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RESEARCH ARTICLE

Changes in persistence of performance over time

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[Correction added on 26 July 2021, after first online publication: The copyright line was changed.]

Abstract

Research Summary: I revisit a research tradition laying out trends in persistence of performance, to create shared facts to inform theory development. I build on prior work in Strategy by: (a) bringing together two distinct measures of persistence of performance and explaining how they complement each other and help distinguish theories, (b) extending the time series from those prior studies and applying modern statistical improvements to demonstrate new patterns. Specifically, while I find ordinal persistence increased monotonically since the 1980s, autocorrelation of performance was not monotonic and is now approaching lows from the mid-1990s. These patterns are inconsistent with mechanisms raised in the debate about declining competition. I suggest that these facts can inspire Strategy theory, which would contribute to that debate.

Managerial Summary: A central concern of managers is how precarious is their position, or for new ventures, whether they will be able to displace current leading firms. Even within the same year, management writing and the media might claim that it is both: a) a time of faster-than-ever turnover, b) or that large firms have become unassailable. This manuscript tracks two measures of performance persistence over time. I find that

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persistence of rank has increased roughly steadily since the 1980s. How associated are performance measures year-to-year was actually at its peak in the mid 1980s, potentially explaining the debate. The final patterns are consistent with top firms separating from followers in performance so much that increasing volatility in their performance does not lead to changes in rank.

KEYWORDS

competition, persistence of performance, rank, strategy, trends

1 | INTRODUCTION

A frequently reoccurring political issue that is currently prominent (Economist, 2016; Fleming & Fox, 2018; Scaggs, 2018), is persistence of business' performance—the tendency for firms with high performance last period to also have high performance this period. Scholars have long been central in this argument, with some arguing that the performance of firms is becoming ever more entrenched, making dominant firms more dominant and potentially leading to increased inequality (Autor, Dorn, Katz, Patterson, & Reenen, 2020) and decreased innovative investment (Gutiérrez & Philippon, 2017). Others, however, suggest that product lifecycles are becoming more rapid (Bayus, 1998) and that it is becoming harder for firms to sustain an advantage (D'Aveni, 1994; D'Aveni, Dagnino, & Smith, 2010; McGrath, 2013; Thomas & D'Aveni, 2009). Both the *Strategic Management Journal* (D'Aveni *et al.*, 2010) and *Organization Science* (Ilinitch, D'Aveni, & Lewin, 1996) have had special issues dedicated to how firms must respond to the asserted decline in persistence.[1]

Arguments differ, in part, because the facts themselves are disputed. For example, much of the work in economics asserting increased entrenchment does not actually measure entrenchment, but rather measures either concentration (e.g., Autor, Dorn, Katz, Patterson, & Reenen, 2017; Gutiérrez & Philippon, 2017) or structurally estimated markups (e.g., De Loecker, Eeckhout, & Unger, 2020). These measures have been criticized by those saying that (a) concentration should not be measured at the national level and, when measured at the market level, it is actually decreasing (e.g., Rossi-Hansberg, Sarte, & Trachter, 2020; Rinz, 2018; Handwerker and Dey, 2019) (b) even correctly measured concentration does not represent competition (Shapiro, 2018), and (c) estimated trends in markups are inconsistent with trends in inflation (Syverson, 2019). Shedding light on what is actually happening in the American marketplace therefore calls for new measures.

Fortunately, Strategy scholars have a long history of studying the persistence of performance. In fact, Rumelt, Schendel, and Teece (1991: 12) argue that this was one of the origins of the field:

Some firms simply do better than others, and they do so consistently. Indeed, it is the fact of these differences that was the origin of the strategy [field]. In standard neoclassical economics,

[1]This assumption was not necessarily a dominant view, as work in the *Strategic Management Journal* has suggested that persistence did not decline (e.g., Jacobsen, 1988; McNamara, Vaaler, & Devers, 2003).

competition should erode the extra profits earned by successful firms[...] Yet empirical studies show that if you do well today, you tend to do well tomorrow; good results persist.

In this article, I hope to reinvigorate and build on Strategy's decade-and-a-half–old literature documenting changes in persistence of performance.[2] For example, McNamara et al. (2003) and Wiggins and Ruefli (2002, 2005) took part in a debate about trends in persistence of performance at the end of the twentieth century, with McNamara et al. (2003) finding little change over time while Wiggins and Ruefli (2002, 2005)—using different methods—find a decrease in persistence. This debate subsequently went dormant, leaving us without facts about persistence in the 21st century, an era in which a number of institutional and technological changes may have led either to the unstable market described by authors in the hypercompetition tradition or to the ossified market described by macroeconomists and some media.

To begin to fill this gap, I apply two measures taken from the Strategy literature—updated with subsequent methodological developments—to more modern data. I hope in this way to contribute facts to the discourse that can fuel theoretical developments.

The first of these measures—the estimated autocorrelation in performance, which I term “Mueller persistence”—was originated by an economist (Mueller, 1977, 1986), but has been adopted primarily by Strategy scholars (e.g., Chacar & Vissa, 2005; Jacobsen, 1988; McGahan & Porter, 1999; Roberts, 1999; Villalonga, 2004). It measures the degree to which performance in the previous period persists into the current period. Economists have described it as indicating market competitiveness (e.g., Cubbin & Geroski, 1987; Mueller, 1977; Sutton, 2007)—essentially, the speed with which innovations can be copied and their rents competed away—though I interpret it more conservatively as entrenchment. It should be noted that Mueller persistence is cardinal in that it measures the persistence of performance *levels*, not of *rankings*.

A second—and complementary—measure, introduced by Powell and Reinhardt (2010), adapts the statistic Spearman's Footrule (Spearman, 1904, 1906) to measure the turnover of performance ranks. Spearman's Footrule is a measure of distance between ranked sets and accounts for how much mobility is possible given the number of included firms. It thus improves on the rank persistence measures used recently in the inequality literature (e.g., Chetty, Hendren, Kline, Saez, & Turner, 2014) by taking into account the change in the number of public firms over time. I discuss the theoretical implications of this difference in Section 2.3 below.

The combination of these two measures allows me to paint a rich picture of the persistence of performance over the last 50 years. The patterns I find are not consistent with either monotonic decrease in sustainability or monotonic entrenchment. I find a strong upward trend in rank friction, suggesting that the persistence of ordinal performance have increased over the sample. The cardinal measure, however, has very different behavior: Mueller persistence declined steadily from the beginning of the sample to shortly before 2000. It then increased until roughly the end of the decade and then turned downward again.

This aggregate effect is driven primarily by two factors: (a) a steady secular[3] decrease in profits for low-performing firms and (b) a decade-long (2000–2010) increase in the persistence

[2]Since the mid-2000s, this effort to document persistence has been replaced by context-specific studies designed to identify causal mechanisms linking specific factors to persistent performance (e.g., Madsen & Leiblein, 2015; Madsen & Walker, 2017; Vaaler & McNamara, 2010). While these studies are vital, they do not—nor are they intended to—produce the broad patterns that were the focus of the population-level studies. McGahan and Porter (2003) lamented the turn in focus, saying: “[W]hile there is no shortage of theories to explain the sources of profitability, there is little empirical evidence about the trajectory of profitability over extended periods of time.”

[3]Here I use the “secular” as it is used in time series econometrics to mean “non-cyclical.”

of performance for high-performing firms. These patterns are consistent with the lowest-performing firms becoming less of a threat to top performers over time and top performers having enjoyed a strongly defensible position from 2000 to 2010 that has since eroded.

These results are robust to accounting for changes in sector mix and the changing population of public firms in the United States. Similar patterns arise in a matched sample of Western European firms, which could be interpreted as evidence of the drivers being common across markets, although much more work is required to understand the causes and effects.

This manuscript continues as follows: I introduce the measures that capture the persistence of performance and describe the construction of the data sample. I then present the results of my analysis. Finally, I provide some initial analysis about which potential explanations are consistent with the observed patterns.

2 | MEASURES

The two measures of performance persistence—Mueller persistence and rank friction—are complementary, but conceptually distinct.

2.1 | Cardinal measure: Convergence interval

In studies on persistence of performance since Mueller (1986), persistence is measured as the correlation of the current-period performance with that of the past period. Formally, we can describe performance trends as an autoregressive process:

$$y_t = \alpha + \beta * y_{\{t-1\}} + \varepsilon \tag{1}$$

Each period's performance is a function of last period's performance and its shocks, where shocks are distributed as follows:

$$\varepsilon \sim N(0, \sigma)$$

When $\beta$is zero, each period's performance is completely independent and idiosyncratic; shocks will dissipate immediately. When β is large and positive, each period depends a great deal on the previous period, meaning that shocks reverberate longer.

A substantial literature estimates the autocorrelation of performance (e.g., Jacobsen, 1988; Waring, 1996), often with the aim of decomposing those shocks into components (e.g., Cubbin & Geroski, 1987; McGahan & Porter, 1999) or estimating the effect of variables of interest (e.g., Chacar, Newburry, & Vissa, 2010; Villalonga, 2004). I adopt the version of this approach introduced by Waring (1996), who defines y to be "firm-specific profits," a firm's return on assets (ROA) less the industry mean ROA. I also adopt the innovation in Villalonga (2004) in which the industry is defined at the segment—not corporate—level, since firms are often diversified. I begin by calculating segment-specific operating ROA (or firm-level ROA for single-segment firms). From this I subtract industry mean ROA, calculated as the average ROA of all segments and single-segment firms within the industry. Finally, for multisegment firms, I aggregate up to the firm level by taking the asset-weighted average across as segments in a firm.[4] This measure allows me, in turn, to measure the persistence of a firm's financial performance relative to that of its competitors, allowing for a diversified position across various industries and removing general industry effects not specific to a firm.

To estimate the autocorrelation of performance, I follow another innovation by Villalonga (2004) and use a dynamic panel approach with an Arellano–Bover/Blundell–Bond (ABBB) AR(1) estimator, as shown in Equation (1).[5] Specifically, I estimate a series of ABBB regressions on a sliding nine-year[6] window of data. I extract the autocorrelation coefficient for each window and plot them over time. For ease of interpretation, I convert the coefficient of autocorrelation into a 95% convergence interval, which reports the number of years it takes for firm-specific performance to dissipate 95% of its magnitude:

$$\text{convergence interval} = \frac{\ln(1-0.95)}{\ln(\beta)}$$

2.2 | Ordinal measure: Rank friction

Powell and Reinhardt (2010), noting that ordinal measures complement cardinal measures to paint a more complete picture of persistence, introduce a new measure of persistence they call rank friction (RF), based on Spearman's Footrule and computed as:

$$RF = 1 - \frac{D}{E(D)}$$

where D is Spearman's Footrule computed on actual shuffling and E(D) is the expected value of D if shuffling were truly random. D is computed as:

$$D = \sum_{r=1}^{n} | r_{t1} - r_{t2} |$$

Consider the following numerical example with four firms that in the first period are ranked (1,2,3,4) and in the second are ranked (3,2,4,1). D would be $D = |1-3| + |2-2| + |3-4| + |4-1| = 6$. Powell and Reinhardt (2010) calculate E(D) for fewer than 15 firms and suggest that for large samples it can be approximated by the closed-competition long-run asymptotic value: $E(D) = \frac{n^2-1}{3}$. Using this approximation, $RF = 1 - \frac{3D}{n^2-1}$. High values of rank friction correspond to firms maintaining similar ranks over time and low values correspond to firms switching frequently. As with the convergence interval, therefore, high values represent greater persistence.

[5]Villalonga uses the original Arellano (1991) estimator in her analysis. More recently, the Arellano–Bover/Blundell–Bond estimator updates the initial Arellano-Bond estimator to account for large autoregressive parameters and a high variance of the panel effect, relative to the variance in the idiosyncratic error (Windmeijer, 2005). Although I conduct my analysis using this updated estimator, it remains essentially unchanged if I use the original Arellano-Bond estimator.

[6]I also document robustness of results to the length of this window in Section 4 below.

2.3 | Differences between measures

Cardinal and ordinal measures capture different aspects of performance persistence, one representing its duration and the other representing the durability of a firm's position relative to its competitors. To illustrate the importance of this distinction, imagine a scenario in which every firm in a given industry experienced the identical competitive shock and no firm had any particular advantage in its response. Imagine that the shock—say, a shortening of patent exclusivity—has the effect of reducing by half the duration for which a firm sustains its relative profits and losses. Mueller persistence—our cardinal measure—would then decline by half, while rank friction—our ordinal measure—would remain unchanged, as each firm experienced the same change to persistence and thus no gain or loss of competitive position.

Alternately, imagine a shock to which firms in an industry are differently positioned to respond: some double the persistence of their firm-specific profits over time, while others halve theirs. For example, the rise of organic certification could entrench firms already using organic farming methods and make others seem more interchangeable to customers, reducing the persistence of their performance. The average convergence interval might then be unchanged, but the churn across firms would be high. In my terms, rank friction would fall while the average convergence interval would remain unchanged.

In each case, important changes to performance persistence are captured by only one of my measures. We can see, then, how they complement each other.

3 | MAIN DATA: COMPUSTAT SAMPLE

Following the literature on persistence of performance, these measures are constructed based on all US publicly traded firms from the Compustat Segment File. These are the only data that provide the granularity of accounting measures across firms needed to construct the performance measure. I extend prior studies by using data between 1976 and 2018, the longest available panel for my study, and include all firms, both surviving and delisted, for which data is available.

I construct my sample following Villalonga (2004). It includes firm-year observations between 1976 and 2018 for which segment industry-adjusted performance data is available.[7] As of June 2018, the Compustat segment file contained 974,927 business segment observations representing 293,535 firm-year pairs. I excluded all observations with missing industry identifier or identifiable total assets (*IAS* or operating profit (*OPS*), and those with SIC codes 6,000–6,999 (finance and banking) and 9,900–9,999 (nonclassifiable establishments). I use the resulting segment-level data to calculate segment-level profit metrics for the convergence interval measures. Following the literature, I use ROA, calculated as operating revenue over total assets, though I show robustness of the results to using return on equity (ROE) instead. I then calculate "firm-specific profits" as two-digit SIC[8] industry-demeaned (at the segment level) ROA, aggregated to the firm level on an asset-weighted basis.[9]

Table 1 presents summary statistics for the resulting sample.

[7]Limitations inherent in using the Compustat sample are addressed in the robustness section.
[8]Results are unchanged using three-digit SIC classifications instead.
[9]See Villalonga (2004) for details on this procedure.

TABLE 1 Compustat sample summary statistics

	Total assets	Operating profit (EBIT)	Employees
Mean	1,799.295	95.06144	4,399.787
SD	10,519.81	621.8343	22,937.59
p10	2.887	−7.724	16
p25	12.866	−.713	74
p50	75.285	2.703482	361
p75	489.609	30.425	1868
p90	2,607.814	164.3592	7,380.657
Count	229,077	229,077	158,237
21,864 unique firms			

Note: Sample is constructed of publicly listed firms from Compustat segment database from 1976–2018. Segment performance is aggregated to the firm level using the methods described in Villalonga (2004). Firms and segments in 2-digit SIC codes 60–69, 91, and 99 are excluded. Segments with negative assets are coded as zero and those with zero employees are coded as missing.

4 | TRENDS IN THE PERSISTENCE OF PERFORMANCE

4.1 | As measured by the convergence interval

For tracking the trends in persistence, I use a nine-year sliding window before the focal year.[10] In other words, a year on the graph represents what had happened in the years leading up to that year. Figure 1 presents the convergence interval over time. As described in Section 2, the annual values of the convergence interval are estimated as an AR(1) coefficient in an Arellano–Bover/Blundell–Bond dynamic panel model with a sliding window of 9 years and then transformed into the time required for 95% decay of a performance shock.

These results suggest that from 1985 to 1997, the convergence interval of performance decreased by 40% from 4.5 years in 1985 to 2.7 years in 1997. Beginning around 2000, that trend reversed itself, with the convergence interval increasing by 40% to 3.8 years in 2007, whereupon it turned down again. By the end of our panel in 2018, the convergence interval is approximately 3.2 years. In sum, persistence has changed substantially over the 40 years in the sample: falling, then rising, then falling again.

4.2 | As measured by rank friction

Figure 2 presents the results of calculating rank friction over time for the sample. The primary insight is that rank friction and convergence interval diverged in the early period. Rank friction has increased monotonically for the entire sample window. There are a number of ways that this is possible, but the intuition is that before 1999, while firms' performance may have converged to its long-run average more quickly, that did not result in them exchanging ordinal positions. After 1999, however, convergence interval begins to trend upward, along with rank

[10]Appendix Figure A1 also presents results for 8- and 10-year windows to demonstrate robustness.

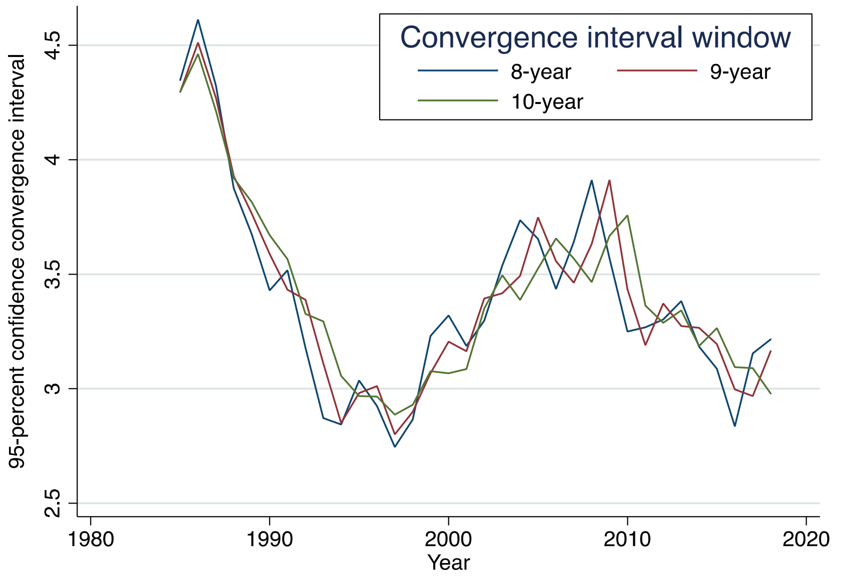

FIGURE 1 Arellano–Bover/Blundell–Bond dynamic panel estimates of convergence interval over time. *Notes:* AR(1) autocorrelation coefficients of firm performance from a series of Arellano–Bover/Blundell–Bond dynamic panel estimates over rolling 10-year periods. Each coefficient has been transformed into a 95% convergence interval. See text for the transformation equation. Firm performance is measured as "firm-specific profits" (Villalonga, 2004). This measure calculates segment-level return on assets (Return on assets (ROA) and is calculated as the ratio of operating profit to total assets using Compustat segment measures OPS and IAS.), demeaned by the average industry profits of that segment, and then aggregating the demeaned performance up to the firm level on an asset-weighted basis. Since Compustat segment data commences in 1976, the first available 10-year interval is 1985, where the figure begins. The joint test of breaks at 1999 and 2009 is significant at the greater-than-99.999% level using the `sbknown` command in Stata [Color figure can be viewed at wileyonlinelibrary.com]

friction. This suggests that while firms were holding their ranks longer, shocks to performance were reverberating longer.

This pattern obtains looking only at top ranks as well, as in Fogel et al. (2008). Appendix Figure A4, which shows the probability that firms will exit the top ranks of performance.

5 | ROBUSTNESS OF TRENDS

5.1 | Sample composition: Set of public companies

Observers have noted that the composition of Compustat changed over this period, due to changes in firms entering the sample through an initial public offering (IPO) (Doidge, Karolyi, & Stulz, 2017; Davis et al., 2014; Gao, Ritter, & Zhu, 2013) and exiting through delisting (Ali, Klasa, & Yeung, 2009; Kahle & Stulz, 2017). To investigate the extent to which my observed patterns are driven by the changing sample composition, I conduct two supplemental analyses. First, I estimate average convergence intervals by IPO cohort. Figure 3 shows that convergence interval estimates are relatively stable across IPO cohorts, suggesting that the observed trends are not driven by entering firms having different convergence intervals on average.

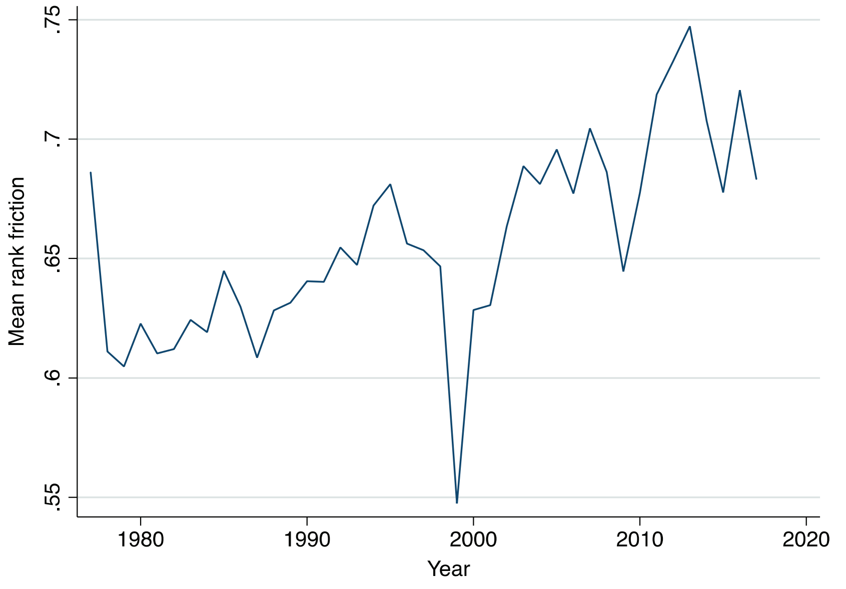

FIGURE 2 Rank friction over time. *Note:* Friction in firms' performance rank year-to-year. Performance is measured as "firm-specific profits" (Villalonga, 2004). Rank friction is calculated as in Powell and Reinhardt (2010). Higher values represent a lower probability of changing within-industry (SIC3) performance rank between time t and $t + 1$ [Color figure can be viewed at wileyonlinelibrary.com]

Second, I estimate average convergence interval by delisting year. For delisting to drive the observed patterns, it would have to be the case that different cohorts exhibit dramatically different patterns. Figure 4 shows that different types of firms exiting in different years do not drive the observed patterns.

5.2 | Sample composition: Sector mix

Another possible year-to-year change in the composition that could be driving the effect would be a change in sector mix. If some sectors had higher convergence intervals and were also becoming less prominent early in the sample, for example, that could explain the early decline in average convergence interval. Figure 5 shows two versions of the sector mix: (a) the share of firms from each sector and (b) the sales-weighted share of the sample from each sector. The results depicted in Figure 5 suggest that there are no major changes in the sectoral mix, which suggests that changes in sectoral mix of the sample is not driving the effect.

Appendix Figures A5 and A6 present the Mueller persistence and Rank Friction estimates over time by sector.

6 | TESTING EXPLANATIONS FOR THE TRENDS

The competition literature has proposed explanations for the secular trends in sustainability of performance. In this section, I lay out a number of them, describe secondary predictions for

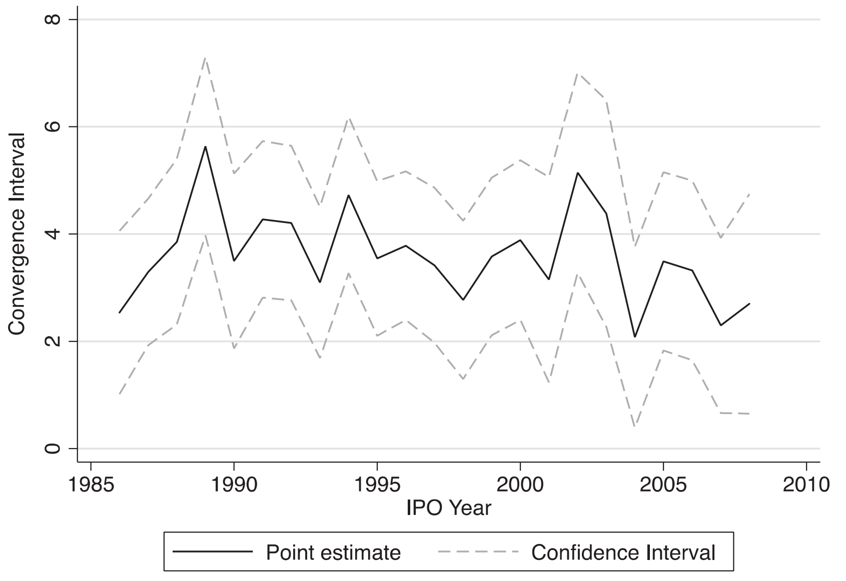

FIGURE 3 Comparing performance autocorrelation (ABBB estimates) for IPO cohorts. *Notes:* AR(1) autocorrelation coefficients of firm performance from a series of Arellano–Bover/Blundell–Bond dynamic panel estimates for entire tenure in the data for firms that had an IPO between 1985 and 2009, leaving time at the end for estimates for the latest cohort. Each coefficient has been transformed into a 95% convergence interval. See text for the transformation equation. Firm performance is measured as "firm-specific profits" (Villalonga, 2004). This measure calculates segment-level return on assets, demeaned by the average industry profits of that segment, and then aggregates the demeaned performance up to the firm level on an asset-weighted basis. Since Compustat segment data commences in 1976, the first available 10-year interval is 1985, where the figure begins

each, and investigate whether patterns in the data are consistent with the predictions of those proposed explanations.

6.1 | Changing production technology

The most common explanation conjectured for changes in persistence of performance is changes in production technology. This usually takes the form of information technology (e.g., Bessen, 2017; Brynjolfsson, McAfee, Sorell, & Zhu, 2008) or physical automation (e.g., Acemoglu & Restrepo, 2018), both of which are described as operating through increasing economies of scale. Dissemination of more lower-marginal-cost production technology, however, would not drive heterogeneity in performance unless it magnified existing differences in productivity or interacted with differences in complementary organizational practices, as argued by Brynjolffson and co-authors (Benzell & Brynjolfsson, 2019; Brynjolfsson, Rock, & Syverson, 2018). The prediction of this model is that leading firms would become marginally more productive, capturing greater market share. One would therefore expect (a) high-performing firms to gain the most performance and autocorrelation in performance, (b) rank friction to increase most at the highest ranks, and (c) leading firms to gain a greater productivity advantage in concentrating industries. Furthermore, if production technologies are common

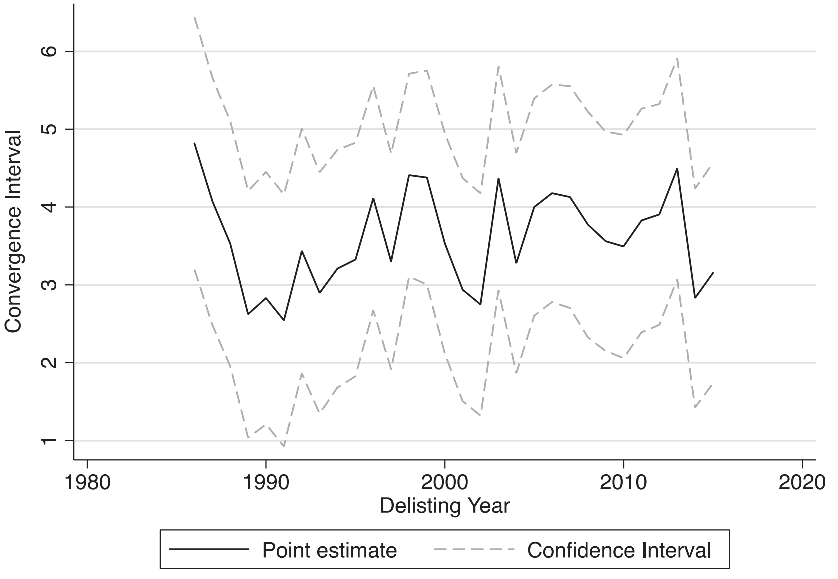

FIGURE 4 Comparing performance autocorrelation (ABBB estimates) for delisting cohorts. *Notes:* AR(1) autocorrelation coefficients of firm performance from a series of Arellano–Bover/Blundell–Bond dynamic panel estimates for entire tenure in the data for firms that delisted between 1985 and 2016, leaving time at the beginning for estimates for the first cohort. Each coefficient has been transformed into a 95% convergence interval. See text for the transformation equation. Firm performance is measured as "firm-specific profits" (Villalonga, 2004). This measure calculates segment-level return on assets, demeaned by the average industry profits of that segment, and then aggregating the demeaned performance up to the firm level on an asset-weighted basis. Since Compustat segment data commences in 1976, the first available 10-year interval is 1985, where the figure begins

across markets, one might expect matched European firms to exhibit similar patterns of performance.

Figure 6 shows the convergence interval estimates divided into three groups of firms: those with positive firm-specific profits for the whole sample, those with negative firm-specific profits for the entire sample, and others.[11] What the figure suggests is that the increase in the late 1990s followed by the decrease during the 2000–2010 window is only echoed in the high-performing firms. This in turn suggests that at least that portion of the sample is driven by something affecting primarily the high performers.

Interestingly, though, Figure 6 also shows that the high performers' average performance is not increasing, only its autocorrelation is, which is inconsistent with the story of greater competitive advantage being driven by increased economies of scale for high performers. If anything, Figure 6 suggests that the effect may be driven by decreasing average performance for low performers. Figure 7 presents a similar result, but instead of classifying firms over their lifetime, it looks at the firm-specific profit levels of firms in each year and suggests that the most dramatic change is the decrease in the lower tails of performance. This could be driven by technological change leading to more entry, with new entrants competing away low performers. That would be consistent with Bennett and Hall (2020), who suggest that dissemination of

[11]This division follows McGahan and Porter (1999).

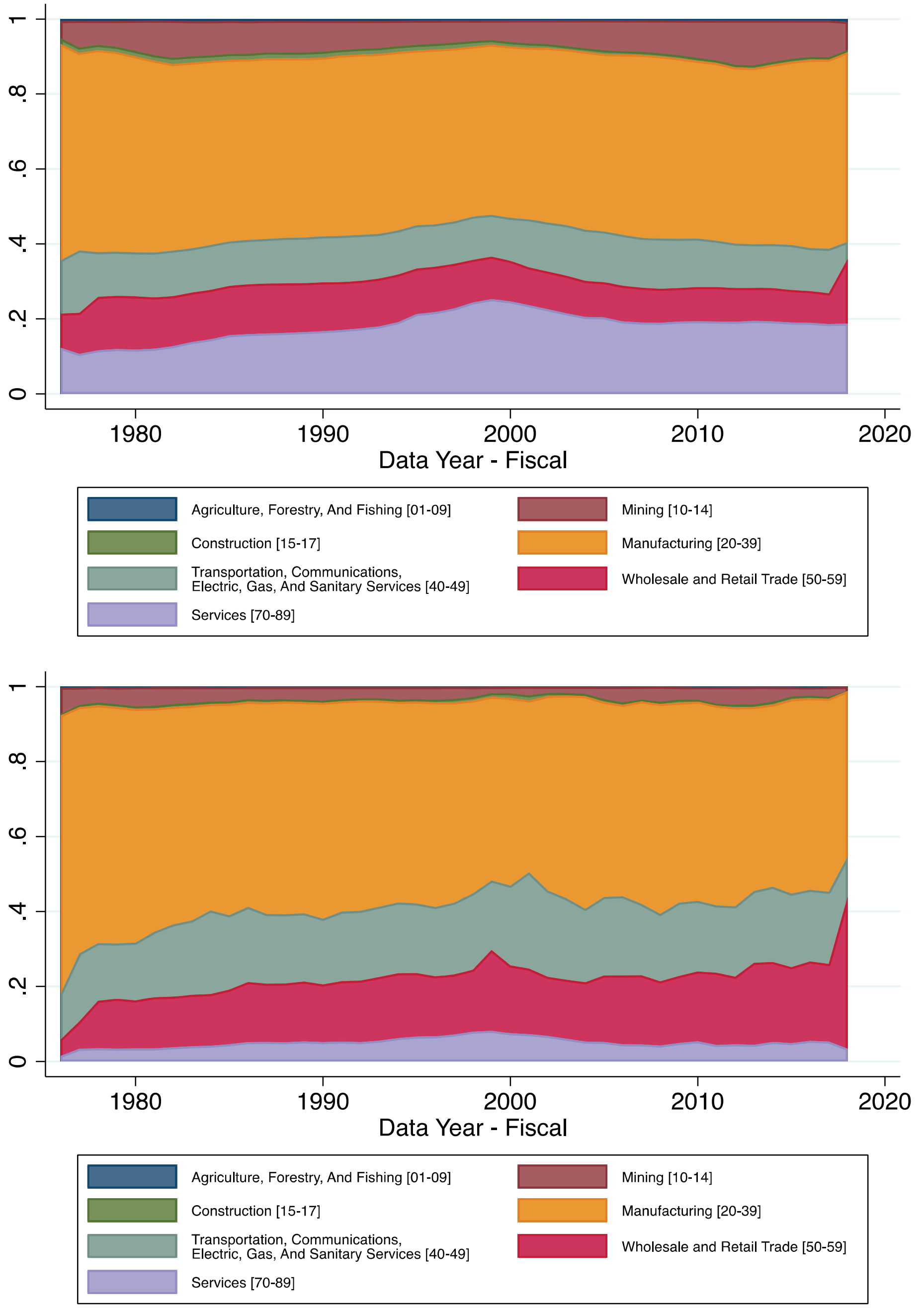

FIGURE 5 Sector mix of the data by firms. *Note:* Percentage of firms in the data in each year accounted for by each sector—defined by 2-digit SIC codes. Figure below shows the sales-weighted proportions by sector [Color figure can be viewed at wileyonlinelibrary.com]

software across industries is associated with increasing entry by new firms and exit by the oldest firms. It is also consistent with the results that productivity is not growing among leading firms and that marginal gains in productivity by leading firms are not associated with concentration (Gutiérrez & Philippon, 2017). It does not, however, seem consistent with Decker, Haltiwanger, Jarmin, and Miranda's (2016) result that entry is decreasing.

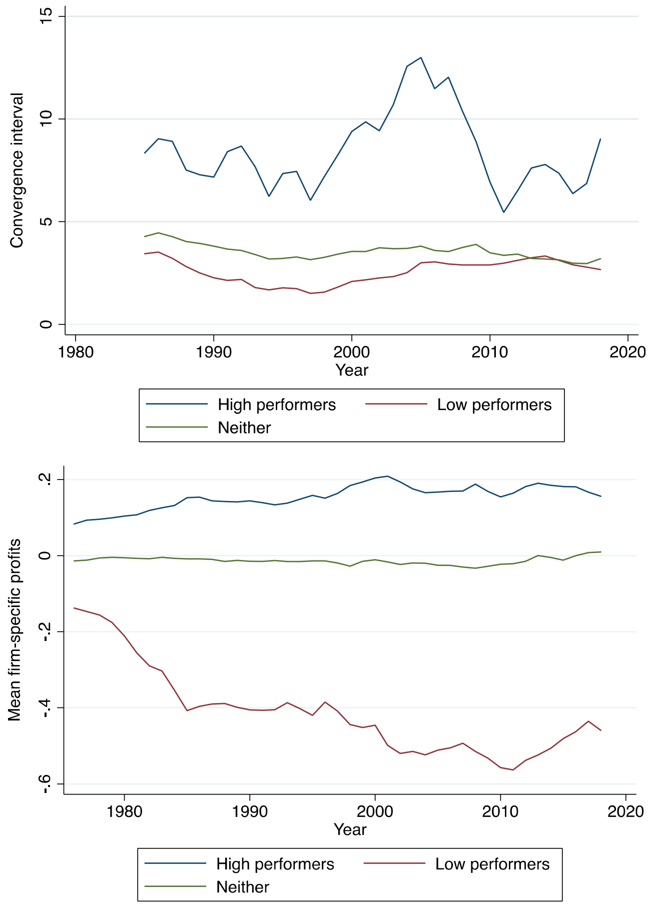

FIGURE 6 Comparing performance autocorrelation (ABBB estimates) for performance levels. *Notes:* AR(1) autocorrelation coefficients of firm performance from a series of Arellano–Bover/Blundell–Bond dynamic panel estimates over rolling 10-year periods. Each coefficient has been transformed into a 95% convergence interval. See text for the transformation equation. "High performers" are those with strictly positive firm-specific profits for the entire sample (4,837 firms). "Low performers" are those with strictly negative firm-specific profits for the entire sample (4,919 firms). Firm performance is measured as "firm-specific profits" (Villalonga, 2004). This measure calculates segment-level return on assets, demeaned by the average industry profits of that segment, and then aggregating the demeaned performance up to the firm level on an asset-weighted basis. Since Compustat segment data commences in 1976, the first available 10-year interval is 1985, where the figure begins. Figure below depicts mean levels of firm-specific profits [Color figure can be viewed at wileyonlinelibrary.com]

Figure 8 presents the results of the ordinal measure divide by high, low, and other performers. The ordinal measure seems to rise consistently for all three categories, which would be consistent with low performers staying low for longer.

I now address Gutiérrez and Philippon's (2017) argument that if production technology is common across an industry, then European and American firms would exhibit similar patterns. I assemble a second dataset, this time from Bureau VanDijk's Orbis product. These data have been used extensively in Strategy (e.g., Belenzon, Bennett, & Patacconi, 2019; Belenzon & Tsolmon, 2015; Bennett and Hall (2020)). To match the Compustat sample, I create a sample of only publicly listed firms headquartered in OECD founding nations. I then construct a dataset with operating revenue (OPPL) and asset (TOAS) information from 1976 through 2017, the

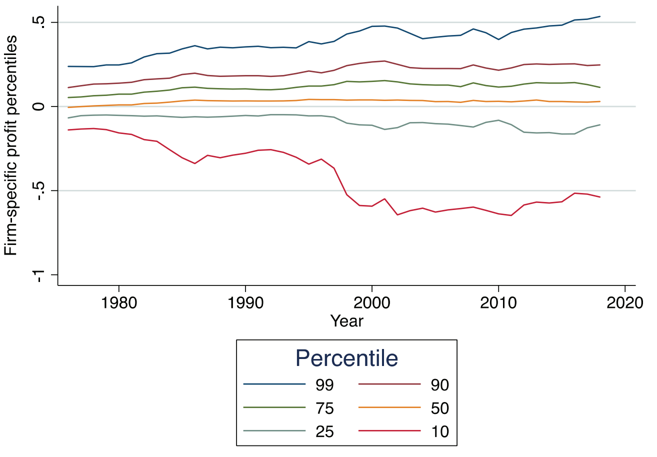

FIGURE 7 Firm-specific profit by percentile over time. *Note:* Firm performance is measured as "firm-specific profits" (Villalonga, 2004). This measure calculates segment-level return on assets, demeaned by the average industry profits of that segment, and then aggregates the demeaned performance up to the firm level on an asset-weighted basis [Color figure can be viewed at wileyonlinelibrary.com]

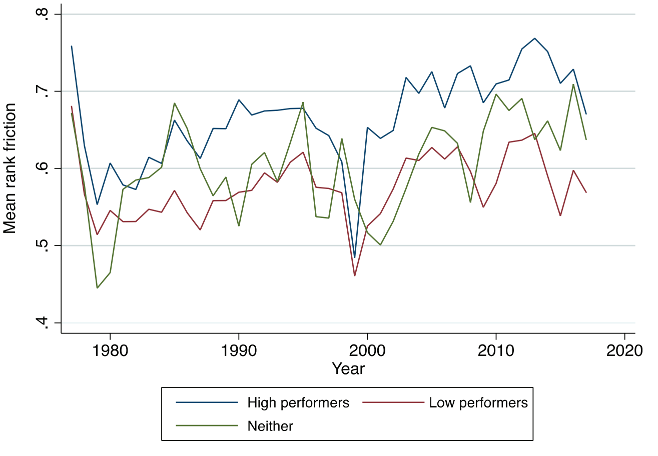

FIGURE 8 Rank friction over time. *Note:* Friction in firms' performance rank year-to-year. Rank friction is calculated as in Powell and Reinhardt (2010). Higher values represent a lower probability of changing within-industry (SIC3) performance rank between time t and $t + 1$. "High performers" are those with strictly positive firm-specific profits for the entire sample (4,837 firms). "Low performers" are those with strictly negative firm-specific profits for the entire sample (4,919 firms). Firm performance is measured as "firm-specific profits" (Villalonga, 2004). This measure calculates segment-level return on assets, demeaned by the average industry profits of that segment, and then aggregates the demeaned performance up to the firm level on an asset-weighted basis. Since Compustat segment data commences in 1976, the first available 10-year interval is 1985, where the figure begins [Color figure can be viewed at wileyonlinelibrary.com]

most recent year available. I match firms in the Orbis sample to the Compustat sample using the Coarsened Exact Matching (CEM) algorithm (Blackwell, Iacus, King, & Porro, 2009). Matched firms are thus those with performance and asset levels "close" to those of the Compustat firms and in the same SIC two-digit industry. I then create a matched data set of only the Compustat and Orbis firms for which I was able to find a match. Table 2 presents summary statistics comparing the matched samples.

I then compute the convergence interval (Figure 9) and rank friction (Figure 10) estimates for the matched sample. The estimates seem somewhat similar, but Compustat firms continue to gain convergence-duration four to 5 years longer than the European firms do. The results are

TABLE 2 Summary statistics for matched sample

	Total assets	Operating profit (EBIT)	Employees
Orbis			
Mean	788.2793	47.73251	3,113.152
SD	1830.158	128.0546	12,547.41
p10	11.82223	−6.582058	36
p25	35.86997	−.192746	110
p50	129.5506	5.834387	474
p75	569.1852	37.19326	1999
p90	2,230.572	152.909	6,675
Count	7,779	7,779	7,779
Compustat			
Mean	338.9043	10.36777	1,367.085
SD	838.9635	67.05877	4,036.159
p10	2.624	−21.11	15
p25	13.76	−5.257	57
p50	64.662	.041	227
p75	265.064	13.15542	832
p90	825.5	49.777	3,604
Count	3,235	3,235	2,476
405 Compustat firms, 822 Orbis firms			

Note: Orbis firms are drawn from the set of listed apex firms in OECD founding countries. Apex firms are defined by having a subsidiary level equal to 1. Listed firms are those that were ever listed, thus including delisted firms. Operating revenue is the OPS variable in Compustat and OPPL in Orbis. Total assets are AT in Compustat and TOAS in Orbis. Firms are matched on 2-digit SIC code sector (exact) as well as operating profit (EBIT) and assets using the CEM procedure (Blackwell et al., 2009).

ambiguous, to say the least, but the similarity in overall shape could be consistent with common technology driving the changes.

6.2 | Globalization

Opening borders to trade has been discussed as a possible determinant of changes in market structure through two mechanisms. In one, new entrants from low-labor-cost countries offer cheaper goods, causing domestic firms to lower prices (Autor, Dorn, & Hanson, 2013). This mechanism is generally treated as increasing competition, though in a fully general model, a low-priced entrant could push out inefficient firms in the entered country, leaving fewer competitors. The other mechanism was proposed by Melitz (2003): the opening of export markets rewards the most efficient domestic firms and causes the less efficient to exit. Both of the mechanisms by which globalization would lead to concentration operate through reallocation of activity to more efficient firms. As noted above, Gutiérrez and Philippon (2017) have shown

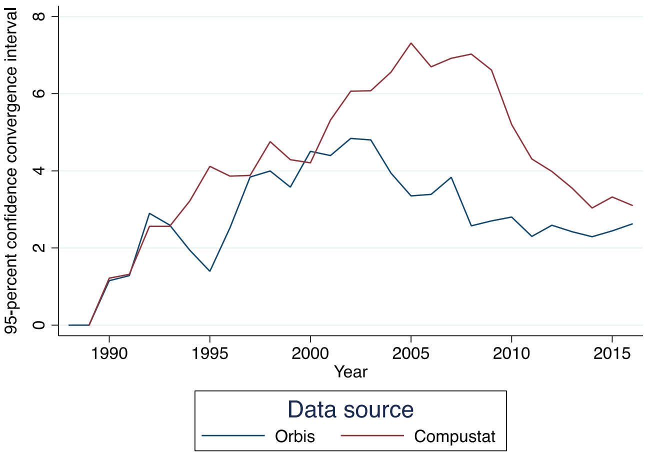

FIGURE 9 Comparing performance autocorrelation (ABBB estimates) for Compustat and Orbis data for OECD founding countries. *Note:* AR(1) autocorrelation coefficients of firm performance, as in Figure 1 above, for a matched sample of firms from two sources: Compustat and BvD Orbis data on listed firms from OECD founding countries. Firms are matched on 2-digit SIC code sector (exact) as well as operating profit (EBIT) and assets using the CEM procedure (Blackwell et al., 2009) [Color figure can be viewed at wileyonlinelibrary.com]

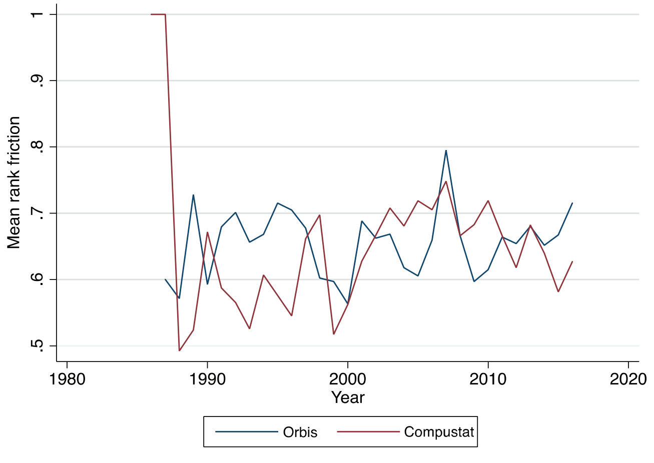

FIGURE 10 Rank friction over time for Compustat and Orbis data for OECD founding countries. *Note:* Friction in firms' performance rank year-to-year, as in Figure 3 above, for a matched sample of firms from two sources: Compustat and BvD Orbis data on listed firms from OECD founding countries. Firms are matched on 2-digit SIC code sector (exact) as well as operating profit (EBIT) and assets using the CEM procedure (Blackwell et al., 2009). Performance is measured as "firm-specific profits" (Villalonga, 2004). Rank friction is calculated as in Powell and Reinhardt (2010). Higher values represent a lower probability of changing within-industry (SIC3) performance rank between time t and $t + 1$ [Color figure can be viewed at wileyonlinelibrary.com]

that concentration is actually negatively correlated with productivity, suggesting that globalization-driven reallocation is not the predominant phenomenon.

Globalization is generally thought of as having increased in 2001 with the accession of China to the WTO, which roughly corresponds with an increase in the cardinal measure of persistence of performance in my data. To test whether the observed change in convergence interval is likely to have been driven by Chinese entry, I exploit variation in the degree of Chinese import penetration. I compute the industry-year–level convergence interval using the process described above and regress it on the industry-year measure of Chinese import penetration from Autor et al. (2013). Table 3 shows the results. Columns 1–3 exhibit standard fixed-effects results

TABLE 3 Import penetration and persistence measure

	(1)	(2)	(3)
Variable	Convergence interval		
Import penetration	−43.41	−51.62	0.159
	(52.82)	(56.18)	(139.6)
Constant	13.45	14.53*	7.701
	(18.65)	(7.409)	(18.41)
Observations	1,151	1,151	1,151
R-squared	0.000	0.066	0.080
Clustered errors	SIC4	SIC4	SIC4
SIC4 FE		Yes	Yes
Year FE			Yes

Note: Import penetration measured at the industry-by-year level and data from Dorn (www.ddorn.net). Robust standard errors in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$.

and show that accounting for time-invariant industry effects and industry-invariant time effects leaves us with a result statistically indistinguishable from zero at conventional levels.[12]

Additional nuance comes from comparing the Orbis and Compustat panels. While Western European Orbis firms matched to Compustat firms seem to have similar patterns of concentration, the unmatched firms do not, suggesting that globalization could affect the persistence of performance of smaller nonpublic firms.

6.3 | Antitrust enforcement

Some scholars have attributed increased persistence to a documented decrease in enforcement of the Sherman Anti-Trust Act (e.g., Grullon, Larkin, & Michaely, 2019). Conceptually, this means that we should expect the greatest increase in concentration after enforcement declined and should see it most in the industries in which enforcement declined the most. To test this hypothesis, I collected the sectors of the firms targeted in antitrust suits under Chapter 2 of the Sherman Act from the Department of Justice and the Federal Trade Commission. Using data for before 2000, when enforcement declined, I regress the count of cases on lagged convergence interval and fixed effects at the year and industry levels. I then predict the number of cases out of sample on the post-2000 data. Essentially, the goal is to predict the counterfactual number of antitrust cases. I then run a regression of convergence interval on the gap between the estimated counterfactual number of cases and the observed number. A positive gap would imply that fewer cases were brought than would have been and the mechanism suggested by Grullon et al. (2019) would imply a positive correlation between observed persistence of performance and the gap in cases. Instead, in Table 4, I find a significant negative correlation between the gap and persistence. There are several possible explanations for this. One is that antitrust enforcement actually increases the persistence of performance. But the more likely explanation

[12]Note that the instrument used in Bloom et al. for import penetration is not available here, as there are too few public companies and the first-stage regression produces significance well below the advocated thresholds.

TABLE 4 Estimating the effect of reduced Sherman act enforcement on persistence of performance

	(1)	(2)
Variable	Sherman act cases	Convergence interval
Convergence interval [lagged]	6.755***	
	(1.273)	
Gap between counterfactual and observed Sherman act cases		−0.000233***
		(2.68e-05)
Constant	104.2***	3.300***
	(4.580)	(0.0180)
Observations	86,378	74,199
R-squared	0.461	0.524
Year FE	Yes	Yes
SIC4 FE	Yes	Yes
Sample	Pre-2000	Post-2000

Note: Standard errors clustered at the SIC4 industry level. ***$p < .01$, **$p < .05$, *$p < .1$.

is that the decrease in cases was greatest for areas in which persistence seemed least likely. That would imply that while there was a major decline in cases brought, the decline was mostly on the lowest-priority targets. That is consistent with a strategic enforcer and suggests that while the decline in cases was large, it likely had limited effect on persistence.

It is also worth noting that to the extent that we consider the matched Orbis sample patterns similar to those in the United States in Appendix Figure A2, that similarity suggests that declining US enforcement is unlikely to be a primary driver.

6.4 | Markets for managerial talent

One might imagine that if the market for managerial talent became more assortative—with better managers matched with better firms—industries would become more winner-take-all. This would also increase the dispersion of executive wages. Using data from Clementi and Cooley (2009), I associate measures of variance in total compensation of non-CEO managers with my convergence interval. The correlation coefficient between the mean absolute deviation of non-CEO salaries and the convergence interval is 0.4722. Limited data access precludes further investigation, but the initial pattern suggests that this is a promising avenue for future research.

6.5 | Importance of intangible capital

A final potential explanation for increasing persistence of performance is an increase in the importance of intangible capital for production by American public firms. That argument combines the argument from Villalonga (2004) that intangible capital is associated with persistence with firm-level work by Tambe, Hitt, and Brynjolfsson (2011) that finds a dramatic increase after 2000 in the differential in the value of intangible IT investments. The time-series results, however, are inconsistent with longer panel work, by Corrado, Hulten, and Sichel (2009), suggesting that investment in intangibles in the US has been steadily increasing since the 1950s. If increases in the importance or prevalence of intangible capital were driving the observed patterns, one would expect a monotonic increase in persistence of performance, rather than the decrease during the 1970s and the moderated recent growth. This suggests that while intangibles are important to persistence in levels, changes in intangibles are unlikely to be driving changes in persistence.

7 | DISCUSSION

There is much public discourse about the increasing power of the largest companies and fear that their positions are becoming unassailable. This contrasts dramatically with concerns by executives that their companies' positions are becoming more at risk and suggestions by Strategy scholars that firms will have to adopt strategies composed of chains of resources instead of relying on existing capabilities.

Given that a motivating question for Strategy as a field is understanding persistence of performance, I believe that it is incumbent on Strategy scholars to attempt to reconcile these differences. This is not possible, however, without an agreed-upon set of facts on which to build.

My goal in this manuscript is to begin the conversation by producing such facts, using statistics adopted and advocated by Strategy scholars. Extremely early comparisons of those facts with the predictions generated by the explanations currently in the public discourse shows the value of this panel of statistics.

The patterns I observe are inconsistent with many of the mechanisms commonly proposed by economists for secular changes in levels of performance persistence: technological change, globalization, and changes in anti-trust enforcement. A very simple first cut fails to reject improved matching in the human capital factor market, a fact identified by Hsieh, Hurst, Jones, and Klenow (2019). Work by Barney (e.g., Barney, 1986) on strategic factor markets and Chatain and Zemsky (2011) and Bennett, Seamans, and Zhu (2014) on frictions in factor markets have provided an early grounding for how changes in access to inputs could provide differential benefits. Additional theorizing on whether those benefits accrue to current leaders or current laggards is necessary to determine whether observed patterns are consistent with this mechanism. In addition, future theorizing can help suggest new mechanisms for secular changes in persistence of performance. Identifying which features lead to increasing returns to scale, as described by Arthur (1994), versus self-leveling systems that reward newer unburdened entrants, can help Strategy scholars contribute to policy debates on persistence of performance; an area in which I believe Strategy has a comparative advantage.

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APPENDIX A

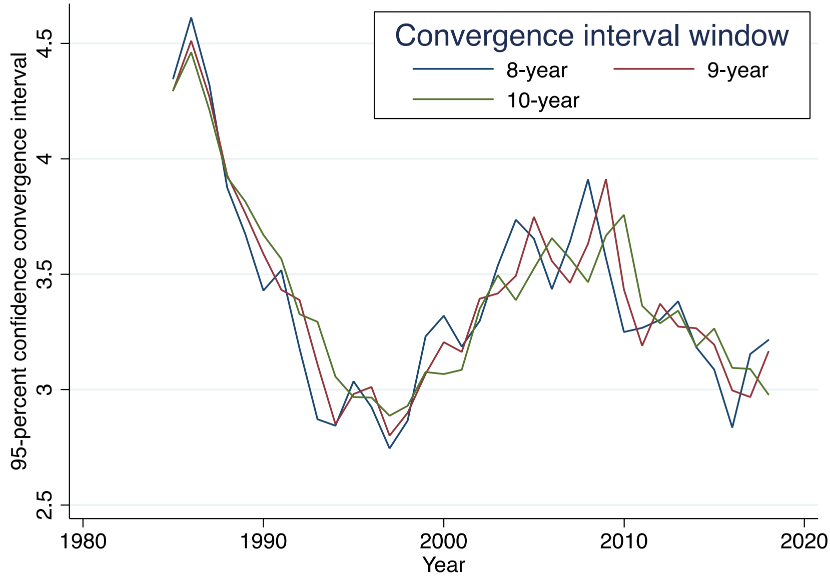

FIGURE A1 Arellano–Bover/Blundell–Bond dynamic panel estimates of convergence interval over time using ROE instead of ROA. *Notes:* AR(1) autocorrelation coefficients of firm performance from a series of Arellano–Bover/Blundell–Bond dynamic panel estimates over rolling 10-year periods. Each coefficient has been transformed into a 95% convergence interval. See text for the transformation equation. Performance is measured as "firm-specific profits" (Villalonga, 2004). This measure calculates segment-level return on equity (Return on equity (ROE) is calculated as the ratio of operating profit to equity using Compustat segment-level measures (OPS and CEQ), demeaned by the average industry profits of that segment, and then aggregating the demeaned performance up to the firm level on an asset-weighted basis. Since Compustat segment data commences in 1976, the first available 10-year interval is 1985, where the figure begins. The joint test of breaks at 1999 and 2009 is significant at the greater-than-99.999% level using the `sbknown` command in Stata [Color figure can be viewed at wileyonlinelibrary.com]

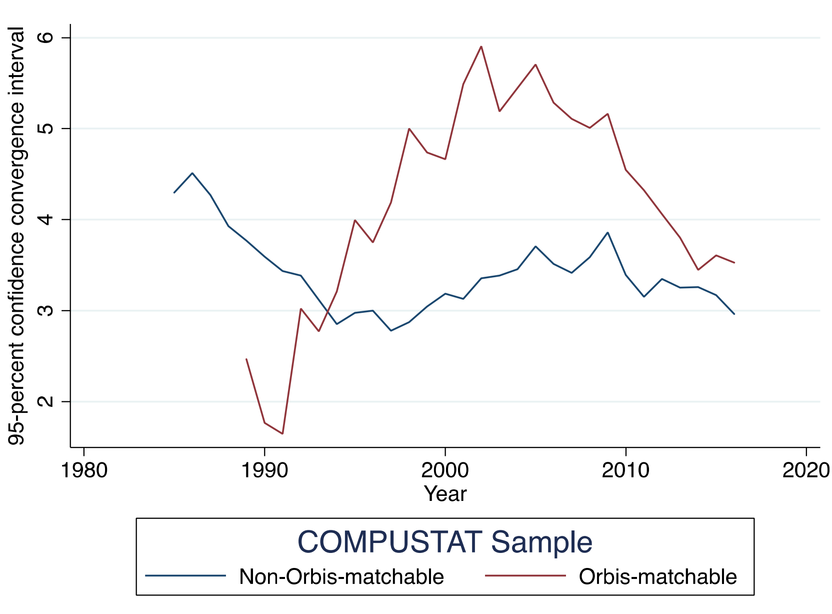

FIGURE A2 ABBB estimates for Compustat firms that were matched—versus not—to the Orbis sample [Color figure can be viewed at wileyonlinelibrary.com]

FIGURE A3 Probability of exiting top performance ranks. *Note:* Probability that a firm that was in the top ranks of performance, measured by total revenue [Color figure can be viewed at wileyonlinelibrary.com]

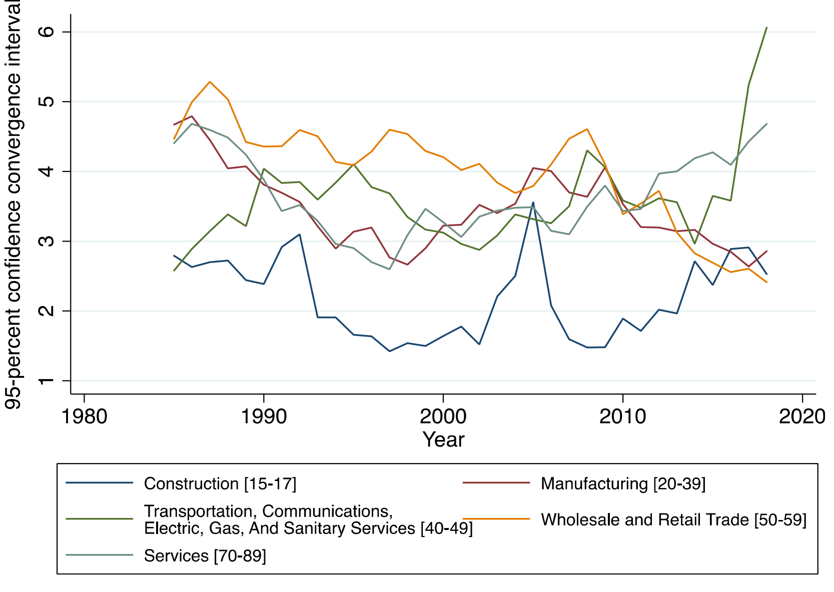

FIGURE A4 Comparing performance autocorrelation (ABBB estimates) for sectors. *Notes:* AR(1) autocorrelation coefficients of firm performance from a series of Arellano–Bover/Blundell–Bond dynamic panel estimates for firms in different sectors—defined by 2-digit SIC codes. Each coefficient has been transformed into a 95% convergence interval. See text for the transformation equation. Performance is measured as "firm-specific profits" (Villalonga, 2004). This measure calculates segment-level return on assets, demeaned by the average industry profits of that segment, and then aggregates the demeaned performance up to the firm level on an asset-weighted basis. Since Compustat segment data commences in 1976, the first available 10-year interval is 1985, where the figure begins [Color figure can be viewed at wileyonlinelibrary.com]

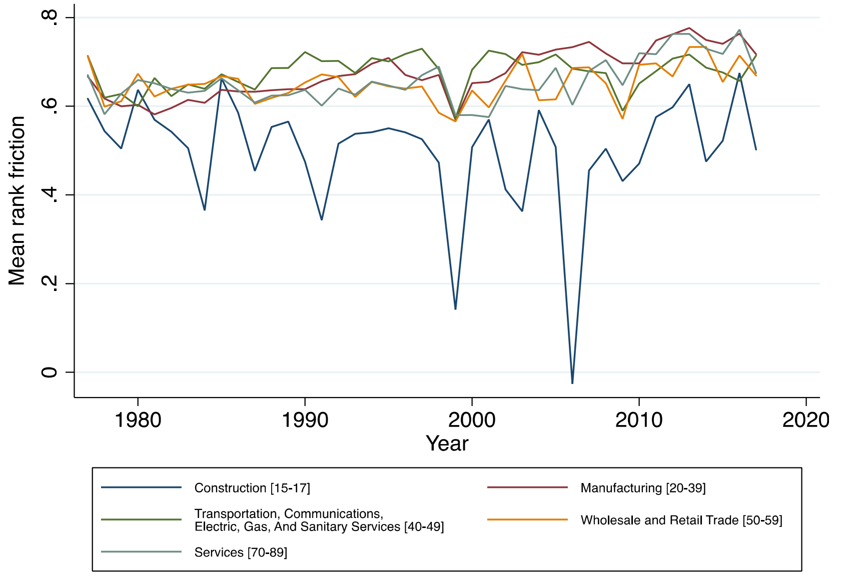

FIGURE A5 Rank friction over time by sector. *Note:* Friction in firms' performance rank year-to-year divided by sector—defined by 2-digit SIC codes. Performance is measured as "firm-specific profits" (Villalonga, 2004). Rank friction is calculated as in Powell and Reinhardt (2010). Higher values represent a lower probability of changing within-industry (SIC3) performance rank between time t and $t + 1$ [Color figure can be viewed at wileyonlinelibrary.com]