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

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The prevailing use of firm fixed effects

- Researchers like to use fixed effects (FE) models because FEs absorb the influences of individual-specific, unobservable, and time-invariant effects (to mitigate endogeneity concerns)
- However, such a “by-default” use of FE regressions may fail to detect important persistent explanatory variables
- To illustrate such a bias, we need a very convincing causal relation:
  - The R&D-patent relation is perhaps the most intuitive example
  - Which factors contribute to corporate innovation has been an important topic (Ederer and Manso, 2011; He and Tian, 2018; Lerner and Seru, 2022)
  - Our review of 200 papers in this filed suggests that, while R&D is an important control variable, only 40%-50% regressions/papers show insignificant or even negative coefficients on R&D.

Example: Luong et al. (2017)

TABLE 2
Baseline Regressions

Table 2 reports the regressions of firm innovation on institutional ownership. Columns 1 and 2 (3 and 4) show the pooled ordinary least squares (OLS) (Firm fixed effects) regression results. The dependent variable is shown as the column heading in columns 1–4. The main independent variable is foreign institutional ownership (FIO). All explanatory variables are lagged by 1 year. Variable definitions are in Appendix B. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	ln(PATENT)	ln(CITEPAT)	ln(PATENT)	ln(CITEPAT)
Variables	1	2	3	4
FIO	0.010***	0.014***	0.008***	0.011***
	(0.003)	(0.004)	(0.003)	(0.004)
DIO	−0.010***	−0.012***	−0.001	−0.001
	(0.002)	(0.003)	(0.001)	(0.002)
INSIDE	−0.072	−0.054	0.062*	0.084*
	(0.063)	(0.070)	(0.032)	(0.044)
ln(AGE)	0.062**	0.062*	0.086**	0.118**
	(0.029)	(0.032)	(0.037)	(0.049)
HHI	0.396	0.400	−0.170	0.152
	(0.292)	(0.326)	(0.274)	(0.347)
HHI^2	−0.277	−0.280	0.152	0.050
	(0.277)	(0.307)	(0.241)	(0.290)
RD	2.267***	2.637***	0.054	−0.232
	(0.238)	(0.288)	(0.132)	(0.215)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	Yes
Industry fixed effects	Yes	Yes	No	No
Country fixed effects	Yes	Yes	No	No

In columns (1) and (2) without firm FE, R&D effect is significant
Once firm FEs are included in columns (3) and (4), R&D effect is gone!

Why? and so what?

- **Why would R&D effect be missing?**
- Innovation economists have been aware of this issue and warned against FE regressions many decades ago (Hall et al., 2005):
  - A firm's R&D changes slowly over time; and is highly correlated with its individual effect -- which will be absorbed by FE regressions
  - FE regressions eliminate all cross-sectional variations in patents, and only inform us about how R&D explains a firm's time-series variations in patents, which weakens the R&D effect
- **So what?**
  - In fact, R&D is important in creating firm heterogeneity
  - Cross-sectional variation is more important than time-series variation (Hausman et al., 1984; Hall et al., 2005)
  - If R&D doesn't work, how much can we trust in other X variables?
- **Implications for empirical researchers:** This econometric issue applies to all persistent variables: ownership, culture, talent, etc.

Feasible solutions for persistent X variables

- Solution 1:

  - present regression results without firm FEs for comparison

  - report between and within R-squared (which is readily available or easy-to-compute) in addition to R-squared

- Solution 2: Adjusted Hausman-Taylor estimator (1981) to correctly estimate the coefficients for persistent variables
- Solution 3: Machine-learning models to "shrink" parameters (i.e., select some informative firm dummies and drop unimportant)
  - E.g., only some firms have innovation culture, all the rest do not
  - Post-regularization LASSO (PRL) and Double machine-learning (DML)
  - These are easy to implement by STATA (or R/Python), and our codes available online: https://github.com/hcchuang
- These solutions can be useful to all empirical researchers

Econometric Tools

- A lack of appropriate econometric tools to address the issue for more reliable statistical inferences.
- Not to include firm fixed effects (Baltagi et al., 2000; Hall et al., 2005; Noel and Schankerman, 2013; Pesaran and Zhou, 2018) may introduce alternative biases.

- Our propositions and contributions:

1. Adjusted Hausman and Taylor ("adj-HT" 1981) method
2. Machine learning
    - Post-Regularization LASSO (**PRL**)
    - Double-machine learning (**DML**)

Our explanations

- OLS allows us to understand R&D's explanatory power for total variations of patents (= <u>cross-sectional/between-firm</u> variations + <u>time-series/within-firm</u> variations)
- FE models absorb all cross-sectional/between-firm variations in patents
  - An analogy: a high (low) tech firm's R&D and patents are persistently high (low). Thus, cross-sectional variation could be more important than time-series variation (Hausman et al., 1984; Hall et al., 2005).
  - However, FE models eliminate all cross-sectional variations in firms' patents – so R&D role is missing
  - So, the estimation results of FE models only tell us R&D's explanatory power for a firm's time-series variations in patents

Sample

- We first collect the financial and accounting data of all US public firms in CRSP/Compustat.
- We exclude financial and utility firms, and firms with negative and missing total asset and sales.
- Public firms' patent and citation are from the PatentsView patent database that is organized by the USPTO.
- As a result, we have 86,341 firm-year observations of 11,544 unique firms in 1976-2000 (to match most prior studies' sample period, which are based on the 1st version of NBER patent data).
- We also consider a patenting firm sample with 45,913 firm-year observations of 4,312 unique firms with at least one patent during the sample period.

Our baseline regressions

$$Innov_{i,t+1} = \beta_0 + \beta_{R\&D} R\&D_{i,t} + \boldsymbol{\beta}_2 \boldsymbol{X}_{i,t} + \sum_{s \in S} \alpha_s dummy_{s,i} + u_{i,t}$$

- We consider OLS here and will discuss the Poisson regression later. $Innov_{i,t+1}$ is one of innovation measures in ln(1+y) format: ln(1+Patent), ln(1+Citation), and ln(1+AdjCitation).
- $R\&D_{i,t}$ is 5-year R&D expenditures/total asset. (We also consider R&D/ME, or ln(1+R&D) for five years for robustness.)
- $\boldsymbol{X}_{i,t}$ denotes firm characteristic controls: R&D missing dummy, capital level, firm age, K/L, Tobin's Q, ROA, leverage, cash divide by the total asset, Institutional ownership ratio, KZ index, Herfindahl-Hirschman index, and Herfindahl-Hirschman index square.
- OLS model includes none of the firm dummies, i.e., S = ∅.
- FE model includes all of the firm dummies, i.e., $S = \{1, \cdots, N\}$.

Solution 1: no-FE results + within R squared

Dependent: Patents	OLS model	FE model
R&D	0.593***	0.041
	(0.042)	(0.028)
Control	YES	YES
Firm dummies	NO	ALL
R2	0.362	0.853
Between R2	0.310	0.209
Within R2	0.020	0.035

- OLS model (no FE) suggest strong R&D effect
- FE model, however, suggests no R&D effect
- **Within R2** is the R2 from regressing demeaned Y on demeaned X (including R&D)
- **Between R2** is the squared correlation between average Y and its predicted value based on average X
- Within R2 is much smaller than between R2 and total R2
- Between R2 drops from OLS to FE (0.31=>0.21) fixed effects steal/absorb the cross-sectional explanatory power of X
- R&D's explanatory power for cross-section is more important!

Solution 2: Adjusted Hausman-Taylor (HT) methods

- Consider the simplified Hausman Taylor (1981) model

$$Y_{i,t+1} = \beta \boldsymbol{Z}_i + \boldsymbol{\beta}_2 \boldsymbol{X}_{i,t} + \alpha_i + \epsilon_{i,t}.$$

- HT allow arbitrary correlation between Z_i (observable) and α_i (unobservable), and can be estimated using moment conditions:

$$E[(\boldsymbol{X}_{i,t} - \overline{\boldsymbol{X}}_i)'(Y_{i,t+1} - \beta Z_i - \boldsymbol{\beta}_2 \boldsymbol{X}_{i,t})] = \boldsymbol{0}.$$

$$E[\boldsymbol{X}_{i,t}{}'(Y_{i,t+1} - \beta Z_i - \boldsymbol{\beta}_2 \boldsymbol{X}_{i,t})] = \boldsymbol{0}.$$

- For our purpose of R&D effect, we replace Z_i with persistent $R\&D_{i,t}$ and add an extra moment condition:
  - $E[(R\&D_{i,t} - \overline{R\&D_i})(Y_{i,t+1} - \beta_{R\&D} R\&D_{i,t} - \boldsymbol{\beta}_2 \boldsymbol{X}_{i,t})] = 0.$
  - The correlation between individual effects (α_i) and $R\&D_{i,t}$ arises from the firm's $\overline{R\&D_i}$ (this is intuitive as R&D-innovation is a long-term effect); thus, deviations from $\overline{R\&D_i}$ are unrelated to individual effects.
- Thus, we can identify $\beta_{R\&D}$ by GMM using these moment conditions

Solution 2: Adjusted Hausman-Taylor (HT)

Dependent: Patents	OLS model	FE model	Adj HT
R&D	0.593***	0.041	0.220***
	(0.042)	(0.028)	(0.027)
Control	YES	YES	YES
R2	0.362	0.853	
Between R2	0.310	0.209	
Within R2	0.020	0.034	

- Our adjusted Hausman-Taylor estimate also supports significant and important R&D effect
- The coefficient 0.220 is smaller than OLS estimates
  - ✓ This is reasonable given that adjusted Hausman-Taylor controls for non-R&D individual effects

Solution 3: Machine learning

$$Innov_{i,t+1} = \beta_0 + \beta_{R\&D} R\&D_{i,t} + \boldsymbol{\beta}_2 \boldsymbol{X}_{i,t} + \boxed{\sum_{s \in \boldsymbol{S}} \alpha_s dummy_{s,i}} + u_{i,t}$$

- Post-regularization LASSO (PRL) (Chernozhukov et al., 2015)
- Double machine-learning (DML) (Chernozhukov et al., 2018)
- By "shrinking" parameters, PRL and DML only use a subset of firm dummies, i.e., $\boldsymbol{S} \in \{1, \cdots, N\}$,, while keep the valid inference of $\beta_{R\&D}$.
  - As important dummies have been selected to control for, we prevent the omitted-variable bias.
  - Since unimportant dummies are not selected, they will not bias our test for the role of persistent R&D.

Intuition of selecting dummies

- If innovation culture is the *only* fixed effect and if only some firms have such 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)
- Those methods suggest us to only add those firms' dummies in regression estimations.
- In other words, those methods also identify firms *without* such culture and advise us not to include their dummies in estimation – these firms do NOT have such effect, so we should not even control for that for these firms

Our proposition-2

- Unobserved heterogeneity exists in some firms but not others.
  - Some managers are aggressive in investing in R&D and pursuing patent output, but others are not.
  - Some firms have a strong, innovation-oriented culture, while others do not.
- A smarter methodology that can select which individual firm dummies to be included is called for.
- In this paper, we proposed the second advanced machine learning method:
  1. Post-regularization LASSO (PRL, Chernozhukov et al., 2015)
  2. Double machine learning (DML, Chernozhukov et al., 2018)
  - to select individual firm dummies (and explanatory variables) in explaining firm-level patent outputs.

Post-Regularization LASSO (PRL)

- **PRL** proceeds in the following 3 steps:

➢ **Step1:** LASSO of $Innov_{i,t+1}$ on firm dummies and force small coefficients of some dummies to 0 by BIC (estimate step). Then, Post LASSO: OLS of $Innov_{i,t+1}$ on selected firm dummies, obtain the residuals, $\hat{r}_{innov}$ (get residual step)

➢ **Step2:**

a) LASSO of $R\&D_{i,t}$ on firm dummies and force small coefficients of some dummies to 0. Then, Post LASSO: OLS of $R\&D_{i,t}$ on selected firm dummies, obtain the residuals, $\hat{r}_{R\&D}$.

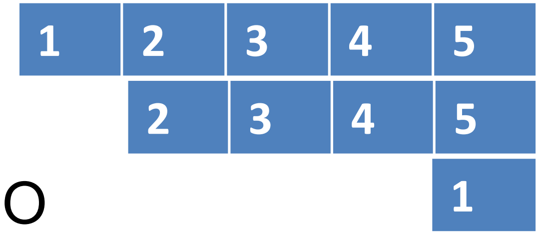
b) LASSO of $X_{i,t}$ on firm dummies and force small coefficients of some dummies to 0. Then, Post LASSO: OLS of $X_{i,t}$ on selected firm dummies, obtain the residuals, $\hat{r}_X$.

➢ **Step3**: OLS of $\hat{r}_{innov}$ on $\hat{r}_{R\&D}$, $\hat{r}_X$ and obtain the coefficient $\hat{\beta}_{R\&D,\,PRL}$.

- If a firm dummy is selected in either Step 1 or Step 2 (partialing-out/residualizing), it is considered informative to $Innov_{i,t+1}$ and $R\&D_{i,t}$.

Double Machine Learning (DML)

- **DML** generalizes the PRL to a general model selection (LASSO, random forests, gradient boosting, neural nets, etc.) and add the cross-fitting procedures to PRL.
- DML proceeds in the following steps:
  - splits sample into random 5 folds,
  - use only 4 folds to do LASSO
  - use the reserved one to do Post LASSO
  - stake all residuals from 5 times, use OLS to obtain $\hat{\beta}_{R\&D,DML}$.



- DML uses sample splitting to eliminates the dependence between the estimation steps, reduce the post-model-selection bias (or, errors in estimated variables) of PRL.
- However, as the cross-fit procedure reduces the sample size, DML also reduces the estimation efficiency.
- DML also takes longer in computation

PRL and DML benefits

- Both allow us to select an appropriate model that contains only important covariates, including separate firm dummies.
- PRL and DML estimator follow the standard asymptotic normal distributions which facilitate the empirical usage by assuming the sparsity condition holds (i.e., the number of strong dummies is bounded from above by an order of $\sqrt{NT}/\ln N$.)

Patent regression: PRL and DML results

Dependent: Patents	OLS model	PRL	DML	FE model	Adj HT
R&D	0.593***	0.199***	0.213***	0.041	0.220***
	(0.042)	(0.018)	(0.014)	(0.028)	(0.027)
# of dummies		11,570	1,1570		
# of selected dummies		1,241 (10.73%)	1,737 (15.01%)		

- In PRL and DML, R&D effect is statistically significant
- The economic magnitude (0.199 and 0.213) is closer adjusted Huasman-Taylor (0.220)
- PRL and DML select about 10% to 15% of firm dummies to be included in estimation
- Bias from adding all firm dummies (FE) overpowers the bias from not adding any at all (OLS) and leads to “missing R&D effect”

PRL and DML results

- In PRL and DML,
- the coefficients on R&D input are statistically significant
- their economic magnitude is much closer to those from OLS models without firm fixed effects and adj-Huasman-Taylor, and is far from FE model.
- PRL and DML select about 10% to 20% of firm dummies to be included in regression models -- the bias from adding all firm dummies overpowers the bias from not adding any at all (the consequence is an insignificant R&D coefficient)
- These results, together with prior analyses, suggest that most firm dummies do not play a crucial role.

Citation regression: PRL and DML results

PRL

	OLS (Year Dummies Only)	PRL (Firm and Year Dummies)	Fixed Effects (All Firm and Year Dummies)
R&D/Asset	1.396***	1.397***	-0.051
	(0.084)	(0.083)	(0.068)
Number of dummies		11,570	
Number of selected dummies		525 (4.54%)	

DML

	OLS (Year Dummies Only)	DML (Firm and Year Dummies)	Fixed Effects (All Firm and Year Dummies)
R&D/Asset	1.396***	1.364***	-0.051
	(0.084)	(0.050)	(0.068)
Number of dummies		11,570	
Number of selected dummies		947 (8.18%)	

Adjusted-Citation regression: PRL and DML results

PRL

	OLS (Year Dummies Only)	PRL (Firm and Year Dummies)	Fixed Effects (All Firm and Year Dummies)
R&D/Asset	0.590***	0.210***	0.033
	(0.045)	(0.019)	(0.031)
Number of dummies		11,570	
Number of selected dummies		1,194 (10.32%)	

DML

	OLS (Year Dummies Only)	DML (Firm and Year Dummies)	Fixed Effects (All Firm and Year Dummies)
R&D/Asset	0.590***	0.198***	0.033
	(0.045)	(0.015)	(0.031)
Number of dummies		11,570	
Number of selected dummies		1,882 (16.27%)	

STATA code

- To implement adjusted Hausman and Taylor:

```
ivregress gmm y z x (z = demean_z demean_x),
      wmatrix(cluster firmID)
```

- To implement PRL

```
poregress y z x, controls(i.firmID)
      vce(cluster firmID)
```

- To implement DML

```
xporegress y z x, controls(i.firmID)
      vce(cluster firmID) xfolds(#folds)
```

Robustness

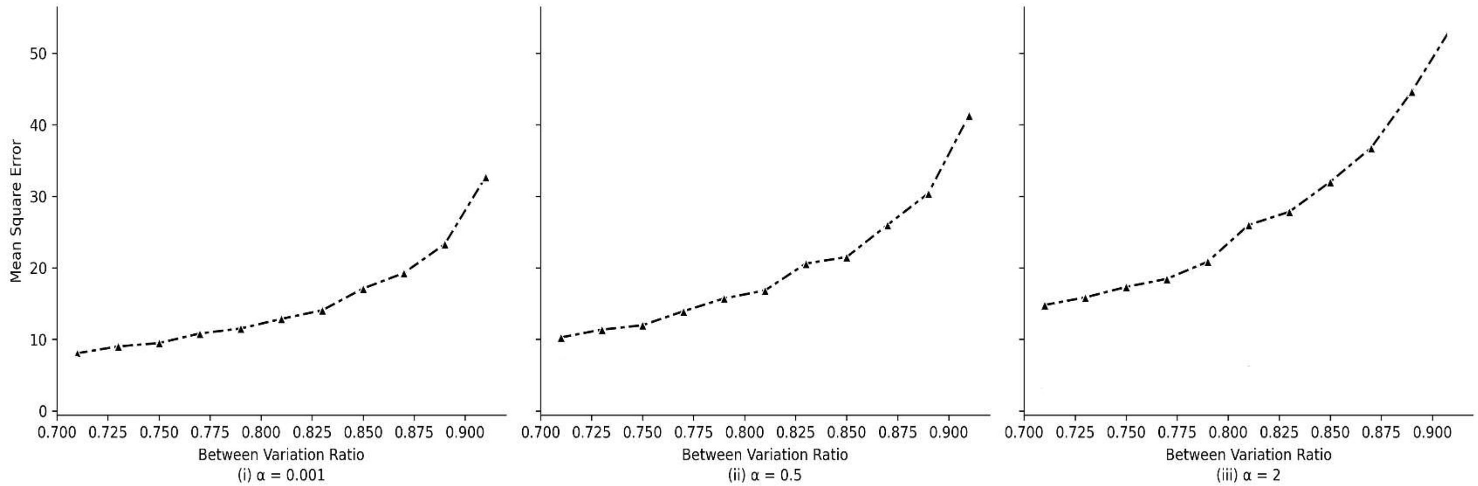
- Alternative innovation measures:
  - Citations and adjusted citations
- Alternative R&D measures:
  - R&D/ME and Ln(1+R&D) in addition to R&D/AT,
- Patenting firms only
  - Excluded firms without any patent for during its sample period.
- Handling missing R&D values
  - Remove firm-year observations with missing R&D
- Alternative specifications in HT, PRL, and DML methods
  - Different fold count from two to five in DML method

Simulation Study

- Innovation outcome (patent, citations) equation:
  - $Innov_{i,t}$ negative binominal distribution with conditional mean
    $$E\left(Innov_{i,t} \middle| z_{i,t}, x_{i,t}\right) = \exp\left(\beta R\&D_{i,t} + x_{i,t}\right)$$
  - and a over-dispersion parameter α, larger value corresponds to a greater dispersion.
- R&D process:
  $$R\&D_{i,t} = 0.5\,\eta_i + 0.5\,v_{i,t}$$
  - η_i : time-invariant firm-fixed effect drawn from $N(0, \sigma_\eta)$
  - $v_{i,t}$: firm and time varying component drawn from $N(0, \sigma_v)$
    - Between variation ratio $= \frac{\sigma_\eta^2}{\sigma_\eta^2 + \sigma_v^2}$
- $x_{i,t}$ drawn from $N(0, 2)$, and $N = 500, T = 10$, Monte Carlo replicate 10,000.

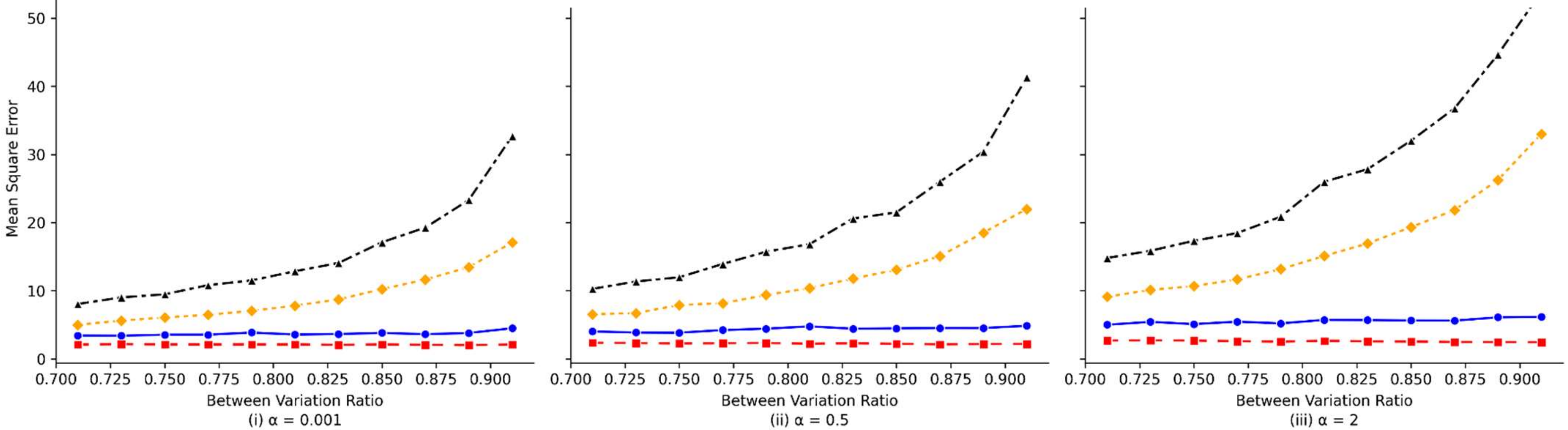
Simulation Study (cont'd)

– Mean Square Error (FE)

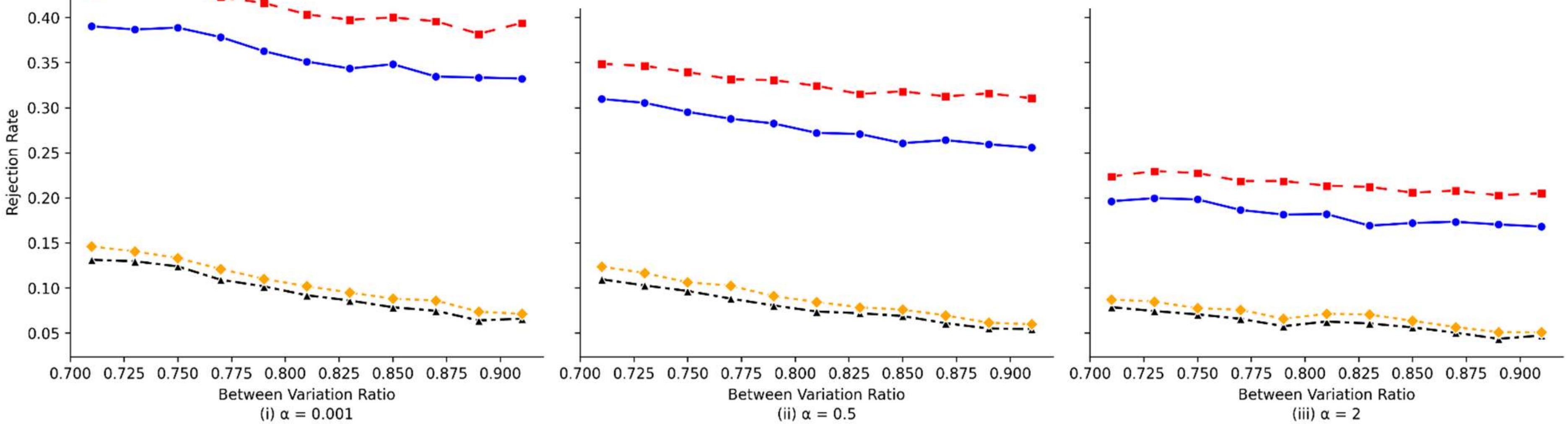


Simulation Study (cont'd)

Mean Square Errors: --- FE --- OLS ---adjHT --- PRL



Rejection rate: --- FE --- OLS ---adjHT --- PRL



Poisson regression

$$E(Innov_{i,t+1} \mid R\&D_{i,t}, x_{i,t}) =$$
$$\exp(\beta_0 + \beta_{R\&D} R\&D_{i,t} + \boldsymbol{\beta}_2 X_{i,t} + \textstyle\sum_{s \in \boldsymbol{S}} \alpha_s dummy_{s,i})$$

- Poisson regression includes none of the firm dummies, i.e., $\boldsymbol{S} = \emptyset$.
- Poisson fixed effect regression includes all of the firm dummies, i.e., $\boldsymbol{S} = \{1, \cdots, N\}$.
- Adjusted Hausman-Taylor uses demeaned $X_{i,t}$ and demeaned $R\&D_{i,t}$ in GMM to identify $\beta_{R\&D}$ of the rarely time-varying R&D.
- PRL Poisson (Belloni, Chernozhukov and Wei, 2016) and DML select some of the firm dummies, i.e., $\boldsymbol{S} \in \{1, \cdots, N\}$.
  - PRL Poisson proceeds in the similar fashion as PRL, except it uses the post LASSO Poisson regression in Step 1 and use GMM in Step 3.
- DML follows the PRL Poisson steps with cross-fitting.

PRL Poisson and DML

Patent Counts

	Poisson	FE Poisson	PRL	DML
	Year Dummies only	All Firm and Year Dummies	Firm and Year Dummies	Firm and Year Dummies
R&D	2.305***	-0.248	2.407***	2.312***
	(0.187)	(0.255)	(0.161)	(0.120)
# of dummies			11,570	11,570
# of selected dummies			1,218 (10.53%)	2,484 (21.47%)

- In PRL and DML Poisson, R&D effect is statistically significant
- The economic magnitude (2.407 and 2.312) is close to Poisson without FE (2.305)
- PRL and DML select about 11% to 21% of firm dummies to be included in estimation
- Bias from adding all firm dummies (FE) overpowers the bias from not adding any at all (OLS) and leads to “missing R&D effect”

PRL Poisson and DML

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Citation Counts

	Poisson	FE Poisson	PRL Poisson	DML Poisson
	Year Dummies only	Firm and Year Dummies	Firm and Year Dummies	Firm and Year Dummies
R&D/Asset	2.094***	-0.125	2.299***	2.262***
	(0.219)	(0.252)	(0.256)	(0.113)
Number of dummies			11,570	11,570
Number of selected dummies			1,226 (10.51%)	2,426 (20.97%)

Our recommendations

Straightforward solutions:

1. Instead of only reporting FE model results, please also present the results without FE and discuss why the coefficient estimates vary
2. We recommend to report between and within R-squared in addition to total R-squared, and discuss the explanatory power in time series (and the rest for cross-section)

Grab-and-go codes:

Use adj. Hausman and Taylor, PRL and DML for "second opinion":

- easy to implement by STATA (or R/Python). We make our data and codes available online: https://github.com/hcchuang

√ These can be applied to many empirical questions in corporate finance, accounting, and economics

Our contributions

- Corporate finance studies tend to solve firm-specific, time-invariant unobservables issues by using fixed effects models (e.g., Angrist and Pischke, 2009; Imbens and Wooldridge, 2009; Roberts and Whited, 2013)
- We illustrate the potential biases of such a practice by using the intuitive R&D-patent relation as our lab.
  - More importantly, we offer two feasible and ready-to-use 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.
  - 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).

Our contributions (Cont.)

- We add to modern machine learning techniques in corporate finance research, for the selection of relevant covariates (e.g., Chinco et al., 2019; Feng et al., 2020; Gu et al., 2020; Erel et al., 2021).
- This study also adds to the economics literature by supporting and 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).

Thank you!

Questions? Comments?

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Codes and data: https://github.com/hcchuang

Chuang, Hui-Ching and Hsu, Po-Hsuan and Kuan, Chung-Ming and Yang, Jui-Chung, Revisiting the Missing R&D-Patent Relation: Challenges and Solutions for Firm Fixed Effects Models (2024). Available at SSRN: https://ssrn.com/abstract=4636846

Thank you!

Questions? Comments?

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Chuang, Hui-Ching and Hsu, Po-Hsuan and Kuan, Chung-Ming and Yang, Jui-Chung, Revisiting the Missing R&D-Patent Relation: Challenges and Solutions for Firm Fixed Effects Models
(2024). Available at SSRN: https://ssrn.com/abstract=4636846

https://github.com/hcchuang/Revisiting-the-Missing-RD-Patent-Relation_Challenges-and-Solutions-for-Firm-Fixed-Effects-Models

Example:

TABLE 2

Baseline Regressions

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DIO	−0.010***	−0.012***	−0.001	−0.001
	(0.002)	(0.003)	(0.001)	[illegible]
INSIDE	−0.072	−0.054	0.062*	0.084*
	(0.063)	(0.070)	(0.032)	[illegible]
ln(AGE)	0.062**	0.062*	0.086**	[illegible]
	(0.029)	(0.032)	(0.037)	(0.049)
HHI	0.396	0.400	−0.170	0.152
	(0.292)	(0.326)	(0.274)	[illegible]
HHI^2	−0.277	−0.280	0.152	0.050
	(0.277)	(0.307)	(0.241)	(0.290)
RD	2.267***	2.637***	0.054	−0.232
	(0.238)	(0.288)	(0.132)	[illegible]
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	No	No	Yes	Yes
Industry fixed effects	Yes	Yes	No	No
Country fixed effects	Yes	Yes	No	No

Dependent variables: innovation output

ln(PATENT): Natural logarithm of the number of patents filed by each firm in a year plus 1.

ln(CITEPAT): Natural logarithm of the number of citations received by each firm's patents in a year plus 1.

Our focus:

RD: Research and development expenditures scaled by total assets.

me R&D does not explain

?

Selected Top 30 Firms

1	INTL BUSINESS MACHINES	11	XEROX HOLDINGS CORP	21	FORD MOTOR CO
2	LUCENT TECHNOLOGIES	12	AT&T INC	22	HONEYWELL INTERNATIONAL INC
3	GENERAL ELECTRIC	13	TEXAS INSTRUMENTS INC	23	CBS CORP -OLD
4	APTIV PLC	14	3M CO	24	RAYTHEON TECHNOLOGIES CORP
5	EASTMAN KODAK	15	RCA CORP	25	PROCTER & GAMBLE CO
6	MOTOROLA SOLUTIONS	16	BROADCOM CORP	26	SUN MICROSYSTEMS INC
7	GENERAL MOTORS CO	17	NORTH AMERICAN PHILIPS CORP	27	QUALCOMM INC
8	DU PONT (E I) DE NEMOURS	18	EXXON MOBIL CORP	28	MOBIL CORP
9	AT&T CORP	19	HP INC	29	CONOCOPHILLIPS
10	DUPONT DE NEMOURS INC	20	MERCK & CO	30	MICRON TECHNOLOGY INC

Alternative R&D measures: Patent regression

	Fixed Effects (Firm and Year Dummies)	OLS (Year Dummies)	adjHT (Year Dummies)	PRL (Firm and Year Dummies)	DML (Firm and Year Dummies)
R&D/ME	0.026	0.502***	0.139***	0.112***	0.123***
	(0.018)	(0.035)	(0.018)	(0.015)	(0.012)
Ln(R&D)	0.023***	0.140***	0.071***	0.032***	0.035***
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)

Firm cluster standard errors in parentheses. *p<0.1, **p<0.05, and ***p<0.01.
We suppress the year and firm characteristics variables to save space.

Alternative R&D measures: Citation regression

	Fixed Effects (Firm and Year Dummies)	OLS (Year Dummies)	adjHT (Year Dummies)	PRL (Firm and Year Dummies)	DML (Firm and Year Dummies)
R&D/ME	-0.024	1.040***	0.286***	1.015***	1.001***
	(0.040)	(0.064)	(0.040)	(0.064)	(0.038)
Ln(R&D)	0.036***	0.286***	0.176***	0.285***	0.285***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.003)

Firm cluster standard errors in parentheses. *p<0.1, **p<0.05, and ***p<0.01.
We suppress the year and firm characteristics variables to save space.

Alternative R&D measures: AdjCitation regression

	Fixed Effects (Firm and Year Dummies)	OLS (Year Dummies)	adjHT (Year Dummies)	PRL (Firm and Year Dummies)	DML (Firm and Year Dummies)
R&D/ME	0.021	0.506***	0.135***	0.119***	0.117***
	(0.019)	(0.037)	(0.019)	(0.016)	(0.012)
Ln(R&D)	0.022***	0.143***	0.071***	0.035***	0.035***
	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)

Firm cluster standard errors in parentheses. *p<0.1, **p<0.05, and ***p<0.01.
We suppress the year and firm characteristics variables to save space.

Patenting firms (Observation: 45,913)

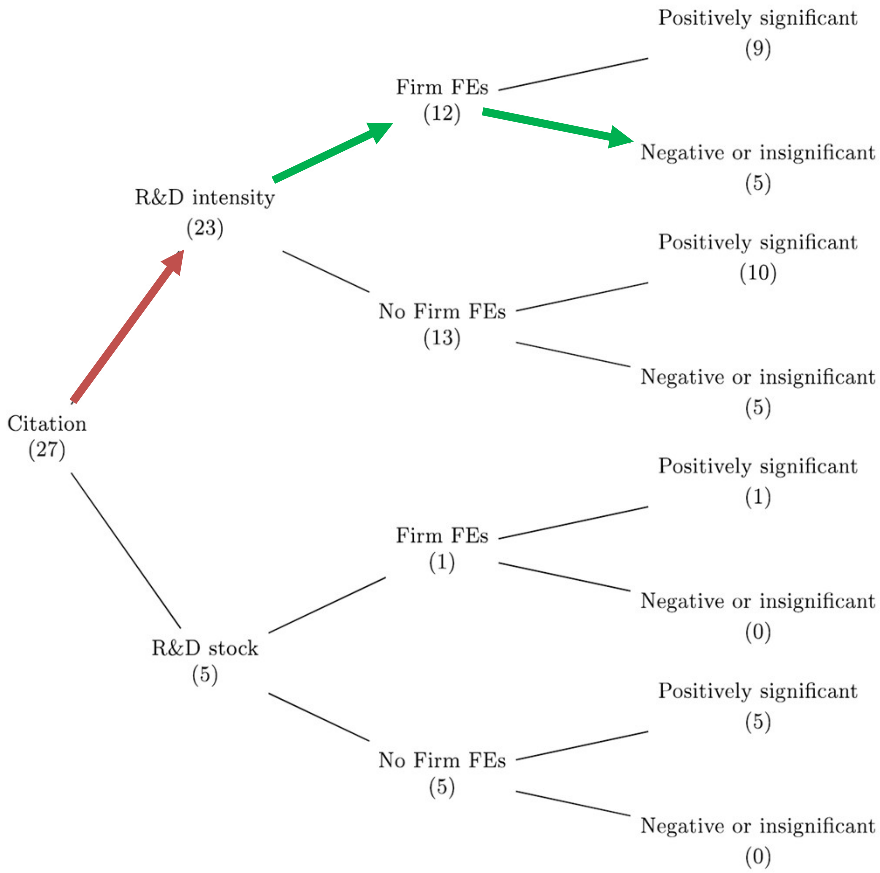
	Fixed Effects (All Firm and Year Dummies)	OLS (Year Dummies)	adjHT (Year Dummies)	PRL (Firm and Year Dummies)	DML (Firm and Year Dummies)
Patent regression					
R&D/AT	0.035	0.448***	0.161***	0.406***	0.399***
	(0.031)	(0.045)	(0.030)	(0.044)	(0.025)
Citation regression					
R&D/AT	-0.061	0.777***	0.317***	0.738***	0.740***
	(0.079)	(0.087)	(0.075)	(0.084)	(0.054)
AdjCitation regression					
R&D/AT	0.033	0.419***	0.175***	0.369***	0.377***
	(0.036)	(0.049)	(0.034)	(0.047)	(0.028)

Firm cluster standard errors in parentheses. *p<0.1, **p<0.05, and ***p<0.01.
We suppress the year and firm characteristics variables to save space.

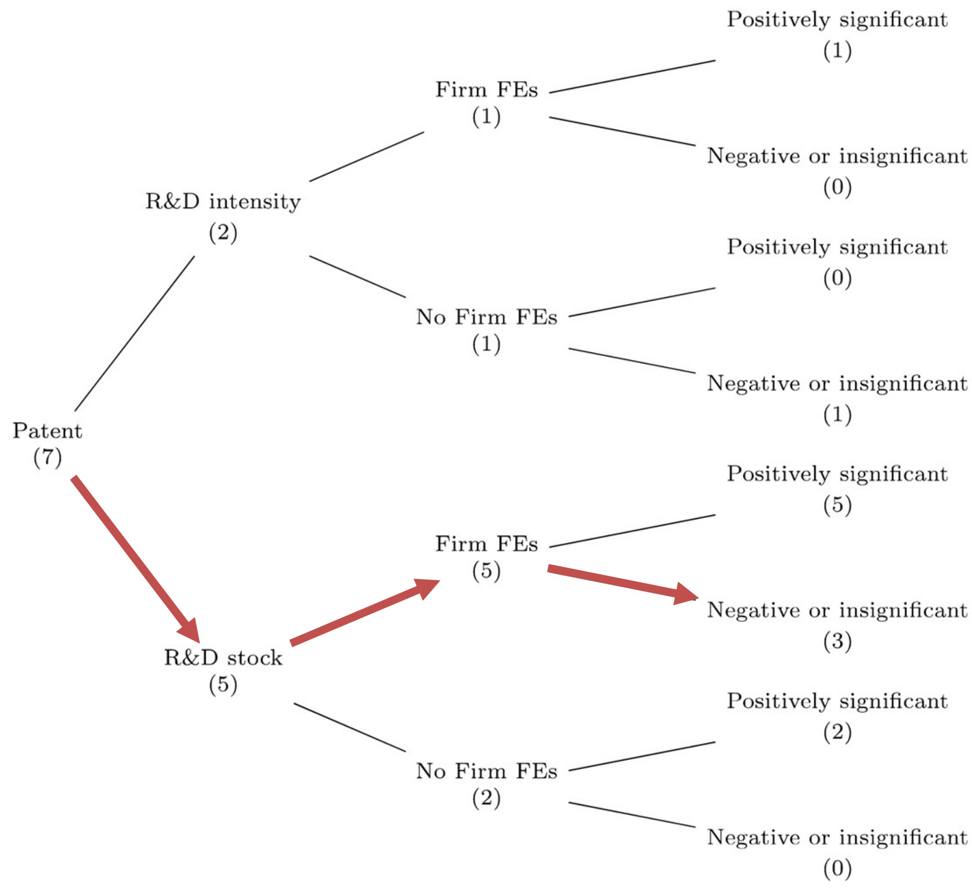
Summary statistics

	Obs.	Mean	Median	Std. dev.	P25	P75
ln(1+Patent)	86,341	0.53	0.00	1.11	0.00	0.69
ln(1+Citation)	86,341	1.25	0.00	2.27	0.00	2.20
ln(1+AdjCitation)	86,341	0.54	0.00	1.16	0.00	0.34
R&D/Asset	86,341	0.13	0.00	0.26	0.00	0.14
ln(ME)	86,341	11.13	10.95	2.07	9.60	12.51
R&D Missing Dummy	86,341	0.43	0.00	0.50	0.00	1.00
ln(1+Age)	86,341	2.48	2.48	0.75	1.95	3.09
ln(K/L)	86,341	10.00	9.85	1.29	9.18	10.64
Tobin Q	86,341	1.76	1.22	1.66	0.94	1.85
ROA	86,341	0.10	0.13	0.18	0.06	0.19
Leverage	86,341	0.23	0.21	0.18	0.07	0.35
Cash/Asset	86,341	0.14	0.07	0.17	0.02	0.18
KZ Index	86,341	-3.42	-0.54	10.77	-3.48	1.03
Institutional ownership	86,341	0.23	0.15	0.24	0.01	0.40
HH Index	86,341	0.25	0.20	0.20	0.11	0.30
HH Index Square	86,341	0.10	0.04	0.18	0.01	0.09

Our survey of the corporate innovation literature
Least square approach on Citation (paper #)



Our survey of the corporate innovation literature
Poisson and negative binominal approach on Patent



Our survey of the corporate innovation literature
Poisson and negative binominal approach on Citation