Does R&D concentration reduce technological diversity? Evidence from global top innovators

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Abstract

This paper investigates whether increasing concentration of R&D expenditure among the world's largest innovators reduces the technological diversity of their innovation output. Using firm-level data from the JRC COR&DIP Top 2000 Innovators matched with patent information from PATSTAT (2010–2022), I construct indicators of sectoral R&D concentration, firm-level technological diversity, and innovation system dynamism. R&D concentration is measured through a Herfindahl–Hirschman Index of sectoral R&D spending, while diversity is captured by a normalized Shannon entropy index of patent portfolios across technological fields. The unbalanced nature of the dataset—where firms enter and exit the global top-2000 ranking over time—is exploited to derive indicators of entry, exit, and rank turbulence as proxies for innovation dynamics. Regression results with country and year fixed effects show that higher sectoral R&D concentration is significantly associated with lower firm-level technological diversity, suggesting that dominant incumbents focus their innovation efforts within narrower technological trajectories. Conversely, larger and more capital-intensive firms tend to display broader technological portfolios, likely exploiting economies of scope. Overall, the findings indicate that growing R&D concentration may undermine technological variety, with implications for innovation and competition policy.

Keywords: R&D concentration, technological diversity, superstar firms, innovation policy

JEL Codes: O14, Q52, L13

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1 Introduction

Over the last two decades, economies and particularly innovation activity have become increasingly concentrated among a handful of large corporations (Bajgar et al., 2023). A growing body of research documents the emergence of "superstar firms" dominating both market shares and R&D spending (De Ridder, 2024). The relationship between concentration and innovation output has been investigated but the debate about either positive or negative monotonic effects is still ongoing.

According to the Schumpeterian hypothesis and the so-called "appropriability issue" (see Levin and Reiss, 1984), concentration (i.e., higher market power) leads to more innovation, since competition reduces expected rents (Romer, 1990; Aghion and Howitt, 1992 and Grossman and Helpman, 1991). On a opposite note, there is a body of empirical literature that found positive effects of competition on innovation (see Blundell et al., 1999; Beneito et al., 2015). Aghion et al. (2005) theorize and test the hypothesis of an inverse-U relationship between competition and innovation which depends on the technology state of different firms[1]. Yet, the implications for the diversity of technological change remain uncovered. This paper seeks to fill this gap by answering the following research question:

RQ: Does the dominance of a few firms at sector level foster cumulative innovation within narrow technological trajectories, or does it support a broader exploration of new fields?

To answer this question, I examine whether rising concentration of R&D among the world's top 2000 innovators reduces the technological diversity of innovation output at the firm-level. Using firm-level data from the JRC COR&DIP dataset matched with patent information from PATSTAT (2010–2022), I construct measures of (i) R&D concentration across firms within each sector, (ii) technological diversity using Shannon entropy of IPC patent classes at firm-level, and (iii) innovation "turbulence," capturing firm entry, exit, and rank mobility within the global top-innovators list. The empirical strategy employs regressions with country and year fixed effects, linking lagged R&D concentration to subsequent changes in technological diversity.

Preliminary findings suggest that firms operating in more concentrated industries tend to reduce technological diversity. This is consistent with a crowding-out effect of dominant incumbents on technological exploration. At the same time, greater dynamism in the innovation system, measured by the degree of market turbulence, shows evidence of a negative relationship with the rate of technological diversification. This result could arise from the strategic behavior of incumbent firms, which find themselves narrowing the technological

[1]These authors were assigned the Nobel Prize in Economics in October 2025.

scope of their innovation efforts to ensure a competitive advantage when the degree of turbulence is high.

These findings align with the most recent theory (Aghion et al., 2005) according to which there is no monotonic relationship between concentration and innovative output and speak directly to ongoing policy debates on competition and innovation policy in advanced economies. They quantify the trade-off between industrial concentration and technological variety, which is a major concern for the innovation and industrial-policy agenda.

2 Related literature

2.1 Competition and Innovation

2.2 Importance of technological diversity and measures

Technological diversity measures the variety of technological classes in which the innovating firm concentrates its activity over time. This characteristic has been studied in the literature from several perspectives, starting from its determinants. In particular, against a basic hypothesis of randomness in the choice to increase the technological scope of innovations, Breschi et al. (2003) find significant evidence of a strategy based on knowledge relatedness. In other words, firms constantly learn and progressively fill the gaps by extending their technological scope to adjacent fields. Furthermore, in the same study, this effect is found to be correlated with size.

Technological diversity has been investigated in its effects on business and innovation performance. Gambardella and Torrisi (1998) find that it impacts positively indicator of business performance as sales, profits and sales intensity (i.e., scaled by size). These results are interpreted by the authors as indicative of the fact that innovating on multiple fronts is not only a way to access new markets but can also improve the quality of existing products. As far as innovation performance is concerned, Garcia-Vega (2006) find that diversity enhances output, thanks to internal spillovers and reduced investment risk. On a similar note, Bolli et al. (2020) find that a positive impact in the discovery stage, allowing for spillovers and knowledge recombination (Moaniba et al., 2018)[2], but a negative effect in the commercialization stage where it is inversely correlated with profits.

[2]While these factors are positive for fostering relevant innovation, the impact on other dimensions of firms' strategies can be negative: Marhold and Kang (2017) find evidence of a negative relationship between firm-level technological diversity and its portfolio of alliances, in a exploration-exploitation paradigm.

3 Data

The empirical analysis draws on the *JRC COR&DIP* database of the top 2000 global R&D investors[3], covering the period 2010–2022. The dataset provides harmonized information on firms' R&D investment, capital expenditures, net sales and operating profits (million $), number of employees. These firm-level data are matched to patent applications (*N_pat*) from the *PATSTAT* database, aggregated by priority year and International Patent Classification (IPC) classes. After matching, the resulting unbalanced panel includes 3,946 firms across 17 NACE 2-digit sectors[4] (see Table 1 for descriptives).

Variable	N	Mean	SD	Min	p25	p50	p75	Max
R&D	27,853	361.4043	1141.163	.020402	50	92.66569	221	37033.58
Net Sales	27,511	9103.131	24467.19	0	675.1653	2174.482	7010.465	601215.1
R&D_int_w	27,407	1.67354	14.92484	.0002615	.0248131	.0518754	.1370161	520.3113
Capex	26,305	624.2138	2300.411	0	22.6	87.39874	340.9196	78460.1
Op_Profit	27,814	941.6825	4606.832	-27703.38	25.12891	165.9949	595.3462	286755.5
Emp	25,707	27201.83	55473.75	0	2600	8800	24827	961000
N_pat	19,803	269.1972	912.5889	1	11	42	162	25399

Table 1: Descriptive statistics

Statistics in Table 1 highlight the strong heterogeneity in firm size and R&D intensity, with mean R&D spending around $361 million and median employment of about 8,800 employees. The distribution of both R&D expenditures and patents is highly skewed, reflecting the well-known concentration of innovation activity among a small number of global leaders. These descriptive patterns are consistent with prior evidence on "superstar" R&D performers (see Aghion and Howitt, 2022; De Ridder, 2024). R&D intensity is measured as the ratio of R&D and Net Sales, which were winsorized at 0.01 level to exclude some outliers[5] and have more reliable ratios without altering distributions. To these variables I add a measure of sectoral-level concentration and a measure of firm-level technological diversity. Furthermore, since this dataset is not a proper panel, I insert a few measures to proxy dynamism in the dataset. In particular, I add two firm-level variables: a dummy indicating whether the firm entered the panel for the first time in a given year and a continuous variable indicating the average variability of a firm global ranking in the observation period. Then I combine and weight this information to create an index of market share turbulence.

[3]See more at https://data.jrc.ec.europa.eu/collection/id-00156

[4]See https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF.pdf/dd5443f5-b886-40e4-920d-9df03590ff91?t=1414781457000.

[5]although negative values are technically possible, their incidence in variables such as R&D, Capex or Net Sales is low enough ($\leq 1\%$) to consider them as outliers. Nevertheless, results of the empirical analysis are robust to the non-winsorized R&D intensity variable.

R&D concentration is measured using the Herfindahl–Hirschman Index (HHI):

$$HHI_{s,t} = \sum_{i \in s} \left(\frac{RD_{i,s,t}}{\sum_{i \in s} RD_{i,s,t}} \right)^2, \tag{1}$$

where a higher value indicates greater concentration of R&D expenditures among a few firms within sector s and year t. For the sake of simplicity, the HHI, which usually is between 0 and 10,000, is rescaled from 0 to 1. While the average yearly HHI has been increasing from 0.026 in 2009 to 0.0346 in 2022 (31%), it remains overall quite low. Looking at specific sectors, the most representative (Manufacturing) increased of only 6%, while others increased way more: wholesale and retail trade (the code referred to Amazon, among others) has increased by more than 37%; information and communication increased by more than 66%.

Technological diversity is captured using the Shannon entropy of the distribution of a firm's patent portfolio across technological fields. For each firm i in year t, let $p_{k,i,t}$ denote the share of patents belonging to technology class k. The (unnormalized) entropy is given by

$$H_{i,t} = -\sum_{k} p_{k,i,t} \ln(p_{k,i,t}),$$

where a higher value indicates a more even distribution of patents across classes. To facilitate comparison across firms, I normalize this measure by the logarithm of the total number of distinct technology classes that appear in the global dataset in each year:

$$H_{i,t}^{\text{norm}} = \frac{H_{i,t}}{\ln K_t},$$

where K_t is the number of unique WIPO (or IPC) technology classes in which any firm patents during year t. This normalization ensures that firms are evaluated relative to the technological space available in that period, so that, for instance, a firm active in three technology fields out of one hundred is considered less diversified than one active in the same number of fields when only ten were available.

Moreover, the COR&DIP Top Innovators dataset is an unbalanced panel, as firms appear intermittently across survey waves depending on their inclusion among the top 2000 R&D performers in each year. This feature reflects the dynamic composition of the global innovation frontier: new firms enter the ranking as their R&D investments rise, while others drop out as their relative effort declines. The analysis exploits it to construct indicators that can control for firm-level and overall innovation system dynamism.

In particular, entry (*Entry*) and exit (*Exit*) are dummy variables equal to 1 if the firm i entered or exited the sample in year t, while the within-firm variance of global rank (*Rank_var*) measures how much the relative position of incumbents fluctuates over time. To these measures I add an index of market share turbulence. I first compute a sectoral turnover rate based on firm entry and exit in the Top 2000 list:

$$Turnover_{s,t} = \frac{\sum_i Entry_{i,s,t} + \sum_i Exit_{i,s,t}}{(N_{s,t} + N_{s,t-1})/2} \quad (2)$$

where $\sum_i Entry_{i,s,t}$ and $\sum_i Exit_{i,s,t}$ are the counts of entering and exiting firms in year t, and $N_{s,t}$ is the total number of firms in sector s at time t. This measure captures the renewal of leading innovators. Then, I use this Turnover indicator to compute a standardized turbulence index at firm-level (*Turb_z*), incorporating the change in rank that an incumbent firm experiences from one year to the following one, as:

$$Turbulence_{i,t} = w \cdot z(Turnover_{s,t}) + (1 - w) \cdot z(\Delta Rank_{i,t}) \quad (3)$$

where w is a weight set at 0.5. These indicators make it possible to assess how the structure of corporate R&D evolves even in the absence of a balanced firm-level panel, providing a way to quantify the intensity of competitive turnover among the world's main innovators.

4 Empirical strategy and results

The baseline specification relates technological diversity to R&D concentration and sector- or firm-level controls:

$$Diversity_{it} = \beta Concentration_{st} + \gamma Controls_{it} + \alpha_s + \lambda_t + \epsilon_{it} \quad (4)$$

All models include year and country fixed effects; standard errors are clustered at the firm level. In extended specifications, I add sectoral entry and turbulence measures to test whether market dynamism mediates the effect of concentration, and sector fixed effects. To have more interpretable coefficients, capex and employees variables were transformed in logs.

Results from Table 2 confirm that concentration within sectors is associated with reduced within-firm technological breadth. The same goes for firms with high R&D intensity level, suggesting that increasing research effort tends to be constrained on a tighter set of technologies. Higher capital expenditure is robustly associated with higher diversity, possibly reflecting specialization in capital-intensive technologies (as is the case for automotive or semiconductors). At the same time, the positive effect of employment shows that larger firms diversify across more technological domains, consistent with economies of scope in

Diversity	(1)	(2)	(3)	(4)
HHI_sec	-0.189***	-0.180***	-0.392***	0.0965
	(0.000)	(0.000)	(0.000)	(0.396)
R&D_int_w	-0.000232***	-0.000222***	-0.000234***	-0.000268***
	(0.000)	(0.000)	(0.001)	(0.000)
ln_Capex	0.00955***	0.00974***	0.0101***	0.0108***
	(0.000)	(0.000)	(0.000)	(0.000)
ln_Emp	0.0316***	0.0304***	0.0300***	0.0287***
	(0.000)	(0.000)	(0.000)	(0.000)
Entry	-0.0205***	-0.0220***		
	(0.000)	(0.000)		
Rank_var		-9.59e-08***	-1.02e-07***	-5.46e-08**
		(0.000)	(0.000)	(0.026)
Turb_z			0.00120	-0.0162***
			(0.746)	(0.000)
Observations	13,757	13,752	12,739	12,738
R-squared	0.242	0.242	0.234	0.245
Year FE	Yes	Yes	Yes	Yes
Sector FE	No	No	No	Yes
Country FE	Yes	Yes	Yes	Yes
r2_a	0.238	0.239	0.230	0.241

Robust pval in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Caption

R&D. Firm-level entry dummy shows a negative coefficient, as is the case for the rank variation. This means that new entrants generally focus on less technologies in order to emerge in the market while rank variability may be a proxy for instability, which in turn leads to the reduction of technological diversity. The negative coefficient for market share turbulence suggests that in case of higher dynamism, incumbent firms tend to narrow the scope of their innovation effort, probably as a strategic response to to new entrants' competition, in line with results from Toh and Kim (2013).

While this might seem in contrast with the result on sectoral concentration, the interpretation of these results is not trivial. In fact, on the one hand, it is important to note how dynamism variables are firm-level proxies for instability of firm ranking, which might be consequence of several factors (e.g., lower (higher) R&D investment due to performance below (above) expectations). These factors could lead firms to increase (reduce) the technological breadth of their innovation effort according to their good (bad) performance. On the other hand, the relationship between competition and innovation was found to have an inverted-U shape (Aghion et al., 2005) suggesting that both competition and concentration may be coherently associated with reduced innovation. With this paper, I find evidence that this might be the case for technological diversity as well.

5 Conclusion

The findings suggest that increasing R&D concentration — especially in ICT and pharmaceutical sectors — may hinder technological variety, potentially slowing cross-domain innovation and diffusion. At the same time, maintaining a dynamic environment with frequent entry and high mobility among innovators could lead to a similar outcome resulting from strategic behavior.

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Appendices