMICALS INC | APD | 2810 | 325120 | Allentown | PA |
| 75 | LINDE PLC | LIN | 2810 | 325120 | Woking | |
| 76 | OWENS CORNING | OC | 3290 | 327993 | Toledo | OH |
| 77 | L3HARRIS TECHNOLOGIES INC | LHX | 3812 | 334511 | Melbourne | FL |
| 78 | UOP INC | UOP.1 | 3350 | | Des Plaines | IL |
| 79 | XILINX INC | XLNX | 3674 | 334413 | San Jose | CA |
| 80 | KIMBERLY-CLARK CORP | KMB | 2621 | 322121 | Dallas | TX |
| 81 | LEAR CORP | LEA | 2531 | 336360 | Southfield | MI |
| 82 | ILLINOIS TOOL WORKS | ITW | 3560 | 33399 | Glenview | IL |
| 83 | ALLERGAN INC | AGN.2 | 2834 | 325412 | Irvine | CA |
| 84 | COLGATE-PALMOLIVE CO | CL | 2844 | 325611 | New York | NY |
| 85 | GRACE (W R) & CO | GRA | 2810 | 325998 | Columbia | MD |
| 86 | CIENA CORP | CIEN | 3661 | 334210 | Hanover | MD |
| 87 | TEKTRONIX INC | TEK.1 | 3825 | 334515 | Beaverton | OR |
| 88 | GTE CORP | GTE.1 | 4813 | 513310 | Irving | TX |
| 89 | ROHM AND HAAS CO | ROH | 2821 | 325211 | Philadelphia | PA |
| 90 | BECTON DICKINSON & CO | BDX | 3841 | 339112 | Franklin Lakes | NJ |
| 91 | DELL TECHNOLOGIES INC | DELL | 3571 | 334111 | Round Rock | TX |
| 92 | MEDTRONIC PLC | MDT | 3845 | 334510 | Dublin | |
| 93 | LOCKHEED MARTIN CORP | LMT | 3760 | 336414 | Bethesda | MD |
| 94 | ALCOA INC | AA.3 | 3720 | 3364 | New York | NY |
| 95 | LSI CORP | LSI.1 | 3674 | 334413 | San Jose | CA |
| 96 | ATLANTIC RICHFIELD CO | ARC.3 | 2911 | 324110 | Wilmington | DE |
| 97 | AUTOLIV INC | ALV | 3714 | 336390 | Stockholm | |
| 98 | IONIS PHARMACEUTICALS INC | IONS | 2834 | 325412 | Carlsbad | CA |
| 99 | HUMAN GENOME SCIENCES INC | HGSI | 2835 | 325413 | Rockville | MD |
| 100 | WYETH | WYE | 2834 | 325412 | New York | NY |

Table IA.5: Regression Results on R&D Measures

| | (1) R&D/Asset | (2) R&D/ME | (3) ln(1 + R&D) |
|---|---|---|---|
| D_selected | 0.0514*** | 0.0387*** | 0.316*** |
| | (0.00475) | (0.00544) | (0.0347) |
| Constant | 0.0547*** | 0.0876*** | 0.504*** |
| | (0.00127) | (0.00184) | (0.0102) |
| Observations | 9,823 | 9,823 | 9,823 |

This table presents the cross-sectional regression of the within standard deviation of R&D measures on the selected dummy, which equals one if the firm is selected, and zero otherwise. Heteroskedasticity-robust standard errors are reported in parentheses. *** denote significance at the 0.1% levels.

Table IA.6: PRL Poisson and DML: R&D intensity (Full table)

| | (1) FE Poisson (Firm, Year) | (2) Poisson (Year) | (3) PRL Poisson (Firm, Year) | (4) DML Poisson (Firm, Year) |
|---|---|---|---|---|
| **Panel A: Patent count model** | | | | |
| R&D/Asset | −0.248 | 2.305*** | 2.407*** | 2.312*** |
| | (0.255) | (0.187) | (0.161) | (0.120) |
| ln(ME) | 0.331*** | 1.054*** | 0.937*** | 0.895*** |
| | (0.063) | (0.052) | (0.081) | (0.082) |
| ln(1+Age) | 0.745*** | 0.335** | 0.469*** | 0.563*** |
| | (0.287) | (0.142) | (0.182) | (0.162) |
| ln(K/L) | −0.072 | −0.038 | 0.062 | 0.080* |
| | (0.146) | (0.061) | (0.044) | (0.044) |
| R&D missing | −0.252* | −2.081*** | −2.099*** | −2.111*** |
| | (0.152) | (0.273) | (0.251) | (0.154) |
| Tobin Q | 0.011 | −0.168*** | −0.161*** | −0.127*** |
| | (0.018) | (0.037) | (0.030) | (0.032) |
| ROA | −0.648* | 0.870** | 1.073*** | 1.024*** |
| | (0.359) | (0.384) | (0.358) | (0.300) |
| Leverage | 0.374 | 0.706* | 0.595 | 0.536* |
| | (0.270) | (0.416) | (0.433) | (0.310) |
| Cash/Asset | 0.074 | 0.676 | 0.305 | 0.244 |
| | (0.167) | (0.445) | (0.486) | (0.428) |
| KZ index | 0.009 | 0.024** | 0.015 | 0.015* |
| | (0.008) | (0.011) | (0.011) | (0.008) |
| InstOwn | −0.808*** | −1.084*** | −0.905*** | −0.888*** |
| | (0.245) | (0.405) | (0.287) | (0.223) |
| (1-HHI) | −3.489*** | 0.842 | 1.420 | 0.452 |
| | (0.985) | (0.704) | (1.355) | (1.451) |
| $(1\text{-HHI})^2$ | 3.206*** | −1.245* | −1.582 | −0.702 |
| | (0.953) | (0.671) | (1.190) | (1.295) |
| Firm FEs | Y | N | Y | Y |
| Year FEs | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 86,341 | 86,341 |
| **Panel B: Citation count model** | | | | |
| R&D/Asset | −0.125 | 2.094*** | 2.299*** | 2.262*** |
| | (0.252) | (0.219) | (0.256) | (0.113) |
| ln(ME) | 0.317*** | 1.107*** | 0.984*** | 0.987*** |
| | (0.071) | (0.070) | (0.149) | (0.044) |
| ln(1+Age) | 0.593** | 0.094 | 0.150 | 0.165* |
| | (0.295) | (0.146) | (0.243) | (0.092) |
| ln(K/L) | −0.055 | −0.081 | 0.055 | 0.036 |
| | (0.139) | (0.070) | (0.096) | (0.031) |
| R&D missing | −0.161 | −2.027*** | −2.660*** | −2.486*** |
| | (0.172) | (0.404) | (0.872) | (0.175) |
| Tobin Q | 0.005 | −0.106** | −0.128** | −0.103*** |
| | (0.019) | (0.047) | (0.059) | (0.028) |
| ROA | −0.549 | 1.282*** | 1.371*** | 1.595*** |
| | (0.353) | (0.358) | (0.480) | (0.242) |
| Leverage | 0.321 | 0.455 | 0.598 | 0.672*** |
| | (0.321) | (0.451) | (0.549) | (0.255) |
| Cash/Asset | 0.211 | 1.072** | 0.471 | 0.651* |
| | (0.216) | (0.547) | (0.869) | (0.334) |
| KZ index | −0.000 | 0.022** | 0.010 | 0.013* |
| | (0.006) | (0.010) | (0.017) | (0.007) |

**Table IA.6 – continued from previous page**

| | (1) FE Poisson (Firm, Year) | (2) Poisson (Year) | (3) PRL Poisson (Firm, Year) | (4) DML Poisson (Firm, Year) |
|---|---|---|---|---|
| InstOwn | −0.909*** | −1.410*** | −1.096** | −1.145*** |
| | (0.230) | (0.468) | (0.469) | (0.184) |
| (1-HHI) | −3.482*** | 1.083 | 1.053 | 2.004** |
| | (0.943) | (0.853) | (2.107) | (0.855) |
| $(1\text{-HHI})^2$ | 3.272*** | −1.229 | −1.053 | −1.856** |
| | (0.897) | (0.780) | (1.888) | (0.746) |
| Firm FEs | Y | N | Y | Y |
| Year FEs | Y | Y | Y | Y |
| Observations | 84,620 | 86,341 | 86,341 | 86,341 |

This table presents the full Poisson regression results of innovation on R&D intensity using different estimation methods, including Post-Regularization LASSO (PRL) Poisson and Double Machine Learning (DML) Poisson estimates. Column (1) reports fixed effects (FE) Poisson estimates with firm and year fixed effects. Column (2) presents Poisson estimates with year fixed effects. Columns (3) and (4) present PRL Poisson and DML Poisson estimates with firm and year fixed effects, respectively. The standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table IA.7: Innovation to R&D Poisson regression for patenting firms

| | (1) FE Poisson (Firm, Year) | (2) Poisson (Year) | (3) PRL Poisson (Firm, Year) | (4) DML Poisson (Firm, Year) |
|---|---|---|---|---|
| **Panel A: Patent count model** | | | | |
| **A.1 R&D scaled by total asset** | | | | |
| R&D/Asset | −0.208 | 1.663*** | 1.937 | 1.752*** |
| | (0.238) | (0.172) | (1.320) | (0.089) |
| Selected ratio | | | 10.44% | 20.86% |
| **A.2 R&D scaled by market equity** | | | | |
| R&D/ME | 0.222 | 1.254*** | 1.429*** | 1.440*** |
| | (0.166) | (0.156) | (0.089) | (0.070) |
| Selected ratio | | | 8.53% | 18.35% |
| **A.3 R&D stock** | | | | |
| ln(1+R&D) | 0.092*** | 0.746*** | 0.604** | 0.667*** |
| | (0.033) | (0.068) | (0.280) | (0.065) |
| Selected ratio | | | 9.29% | 21.60% |
| Control variables | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | Y |
| Year FEs | Y | Y | Y | Y |
| Observations | 45,679 | 45,913 | 45,913 | 45,913 |
| **Panel B: Citation count model** | | | | |
| **B.1 R&D scaled by total asset** | | | | |
| R&D/Asset | −0.111 | 1.480*** | 1.575*** | 1.590*** |
| | (0.231) | (0.188) | (0.144) | (0.082) |
| Selected ratio | | | 10.30% | 19.89% |
| **B.2 R&D scaled by market equity** | | | | |
| R&D/ME | 0.240 | 1.311*** | 1.449*** | 1.508*** |
| | (0.174) | (0.156) | (0.110) | (0.117) |
| Selected ratio | | | 9.73% | 18.49% |
| **B.3 R&D stock** | | | | |
| ln(1+R&D) | 0.136*** | 0.746*** | 0.654*** | 0.587** |
| | (0.050) | (0.099) | (0.112) | (0.276) |
| Selected ratio | | | 8.53% | 21.32% |
| Control variables | Y | Y | Y | Y |
| Firm FEs | Y | N | Y | Y |
| Year FEs | Y | Y | Y | Y |
| Observations | 45,679 | 45,913 | 45,913 | 45,913 |

This table presents the Poisson regression results of innovation on R&D measures for patenting firms using different estimation methods. Column (1) reports fixed effects (FE) Poisson estimates with firm and year fixed effects. Column (2) presents Poisson estimates with year fixed effects. Columns (3) and (4) present Post-Regularization LASSO (PRL) Poisson and Double Machine Learning (DML) Poisson estimates with firm and year fixed effects, respectively. The standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The selected ratio is the number of selected year and firm dummies divided by the total number of year and firm dummies.