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Abstract

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Disciplines

Management Sciences and Quantitative Methods

Changes in Persistence of Performance Over Time

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One of the central puzzles of strategy is the persistence of performance. We revisit a research tradition that lays out trends in persistence of performance, to create shared facts for strategy scholars to explain. We extend the time series from prior studies and apply recent methods for measuring performance persistence. We show that persistence of performance is not stable. Notably, our measure shows a decrease in persistence from the beginning of the sample to roughly 2000, followed by a marked increase thereafter. Our evidence suggests that the post-2000 increase in persistence is at least partly attributable to increases in industry concentration associated with the greater importance of software across industries in the late 1990s.

Changes in Persistence of Performance Over Time

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One of the central constructs of interest within strategy is the persistence of superior performance—the ability of an organization to maintain higher profits than comparable firms over time. As Rumelt, Schendel, and Teece (1991: 12) wrote: “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, 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 study, we report updated trends on persistence, as well as an exploration of underlying drivers of these trends.

Beginning as early as Epstein (1935) and peaking in the 1970s through 1990s, there was an effort within the field to produce a set of empirical patterns to inform the development and testing of theory (e.g., Cubbin and Geroski, 1987; Jacobsen, 1988; McGahan and Porter, 1999; 2003; Mueller, 1977; Villalonga, 2004; Waring, 1996), with the timeframes of the analyses ending before 2000.

Since the mid-2000s, however, this effort has diminished, replaced by context-specific studies designed to identify causal mechanisms linking specific factors to persistent performance (Madsen and Leiblein, 2015; Madsen and Walker, 2017; Suarez, Cusumano, and Kahl, 2012; Vaaler and 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.

Given this shift of focus within the field, a question arises of whether the patterns of performance persistence found among firms during the twentieth century continue to describe firms in more current periods. More generally, there are relatively few calendar-time studies of persistence that discuss whether or why performance persistence has changed over time, particularly relative to the centrality of this construct to the field of strategy. Understanding how

persistence has changed over time is crucial to understanding the changing nature of competition, as well as whether the conclusions drawn from one period are likely to apply to other periods.

The common theories in strategy, as well as existing empirical work, provide limited guidance on either the levels of persistence, or how persistence might change over time (either calendar time, as with our study, or clock time for firms, as with McGahan and Porter, 2003). McGahan and Porter (2003) address this undeveloped state of the literature directly: “while 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.”

The positioning school (e.g., Porter, 1980), deriving from the economics of industrial organization, suggests that persistence arises from entry barriers or, relatedly, mobility barriers within an industry (Caves and Porter, 1977). These barriers are structural factors that impede other firms from capturing excess profits of an advantageous industry niche. These factors may include scale and scope economies that enable incumbent firms to capture quasi-monopoly rents over extended periods. This research, however, does not have clear guidance on how these barriers should change over time, as technology, markets, and regulations evolve. Research based on the resource-based view (RBV) also provides limited guidance on this question. The simplest version of RBV argues that superior performance is due to particular scarce resources—acquired by either skill or luck—whose value persists across periods, allowing performance to persist (Barney, 1996; Peteraf, 1993; Wernerfelt, 1984). As with the positioning school, there are few predictions regarding how this resource-driven persistence changes over time.

In contrast to the positioning school and RBV, Schumpeterian theory explicitly focuses on persistence and the dynamic forces that create and erode performance. Schumpeter himself argued that (1942: 87) “Both as a fact and as a threat, the impact of new things—new

technologies for instance—on the existing structure of an industry considerably reduces the long-run scope and importance of practices that aim, through restricting output, at conserving established positions and at maximizing the profits accruing from them.” Few would argue against many “new things” having arisen in the past 20 years, and many argue that technologies are emerging at accelerating rates (e.g., Brown and Eisenhardt, 1997).

However, while this view implies that evolving technology will diminish rent levels, it is unclear that it necessarily implies that the duration of these rents will be ever-decreasing. Instead this logic could simply justify durations fixed at low but stable rates as new technologies supplant earlier ones (McNamara, Vaaler, and Devers, 2003). Moreover, as D’Aveni (1994) and D’Aveni, Dagnino, and Smith (2010) highlight, even as Schumpeterian competition increases, certain firms may be better at capturing dynamic rents by creating a chain of temporary advantages, thereby realizing greater persistence even in the face of more intense competition. Empirically, two studies that have explicitly focused on calendar time trends of persistence have found mixed results. McNamara *et al.* (2003), find no discernable change in persistence between 1978 and 1997. In contrast, Wiggins and Ruefli (2005) find the opposite result using similar data, that persistence has steadily eroded between 1978 and 1997. Wiggins and Ruefli attribute the differences to different methods and measures between the two studies.

The goal of our study, therefore, is to report updated patterns of performance persistence and, in the process, contribute to the renewal of interest in macro-strategy patterns to inform strategy research. We present time trends of persistence that extend until 2015, nearly two decades after most of the prior persistence studies ended. In doing so, this study differs from this earlier work not only in the updated panel, but also in the presentation of time trends, whereby

most earlier studies calculated average persistence over the sample period.¹ As with Mueller (1986), Jacobsen (1988), McGahan and Porter (1999; 2003), Villalonga (2004) and related studies, we define persistence as between-period correlation of performance. As initially highlighted by Epstein (1935), this definition implies two conceptually distinct dimensions along which persistence can manifest itself and therefore be measured. One measure captures cardinal performance levels and has been the focus of most studies from Mueller (1977) onward. A second measure captures ordinal (relative) performance, and has received substantially less attention.² Correspondingly, we report two sets of measures, which we propose must be taken together to understand overall patterns of performance persistence.

Our cardinal dimension is the between-period correlation of firm-specific performance, which we measure as segment industry-demeaned return on assets earned by a firm, following Cubbin and Geroski (1987), McGahan and Porter (2003) and Villalonga (2004). To make this measure easily interpretable, we report it as the 95% convergence interval, the estimated number of years in which firm-specific performance decays by 95% to industry average returns. The longer the convergence interval, the greater the persistence of firm-specific profits.

The ordinal dimension of persistence, which we refer to as rank persistence, focuses on relative, ranked performance. As Epstein (1935) first described, the question of sustainability of competitive advantage rests not just on the stability of performance levels, but also on the degree to which firms persist in their position relative to their rivals. While there are several approaches

¹ These studies generally focused on other aspects of persistence, including its association with “strategic factors” (Jacobsen, 1988; Waring, 1996), including intangibles (Villalonga, 2004) and reputation (Roberts and Dowling, 2002), differences across countries (Chacar, Newbury, and Vissa, 2010), and the extent to which industries versus business effects influence its magnitude (McGahan and Porter, 1999; 2003), among others. Given these different focuses, explaining calendar trends were not central to the research approach.

² We found one study that focused on ordinal stability: Powell and Reinhardt (2010), who, like prior studies, do not focus on calendar time trends. Their measure is related, but not identical, to ours.

to capturing this notion of persistence in relative ranking, in this paper, we adopt a recent approach that has become one of the core measures of social mobility (the converse of persistence) within labor economics (Chetty *et al.*, 2014a; 2014b): the correlation of one's ordinal position between one period and the next. The larger the correlation, the greater the persistence of firm position relative to its competitors.

These two dimensions of persistence are conceptually distinct: one captures the sustainability of *absolute* performance of a firm relative to its peers, while the other captures the degree of churn in *relative* positions of firms within an industry. As we discuss in the next section, these dimensions need not be related, and together form a more complete picture of performance persistence than either measure alone.

Interestingly, both sets of the measures yield similar patterns about trends from 1965 to 2010: i) convergence interval declines from the 1965 through approximately 2000, while rank persistence initially declines and then remains relatively stable during the period, ii) around 2000, a pronounced reversal occurs across both time trends in which persistence measurably *increases* through 2010. Thereafter, the convergence interval moderates somewhat, while rank persistence continues to rise. In sum, while sustainability of performance declines prior to the millennium, it reverses and increases thereafter, in contrast to the simplest interpretation of Schumpeterian competition that performance persistence should be continually on the decline.

We investigate potential contributing factors to this increase in persistence and find suggestive evidence that increasing industry concentration—particularly the concentration that is associated with centrality of software within an industry—is associated with the increase in persistence of performance.

This paper makes contributions to three separate areas. The first is the literature on the persistence of performance (Cubbin and Geroski, 1987; McGahan and Porter, 1999; 2003; McNamara *et al.*, 2003; Mueller, 1986; Waring, 1996; Wiggins and Ruefli, 2002; 2005). We provide an updated analysis, with our panel ending twenty years after the most recent large sample analysis of US firms, using recent econometric methods. Unlike most of these studies, we also provide calendar time trends of performance persistence. Our results show that patterns in persistence during the late 20th century, as well as its relationship with underlying drivers, do not correspond to patterns in the early 21st century. This finding provides a cautionary note that insights regarding performance persistence drawn from earlier time periods may not generalize to more recent periods, and suggests that researchers examine the stability of empirical conclusions over time.

Further, we further provide some initial suggestive evidence on one particular driver of this change, the increasing importance of software within industries that began around 2000, is associated with more concentrated industries and greater persistence. This finding suggests that the net effect of increased importance of software is to increase performance persistence, both of high performing firms (positive performance) and low performing firms (negative performance).

The second area to which we contribute is the literature on the impact of digitization. This literature has looked at the impact of software adoption on firm performance, both the adoption of IT (Arora, Branstetter, and Drev, 2013; Bloom, Eifert, and Mahajan, 2013; Brynjolfsson and Hitt, 2000) and data driven decision making tools (Brynjolfsson and McElheran, 2016), as well as of manufacturing firms making larger portions of their product software (Branstetter, Drev, and Kwon, 2015). Our results provide large-sample evidence that digitization may have implications for performance persistence, in ways that depart from the

simplest Schumpeterian interpretation that technological innovation generally increases overall churn and decreases the duration of abnormal performance.

Lastly, we also contribute to the discussion that has arisen in policy and practitioner realms regarding the decline in competitiveness within the United States (Decker *et al.*, 2016). Our paper provides evidence that, along with rising markups (De Loecker and Eeckhout, 2017), increasing concentration (Grullon, Larkin, and Michaely, 2016), decreasing rates of firm entry and exit (Council of Economic Advisors, 2016), growing performance differences between firms and the rise of “superstar” firms (Autor *et al.*, 2017), that average performance persistence – both among top and bottom performers – is also increasing and churn between firms is declining. While we do not interpret our results as a definitive signal of declining competitiveness, our findings suggest additional areas to explore to understand how strategy and competition has changed since the turn of the millennium.

Our paper continues as follows. We begin by introducing the measures that capture the persistence of performance, followed by a description of the construction of our data sample. We then present the results of our analysis. Finally, we conclude with discussion of the theoretical and practical implications of our results.

2. Measures

In this paper, we present two measures of performance persistence: a cardinal measure that reports the persistence of firm-specific performance between periods, and an ordinal measure that reports the persistence of a firm’s rank relative to its peers between periods. These measures, while complementary, are conceptually distinct. First, we describe the measures and then discuss the difference aspects of persistence captured by each one.

2.1 Cardinal measure: convergence interval

In studies on persistence of performance (e.g., 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.

$$y_t = \alpha + \beta * y_{t-1} + \varepsilon \quad (1)$$

Each period's performance is a function of last period's performance and whatever shocks occur in the previous period, where shocks are distributed as follows.

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

When β is zero, each period's performance is completely independent and idiosyncratic, shocks will dissipate immediately. When β is high, each period depends a great deal on the previous period, meaning shocks reverberate for longer.

A substantial literature estimates the autocorrelation of performance (e.g., Jacobsen, 1988; Waring, 1996), largely with the aim of decomposing those shocks into components (McGahan and Porter, 1999; e.g., 2003) or estimating the effect of variables of interest on autocorrelation of performance (Chacar *et al.*, 2010; Villalonga, 2004).

For our measure of firm performance, we adopt the approach of Villalonga (2004), who defines y to be “firm-specific profits,” a firm's return on assets (ROA) less the industry mean ROA. Since firms are often diversified, the industry is defined at the segment, not corporate, level. Therefore, we begin by calculating segment-specific operating ROA (or firm-level ROA for single-segment firms). We then subtract industry mean ROA from this measure, where we calculate the mean ROA by taking the average ROA of all segments and single-segment firms within the industry. Finally, for multi-segment firms, we aggregate up to the firm level by taking

the asset-weighted average across segments in a firm.³ This measure allows us to measure the persistence of a firm's financial performance relative to its competitors, allowing for a diversified position across various industries, and removing general industry effects that are not specific to a firm.

To estimate the autocorrelation of performance, we follow Villalonga (2004) and adopt a dynamic panel approach with an Arellano-Bover/Blundell-Bond AR(1) estimator, as shown in equation (1).⁴ Using the same sample from above, we estimate a series of ABBB regressions on a sliding 10-year window of data. We extract the autocorrelation coefficient for each window and plot these coefficients over time. For ease of interpretation, we convert the coefficient of autocorrelation into a 95% convergence interval, which reports how the number of years for firm-specific performance to dissipate 95 percent of its magnitude:

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

We explicitly do not include firm fixed effects in our estimation of convergence interval, thereby allowing our estimates of convergence to represent the average of long-run firm-specific determinants of persistence and short-run response to performance shocks.⁵

³ See Villalonga (2004) for further details on this procedure.

⁴ Villalonga uses the original Arellano-Bond (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). We conduct our analysis using this updated estimator; however, our analysis remains essentially unchanged when we conduct our analysis with the original Arellano-Bond estimator.

⁵ Note that the convergence interval is strictly a statistical measure and can be interpreted either as sustainable advantage or a series temporary advantages, or both as they may exist concurrently.

2.2.1 Extremes of the performance distribution

The measure in section 2.2 captures the convergence interval of firm-specific performance regardless of whether that performance is above or below industry average. Conceptually, however, there is a difference between the convergence of superior performance (competitive advantage, or how long advantaged firms can maintain their position) and inferior performance (competitive disadvantage, or how long disadvantaged firms take to reverse their inferior performance). Further, a substantial literature suggests that the degrees of persistence differ between high and low performers (e.g., Abrahamson and Kumar, 2017; Chacar and Vissa, 2005; McGahan and Porter, 2003; Villalonga, 2004). To report the trends at the different ends of the distribution, we divide our data into two subsamples: “high performers”—those firms that maintain positive relative performance for their entire tenure in our sample, and “low performers”—those firms that maintain negative relative performance for their entire tenure in our sample. We then re-estimate the dynamic panel models on 10-year sliding windows, as described in Section 2.2, on the two subsamples.

2.3 Ordinal measure: rank persistence

For our ordinal measure, rank persistence, we assign a rank to all firms in the population by their operating return on assets. Following Dahl and DeLeire (2008) and Chetty *et. al.*, (2014b), we operationalize this rank as a binned percentile, normalized between 0 and 1 to account for changing number of firms year by year. Firms in the highest percentile of operating return on assets are assigned a rank value of 0.99, and firms in the bottom percentile are assigned a rank value of 0.01. We allocate even numbers of firms across each bin on an annual basis.

Rank persistence captures the correlation between previous period rank and current period rank in the performance distribution. A higher correlation corresponds to more persistent

ordinal rankings. The maximum correlation of one indicates perfect stability in ranks between periods and a minimum correlation of zero indicates perfect re-sorting of firms between periods. This conceptualization is analogous to the emerging economic work on social mobility. Social mobility, conceptually the opposite of rank persistence, is often described as the likelihood that a child born into lower quantiles of the earnings distribution will move into the upper quantiles. Recent availability of data has led to a surge in empirical studies comparing differences in social mobility over time (Chetty *et al.*, 2014b) and across geography (Chetty *et al.*, 2014a). The standard model for analyzing intergenerational mobility is a copula model that captures the correlation between an individual's rank in the income distribution and his or her parents' rank.⁶ To the best of our knowledge, rank-rank models have not been used to study mobility and performance persistence.

Following the social mobility literature, we estimate rank-rank models of performance over time to track the changing elasticity of performance ranking to prior ranking. Essentially, this approach correlates lagged percentile rank in the performance distribution with current period performance percentile rank. These ranks are computed across all Compustat firms.⁷ We do not include a high and low performer analysis for this measure since the changing number of

⁶ These models, by construction, do not instrument for unobservable correlates of rank. Hence, we use a simple linear estimator for this measure rather than the Arellano-Bond approach used for the prior measure. In this sense, this choice makes these two measures more complementary, as we may in fact be interested in the persistence of unobservables within firms as well as performance shocks, which this model allows us to estimate, albeit in a combined way. To our knowledge, none of the research in labor economies on social mobility adjusts for unobservable correlates of social rank.

⁷ While we use the full population of public firms to calculate each firm's rank, we can also calculate rank within a firm's home industry. The two ranking approaches yield nearly identical similar time trends, while using the full population of firms as the comparison set is a more robust approach to changing numbers of firms in an industry, as well as treatment of diversified firms.

firms in Compustat can mechanically affect the rank yearly, without that change reflecting actual economic churn.

2.4 Differences between measures

Our cardinal and ordinal measure capture fundamentally different aspects of performance persistence, with one representing the duration of performance persistence 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 all firms within a given industry experienced the identical competitive shock in which no particular firm had any particular advantage in its response. The net effect of the shock is to reduce by half the duration in which each firm sustains its relative profits and losses. In this example, convergence interval, our cardinal measure, would decline by half. In contrast, rank persistence, our ordinal measure, would remain unchanged: each firm experienced the same change to persistence and hence experienced no gain or loss of competitive position relative to each firm's competition. Alternately, imagine a shock to which firms in an industry are very differently positioned to respond. In this second case, some firms double the persistence of their firm specific profits over time, while others halve theirs. As a consequence, the average convergence interval will be unchanged after this shock, but the churn across firms will be high. Hence, in contrast to our first example, rank persistence will fall while average convergence interval would remain unchanged.

Each of these examples describes real, important changes to performance persistence captured by only one of our measures. Cardinal persistence captures the average tendency of firms to earn similar returns from one period to the next. In contrast, ordinal persistence captures the average tendency of firms to hold their position relative to their competition over time. Common shocks will particularly affect cardinal persistence, while differential shocks will affect

rank persistence. Together, they illustrate how our two measures capture different aspects of the same phenomenon and why they do not substitute for each other.

3. Data

We construct our measures based on all US publicly-traded firms between 1965 and 2015 from the Compustat Fundamentals Annual File for our firm-based performance measures and 1976 and 2015 from the Compustat Segment File for our segment-based measures. These years represent the longest available panels for our study and include all firms, both surviving and delisted, for which data is available.

Before we describe our sample selection, we make two observations about this data source. First, Compustat includes both surviving and delisted firms, mitigating survivorship bias that may have been a larger issue in early studies for which historical data was only available for existing firms. On the other hand, as with all studies of public firms, once a firm is delisted, it drops out of the dataset, after which no performance information is available. Following other studies using Compustat (e.g. McGahan and Porter, 1997; McNamara *et al.*, 2003), we treat these exits as non-informative events, in that we do not code them as negative or positive performance and we retain these exiting firms in our main sample. This retention differs from several studies that enforced full coverage by firms to be included in the sample (e.g., Villalonga, 2004). We choose to include all firms as the broadest possible inclusion criterion in order to reduce any bias that might be introduced by including only firms that were listed for a set number of years.⁸

Our second observation is that we include only public firms, a constraint common to these studies, but perhaps more of a challenge with recent data than earlier research. As Davis et

⁸ These criteria can substantially reduce the sample size, which we were concerned about, given our desire for representativeness.

al. (2014) and Doidge, Karolyo, and Stulz (2017) note, the number of firms, including large firms, has fallen considerably since 2000: in 1999, Compustat shows 11,092 distinct firms with positive revenues, and only 7,154 distinct firms in 2015. To the extent this reduction reflects increasing selection into private ownership, the use of Compustat data introduces the potential for a significant bias in our sample relative to the representative large firm in the United States. This is a more general challenge regarding using recent Compustat data for large sample studies. We acknowledge this limitation and that our results hold for public companies only and not firms overall. We do discuss this increasing shift from public to private ownership later in interpreting our results.

All together, our sample includes 284,996 firm-year observations between 1965 and 2015 and 234,997 firm-year observations between 1976 and 2015 for which segment industry-adjusted performance data is available. We made the following decisions to obtain this final sample, choosing the most inclusive approach to enable the broadest sample feasible. As of February 2017, the Compustat annual file contained 479,043 firm-year observations. We excluded i) all firms with negative or missing revenue (79,570 observations), ii) firms in 4-digit SIC codes with less than ten firms in a given year⁹ (63,461 observations), SIC codes 9100-9199 (“government, excluding finance”) and 9900-9999 (“non-classifiable establishments”) (3,985 observations), and firms missing data used in our performance measures (return on assets and equity)¹⁰ (47,031 observations). These exclusions leave 284,996 remaining observations, representing 26,308

⁹ This approach is similar to Waring (1996), McGahan and Porter (2003), and Villalonga (2004) who exclude firms with SICs with one firm. We chose a more restrictive approach in this case because of our rank-rank calculations

¹⁰ We define return on assets as EBIAT/assets for our firm-level measure and segment income/assets, weighted by segment assets for our segment-level measure.

firms. The average duration of each firm in our sample is 20 years and covers 334 4-digit SIC codes at the parent SIC level.¹¹

We then merge this sample with Compustat Historical Segment data in order to calculate segment-level profit metrics for our convergence interval measures (Villalonga, 2004). We calculate these “firm-specific profits” as 2-digit SIC industry-demeaned (at the segment-level) return on assets, aggregated up to the firm level on an asset-weighted basis.¹² See Villalonga (2004) for details on this procedure.

This is the sample on which we observe persistence over time.

4. Results

4.1 Convergence interval

Figure 1 presents the convergence interval over time. As described in the Measures section, the annual values of convergence interval are estimated as an AR(1) coefficient in a Arellano-Bover/Blundell-Bond dynamic panel model with a sliding window of ten years, and then transformed into the time required for a 95 percent decay of a performance shock. Since we calculate firm-specific profits using segment data, which are first available in Compustat in 1976, the first window is 1976-1985 and so our figure begins in 1985.

--Insert Figure 1 about here--

These results suggest that from 1985 to 1997, convergence interval of performance decreased by 35% from a high of 4.9 years in 1985 to 3.2 years in 1997. Beginning in 1998, that

¹¹ Unlike Villalonga (2004), we make no exclusions for number of contiguous years in the sample. We also make no exclusions for assets, as we are not analyzing market value, in order to retain the largest possible sample.

¹² Our results are unchanged using 3-digit SIC classifications as well.

trend reversed itself, with convergence interval increasing by 21% to 3.9 years until 2007, and then again turning down. By the end of our panel in 2015, the convergence interval is approximately 3.6 years. In sum, persistence has changed substantially over the forty years in our sample: first falling steadily until the turn of the millennium, and then reversing itself around the 2007 Great Recession.

4.1.1 High and low performers

To differentiate persistent competitive advantage from competitive disadvantage, we divide our sample into three subsamples: 5,636 “high performing” firms whose firm specific profitability has been positive for their entire life in the sample, 5,265 “low performing” firms whose firm specific profitability has been negative for their entire life in the sample, and 14,640 firms that fall into neither category. Figure 2 presents the results of estimating our main dynamic panel model on 10-year sliding windows on the three subsamples.

Several insights emerge from this figure. First, high performers consistently have longer convergence intervals than low performers, with an average of 6.8 years over the course of the panel, versus 2.6 years for low performers and 3.9 years for all other firms. Second, all three subsamples exhibit similar time trends: decline in persistence until the late 1990s, followed by an increase in persistence, and then a moderation in the final years of the sample. In sum, the broad trends shown in Figure 1 are confirmed across the performance distribution and are not driven by high or low performing firms alone.

--Insert Figure 2 about here--

4.2 Rank persistence

Figure 3 presents the results of the rank-rank models over time.¹³ Several observations are apparent from the figure. First, inter-temporal rank persistence decreased or remained stable from the mid-1960s to the end of the 1990s. As such, firms with high rankings in one period were either less likely or no likelier to maintain their high ranks in subsequent years as time progressed. Second, and consistent with the results from our cardinal measure of convergence interval, the beginning of the 21st century saw the reversal of this trend. After a near-trough of 0.57 in 1998, the inter-temporal correlation of rank increased to 0.70 by 2015, the final year of our panel, returning to 1970 levels.¹⁴

--Insert Figure 3 about here--

In sum, persistence of performance is neither constant nor monotonically in decline. Our analyses suggest that from 1976 to the late 1990s, there was a downward or stable trend in performance persistence. From the late 1990s until roughly 2008, performance persistence actually increased. Since 2008, that upward trend moderated in our cardinal measure, and remained in our ordinal measure.¹⁵ This pattern holds true for high and low performers alike, suggesting that similar factors are driving these changes across the performance distribution.

5. Why is persistence increasing?

¹³ Note that the time period of this figure extends earlier than in our first analysis of convergence interval. We are able to analyze a longer period since our ordinal rank measures are based on absolute performance and not firm-specific profits that requires more recent segment-level profits to calculate.

¹⁴ We see a large drop in rank persistence between 2008 and 2010, contemporaneous with the financial crisis, during which time, significant capital constraints and distress firms likely led to large reshuffling within industries.

¹⁵ This moderation is likely an artifact of our 10-year estimation window around the financial crisis. Unreported estimates using shorter windows shows a rebound in convergence interval after 2010, and we see a similar disruption in our rank persistence measure during the same time period.

What could drive these results? Specifically, why might performance persistence have declined or remained stable until the late 1990s and then reversed and increased for a decade or more? These large swings in persistence imply fundamental shifts in the aggregate competitive context that served first to weaken, then strengthen, firms' ability to sustain their competitive positions. In this section, we explore potential underlying factors that might influence these changes.¹⁶ This analysis is not intended to be exhaustive, but rather suggestive of potential directions for further study into long-term changes in persistence.¹⁷

5.1 Industry concentration and hedonic Tobin's Q

To provide structure in addressing this question, we appeal to two established theories for performance persistence: the positioning school, which focuses on a firm's competitive position as well as overall industry structure (McGahan and Porter, 1999; Porter, 1979), and the resource-based view, which focuses on a firm's internal resources and capabilities (Barney, 1991; Wernerfelt, 1984). Each of these theories suggests different factors that affect persistence, and in this analysis, we ask whether these factors can account for our observed patterns reported above. In particular, we examine whether drivers of persistence predicted by each of these theories have evolved in conjunction with persistence and whether these changes can explain our results.

¹⁶ In this section, we focus on explaining the reversal that occurred during the late 1990s. While the convergence interval appears to moderate around 2007-8, as the previous footnote discusses, this is likely an artifact of our 10-year estimation window around the financial crisis

¹⁷ Related research on changes in competitive environment have either speculated on or explicitly studied drivers in changes in the degree of competitiveness over similar timeframes. See, for example, D'Aveni (1994) and D'Aveni, Dagnino, and Smith (2010) and the related issue of *Strategic Management Journal* devoted to "The age of temporary advantage." Many of these drivers, particularly those that are related to technology and globalization, are related to our discussion in this section.

For simplicity, we limit our analysis to one proxy for each theory.¹⁸ For our proxy for the positioning school, we use industry concentration as the Herfindahl-Hirschman Index at the 3-digit SIC level. As Porter (1980; 1985) and Schmalensee (1985) argue, higher concentrations within industries may be evidence of increased market power or efficiency or both. Increased market power is plausibly associated with a greater ability of firms to pass cost shocks through to customers, resulting in less variable performance under higher concentration. Since concentration is likely associated, *ceteris paribus*, with more skewed distributions of market power within industries, we may therefore expect to observe greater persistence across the performance distribution (both high and low performers) within those industries with higher industry concentrations.

For resource arguments, we use Tobin's Q, and specifically the hedonic (predicted) Q based on investments in research, advertising and other key intangibles, as in Villalonga (2004). Villalonga has shown this hedonic Q to be positively associated with performance persistence, which she argues to be evidence for internal resources driving persistence.

Figure 4 shows how both of these factors have evolved over time, overlaid with our previously reported trends in convergence interval. Panel A focuses on industry concentration. This panel shows that concentration corresponds closely over time to our persistence results: industry concentration decreases prior to 2000, and increases thereafter, with a similar moderation around 2010. Both inflections – around 2000 and 2010 – coincide in time with the changes in convergence interval. Panel B shows the trends in hedonic Tobin's Q over time. In contrast to concentration in Panel A, as well as our two measure of persistence, hedonic Tobin's Q shows continual increase over time, with no discontinuity around 2000. The low correlation

¹⁸ Note that the goal of this analysis is simply exploratory rather than attempting to explain all the variance in convergence interval.

between hedonic Tobin's Q and persistence does not imply that these two measures are unlinked. Rather, it suggests that the *changes* in levels of persistence are not – at least directly – driven by *changes* in levels of hedonic Tobin's Q over time.

---Insert Figure 4 about here ---

Because of the close correspondence of industry concentration and performance persistence, we hereafter focus on concentration to explain changes in persistence. To test the relationship between concentration and persistence more systematically, we turn to a multivariate, industry-level (3-digit SIC) approach. Moving to a panel allows us to move beyond correlating time trends to a panel analysis wherein we can associate changes in concentration and persistence across and within industries. While these associations remain correlational, the added requirement of explaining variation across industries introduces a layer of robustness to the market-level correlation shown in Figure 1.

We construct a panel at the industry-year level from 1985 to 2015. For the dependent variables, we re-estimate our measure of performance persistence – convergence interval and rank persistence at an annual, 3-digit SIC industry level. For concentration, we use the Herfindahl-Hirschman index at the industry level using positive firm sales as our concentration measure.

----- Insert Table 1 here -----

We begin in Table 2 by verifying, in a multivariate regression framework, that the trend in persistence changes after 2000. To do this, we estimate the following equation:

$$Persistence_{it} = \alpha + \beta_1 Year_{it} + \beta_2 Post2000_{it} + \beta_3 Year_{it} X Post2000_{it} + \epsilon_{it} \quad (2)$$

Persistence is either the convergence interval or rank persistence, for industry *i* in year *t*, depending on the specification. *Year* is the year of the observation, *Post2000* is an indicator variable equal to 1 if the observation occurs on or after 2000, and *YearXPost2000* is the interaction between the year and the Post 2000 indicator. With this specification, β_1 should capture the average slope of (in other words, increase or decrease in) persistence prior to 2000, while β_3 captures the change in the slope after 2000. To correspond with Figure 1, we would expect β_1 to be negative or zero, and β_3 to be positive, representing the upward trend in persistence that occurs after the late 1990s.

Table 2 does, in fact, confirm the time trends reported in Figures 1 and 2. In Column (1), we find that *Convergence interval* declines by an average of 17 days (0.049 years, $p=0.009$) per year prior to 2000 to a net zero change thereafter (the sum of *Year* and *YearXPost 2000*). This result corresponds to Figure 1, which show convergence interval first increasing in the years immediately following 2000, and then moderating around 2010.

Column (2) shows that this result is robust to the inclusion of industry fixed effects. Column (3) repeats Column (1) with Rank Persistence as the dependent variable. The results confirm the pattern shown in Figure 2. Rank persistence marginally decreases by 0.0018 ($p=0.133$), or less than 1% on average per year prior to 2000. After 2000, rank persistence markedly increases by 0.0048 (the sum of *Year* and *YearXPost 2000*, $p=0.001$), or about 1% per year.

Overall, this table confirms our initial insight from Figure 2 that persistence declines or remains stable prior to 2000 and then increases thereafter.¹⁹

----- Insert Table 2 here -----

Table 3 explores the relation between industry concentration and performance persistence. To do this analysis, we add *Concentration X Post 2000* into the specification shown in Equation 2. This addition allows us to see if this interaction explains our *Year X Post 2000* time trends. In addition, the specification is sufficiently flexible so that we can also measure whether the association between concentration and persistence changed around the same period as persistence changed.

This table yields two main insights. First, industry concentration does not predict performance persistence prior to 2000, and, in fact, the coefficients on *Concentration* are negative across all specifications. Second, industry concentration does weakly predict the change in convergence interval relatively more after 2000. The coefficients on *Concentration X Post 2000* are positive in both Columns (1) and (2) and significant by conventional thresholds ($p=0.079$ and $p=0.074$) in both of the models. While the coefficients are similarly positive on *Concentration X Post 2000* in Columns (3) and (4) with rank persistence as the dependent variable, they are not significant. Notably, however, the coefficient on *Year X Post 2000* does not attenuate relative to Table 2.

Overall, Table 3 provides evidence that the increased concentration that occurred after 2000 is associated with increased persistence, although these associations are not statistically

¹⁹ It is possible that our observed change starting in 1995 is actually the result of a series of shocks starting in the early 2000's and that the data will return to their prior trend in the future. Below, however, we find a strong correlate of the trend, the growing importance of software to American businesses. If softwarization does drive increased persistence of performance, it is unlikely that convergence intervals would return to their prior trend.

strongly significant. Notably, the positive associations did not exist prior to 2000, suggesting that the underlying mechanism linking concentration to persistence of performance may have changed between these two periods.

----- Insert Table 3 here -----

5.2 Industry concentration and software

In this section, we seek to examine one potential driver that underlies the apparent link between rising concentration and rising persistence around 2000. To do this, we specifically focus on the role of softwarization in driving concentration and, simultaneously, persistence. In doing so, we split our concentration measure into the portion correlated with software penetration and the portion attributable to other factors.

We adopt this approach because is that there is growing evidence that the software and overall information technology revolution that occurring during the late 1990s through recent years may have influenced economies of scope and scale and, by extension, industry concentration. Bessen (2017) finds suggestive evidence that IT adoption disproportionately benefits the top performing firms, thereby increasing concentration. Using different methods, Kurz (2017) also attributes raising concentration to IT adoption. Relatedly, Bloom, Sadun and Van Reenen (2012) find that IT investment drove a productivity boom within US firms after 1995, and in particular, within industries that use IT intensively. Much of these IT gains appear attributable not simply to IT in general, but specifically to the adoption of software-related technologies. Aral, Brynjolfsson, and Wu (2006) find evidence that adoption between 1998 and 2005 of “enterprise resource management” software systems significantly increased firm productivity and performance, while both Brynjolfsson, Hitt and Kim (2011) and

Brynjolfsson and McElheran (2016) find evidence that decision support systems (what they term DDD or “data driven decision-making”) improves productivity. The latter study, using US Census data, finds that the adoption of this software leads to a 3% increase in value-added over and above other IT usage. Platform software technology and business models, which also matured during this period, have also substantially altered economies of scale and competitive dynamics within industries (2016).

Given this growing evidence that software adoption has altered returns to scale and productivity particularly around 2000, our period of interest, we examine its role in influencing our results. We use a new measure of the degree of the importance of software within an industry developed by Bennett and Hall (2017). This measure captures whether or not a firm mentions the word “software” in its annual 10-K report, averaged to the industry level. This “softwarization” measure is different from simple software adoption by firms. Instead of capturing simple purchases of software, this measure captures the changing importance of software to the firm’s business model, in that it must be of sufficient importance to merit mention in the firm’s annual regulatory filings. To illustrate this significance, Bennett and Hall (2017) discuss several cases. One illustrative case is the case of Arconic Inc. This provider of nickel and titanium did not mention software in its 10-K through much of its history, but in recent years has mentioned what a large role software plays in its productivity improvement and cost reduction. The example of Arconic corresponds to the IT adoption construct in Bessen (2017) and Kurz (2017) in that it may lead to Arconic to be more efficient and capturing more of the market, leading to additional concentration. What the traditional IT adoption measures do not capture, are cases like the case of American Greetings Corp. American Greetings, a traditional greeting card manufacturer, began mentioning software in the business section of their 10-k filings in 1998 because its

business model shifted from an exclusive focus on paper cards with the exponential rise of e-cards. While this is not IT adoption, it may similarly have the effect of moving the firm to a lower marginal cost model, which could lead to a larger firm and higher concentration.

The *software* variable takes a value of 1 if the string “software” appears in the text of the 10-K filing for the given year and 0 otherwise. While not a perfect measure, as firms within an industry increasingly adopt software into their core businesses, this measure should increase over time and vary across industry. Figure 5 shows this to be the case. In Panel A, in 1994, the earliest date in which this measure is available, software is mentioned in 31 percent of all 10-Ks, while by 2015, that value had increased to 66 percent (with a large spike around the millennium largely attributable to firms discussing the so-called “Y2K” issue – the need to upgrade their systems to allow for four-digit years after 2000). Panel B shows the penetration by industry in 1995 and 2015. As expected, in 1995, software penetration was highest within SIC 3000, which includes computer equipment and other IT-intensive industries, and SIC 5000, which includes industrial and office equipment. By 2015, the overall level of software penetration had risen considerably, and the other industries had closed the gap with the IT-intensive industries. See Table 1 for descriptive statistics.

Using this measure, we explore whether software is associated with the observed increase in concentration after 2000 and, by association, the increase in performance persistence. Table 4 reports the results of our analysis using this software measure. First, we confirm that the degree of softwarization is associated with increased industry concentration, consistent with Bessen (2017). Table 4 Columns (1) and (2) show this association: using the cross-sectional estimates in Column (1), an increase from no software to the median level after 2000 of 0.71 is associated with an increase in HHI of 0.03 relative to a median level of 0.19 within the sample.

Next, we separate the industry concentration into two categories: concentration directly associated with the degree of softwarization, and the concentration attributable to other factors. To do this, we predict the level and residuals of concentration based on Models (1) and (2), *Concentration (software)* and *Concentration (other)*, respectively. We use the cross-sectional predictions from Model (1) in our cross-sectional specifications in (3) and (5), and the fixed-effects predictions from Model (2) in our fixed effects specifications in (4) and (6).

Because software may drive persistence directly, we cannot consider software an instrument for concentration to infer causality. As such, this analysis, as with our previous analyses, remains correlational. However, it does allow us to consider software-related changes in concentration separately from other drivers of concentration changes, including compositional shifts in Compustat from firms going private. In doing so, we can explore which type of concentration increases are most associated with changes in persistence.

We show the results of this analysis in Table 4, Columns (3) to (6). We replicate the analysis in Table 3, replacing our aggregate measure of concentration with our two sub-measures, *Concentration (software)*, derived from the predicted values of concentration, and *Concentration (other)*, derived from the residual values. Column (3) shows the cross-sectional results using *Convergence Interval* as our measure of persistence. As in Table 3, we find neither measure of concentration to be associated with convergence interval prior to 2000. Both point estimates on *Concentration (software)* and *Concentration (other)* are in fact negative, but far from statistically significant ($p=0.961$ and 0.386 , respectively). After 2000, however, concentration associated with software becomes strongly predictive of convergence. Using the estimate in Column (3), the difference between the bottom and top decile of *Concentration (software) * Post 2000* is associated with an increase of 0.91 years in convergence interval, from

a mean level of 4.16 years to 5.07 years, relative to the pre-2000 trend. In contrast, the coefficient on *Concentration (other) * Post 2000* of 1.687 ($p=0.148$) does not meet standard thresholds of significance. Further, the economic magnitude of the estimate is also substantially less than that of the coefficient on *Concentration (software) * Post 2000*. The difference between the bottom and top decile of *Concentration (other) * Post 2000* is associated with a 0.25 increase in convergence interval, less than third that of the 0.91 years associated with *Concentration (software) * Post 2000*. Finally, the coefficient on *Year X Post 2000* is statistically insignificant by standard thresholds ($p=0.264$), indicating that post-2000 upturn in persistence is absorbed by the software concentration measures.

These patterns are similar across the remaining models in Table 4, whereby i) the coefficient estimates on *Concentration (software) * Post 2000* are consistently substantially larger in magnitude and statistical significance than *Concentration (other) * Post 2000*, and ii) neither measure of concentration predicts persistence prior to 2000. Notably, the magnitude of *Year X Post 2000* does not decline substantially relative to Table 2, and it continues to be significant in two of the four models and close to significance one more. As such, we infer that our analysis does not comprehensively explain the changes in persistence over time, either because our measures are blunt or because other factors are also driving the trends over time that merit further study.

--- Insert Table 4 about here ---

In sum, from Table 4, it is apparent that the link between industry concentration and persistence is tied to the importance of software within industries after the millennium, and much less so to other concurrent factors. It also appears that the growing importance of software to

firms changed the relationship between industry concentration and persistence of firm performance. Prior to 2000, persistence declined, as did concentration. There also seemed to be little, if any, direct relationship between concentration and persistence. Post 2000, both persistence of performance and concentration took a sharp turn upwards, and a relationship developed between the two. We conjecture that the increasing importance of software to business was partially behind the trend, as also speculated by Brynjolfsson *et al.* (2008) and Bessen (2017).

5.3 Other drivers of industry concentration

While the findings in prior section appear to suggest that software played a role in increasing industry concentration and performance persistence, we are not suggesting that this factor explains all or even a plurality of the variance in performance persistence. There are myriad other factors which likely contribute both to industry concentration and also to changes in performance persistence. Here we consider two more, but under the caveat that these two factors are by no means comprehensive, nor are our analyses of these factors.

5.3.1 Anti-trust enforcement

One possible driver of concentration that has been suggested is the change in enforcement of the Sherman act around 2000. Notably, enforcement of section 2 of the Sherman Act fell to nearly zero around 2000, which Grullon et al. (2016) argue was associated with increases in concentration. Figure 6, however, seems to suggest that, while the changes in anti-trust enforcement were dramatic, they are not contemporaneous with the trends in convergence interval.

----- Insert Figure 6 here -----

5.3.2 Trade

A large literature across strategy (e.g. Flammer, 2015; Gartenberg and Wulf, 2016) and economics (e.g. Autor, Dorn, and Hanson, 2013; Chen and Steinwender, 2016; Cuñat and Guadalupe, 2005; Guadalupe and Wulf, 2010) has looked at the competitive and strategic implications of trade shocks. For our analysis, this is particularly relevant because of the dramatic changes in the trade landscape around 2000 due to the accession of China to the World Trade Organization. To analyze this possibility, we use the data from Autor *et al.*, (2013) to create a measure of trade exposure to China by industry-year. Specifically we divide imports from China by total imports to obtain the share of total imports from China. For the subset of industries whose tariffs were relaxed following China's accession to the WTO, these measures increase in 2002. We then replicate our analysis from section 5.2, but replacing software with Chinese import penetration. Interestingly, Table 5 suggests that component of concentration driven by Chinese import penetration's impact on convergence interval is indistinguishable from zero at even very permissive levels. The residual, on the other hand, has a significant effect after 2000 for one of our two persistence measures.

----- Insert Table 5 here -----

While we do not find a strong statistical effect, we caution that this analysis is not definitive: our measures of trade are quite blunt and only apply to manufacturing industries. Also, we are explicitly focused on identifying factors that affect industry concentration that, in turn, is associated with persistence. Other factors may operate via other channels aside from industry concentration. A deeper investigation that uses richer measures, covers more firms, and

explores channels other than industry concentration may well find an association between trade activity and performance persistence during this period.

5.3.3 Market for managerial talent

One might imagine that if the market for managerial talent were to become more assortative, better managers being 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 (2010) we associate measures of variance in total compensation of non-CEO managers with our convergence interval. The correlation coefficient between the mean absolute deviation of non-CEO salaries and the convergence interval is 0.4722. Our limited access to the data precludes further investigation, but the initial pattern seems to suggest this may be a promising avenue for future research.

--- Insert Figure 7 ---

In summary, there are a number of different theoretically valid explanations for the increase in concentration, and associated increase in persistence of performance that we observe. We begin with two theoretical lenses that provide guidance on possible drivers of persistent performance. One lens is the resource-based view, which predicts persistence driven by firm resources. We proxy for resources using hedonic Tobin's Q, following Villalonga (2004). The second lens is the positioning school (e.g., Porter, 1980; 1985), which predicts persistence driven by market power. We proxy for this factor using industry concentration. We find an association between concentration and performance persistence. Appealing to growing research that has found that technology – and, specifically, software—advances around 2000 has led to increases

in industry concentration, we then provide some very preliminary analyses suggesting that software penetration within industries is a promising avenue for future research.

7. Discussion and limitations

One important caveat to this approach is our Compustat sample of public firms. As noted by Ali, Klasa, and Yeung (2009), the dramatic fall of publicly traded firms and transition of many large firms from public to private ownership since 2000 may have created biases in calculating concentration data from public firm data alone.

The essence of this concern, as highlighted by Ali, Klasa and Yeung (2009) is that there has been significant substitution from public to private ownership beginning around 2000, a fact also noted by Gao, Ritter, and Zhu (2013) and Kahle and Stulz (2017). Given that this substitution results in fewer public firms on which to calculate concentration ratios, the ratios themselves may be biased upwards. In particular, these ratios may be biased upwards particularly in industries with higher rates of firms transitioning to private ownership. Ali, Klasa and Yeung (2009) argue that Compustat-based concentration is correlated with declining industries in which firms have higher rates of delisting and potentially being sold to private owners, and hence is not a reliable measure of actual industry concentration.

To address this possibility, we conduct the following additional analysis. We obtain data on the total number of firms in a focal industry from the Statistics of US Businesses (SUSB), and then compute the ratio of public firms to total firms. If it is the case that our measures of concentration capture declining industries instead of true increases in concentration, we would expect declines in the ratio of public firms to be associated with our concentration measures. We compute differences between periods within 3-digit SIC codes and then correlate those with our concentration measures. We find a limited correlation of .022 with our HHI measure and .031

with 4-firm concentration ratio. While this is not definitive proof, we argue that it is suggestive that over this time period, and using our set of industries, the concentration variable is not a proxy for industry decline.

8. Conclusion

In this study, we provide thirty and fifty-year long calendar time trends of performance persistence. By doing so, we update a relatively dormant research effort to provide strategy scholars with facts on performance persistence to inform theoretical and empirical research. In addition to updating statistics and measurement techniques on persistence, our study differs from prior studies in two main ways: first, we introduce an ordinal measure on rank persistence that complements standard cardinal measures of profit convergence common in earlier work. Second, we highlight calendar time trends of performance persistence, thereby investigating the stability of persistence levels within the population of firms over time.

We identify five main results:

1. *Performance persistence declined until the end of the twentieth century*, indicating that it became increasingly difficult to sustain performance during this period. This result accords with speculation that Schumpeterian competition increased during the latter half of the century.
2. *Around 2000, persistence began to increase, and continued for at least ten years (cardinal persistence) and beyond (ordinal persistence)*. During this period, persistence duration became longer and churn among peer firms declined. This finding suggests that important strategic and competitive changes occurred between the pre- and post-2000 periods.

3. *These trends are reflected both in high and low performing firms, suggesting that similar factors are influencing firms across the performance distribution.* While low performers appear to have lower persistence than high performers, this difference is relatively stable throughout time: both high and low performers experienced a similar inflection around 2000.
4. *Software-driven increases in concentration most strongly predict increases in persistence.* This association suggests that structural changes within industries, possibly resulting in greater scale economies and market power, may have occurred around this inflection point and also have affected persistence rates of firms.
5. *The association between software-driven concentration and persistence only begins after 2000,* suggesting an underlying shift in strategy and competition occurring at the same time as persistence itself increased. One potential interpretation of this result, as has been suggested by Brynjolfsson and co-authors and Bessen (2017), is that major software innovations within industries transformed the scale and scope economies of firms to favor larger firms with greater market shares after 2000.

These results all together suggest that the simplest interpretation of Schumpeterian competition—that competition consistently decreases persistence—has not been dominant since the beginning of the 21st century, and that technological changes themselves may account, at least in part, for this shift. A definitive explanation of these changes, however, remains open for further study.

These findings suggest several avenues for future research. First, our findings attributing the reversal in persistence to software-driven industry concentration increases are only

suggestive and merit further exploration. They do, however, accord with a study by Tambe, Hitt and Brynjolfsson (2011) that finds a dramatic increase after 2000 in the differential in the value of intangible IT investments among firms. These studies together suggest that a deep competitive shift occurred around 2000 that has implications for firm strategy.

Second, while statistically and economically important, our software-concentration measures do not explain a large portion of our variation in persistence time trends, nor were our time trends invalidated after accounting for our concentration measures. This suggests that we have yet to fully explain the shift in persistence that occurred around 2000, leaving open important factors that influence persistence over this period. As one example, global trade dramatically expanded during this period. While our preliminary analysis did not find a strong association between trade exposure and persistence, we do not consider these null findings to be definitive, as our measures were both blunt and only applied to a small portion of our data. Financial development during this period, including the increased power of institutional shareholders and common ownership between institutions, may also be a factor in increasing persistence, as the low interest-rate policy of the Federal Reserve Bank after 2000. The selection of firms from public to private ownership may also have had an effect on the survivors that we may not have fully accounted for by using our software-driven concentration measures.

Lastly and most generally, this study highlights the need for research that addresses the reality that insights drawn from earlier periods may not apply to more current periods and to investigate mechanisms that underlie the changes between periods. In that sense, calendar-time studies, which are relatively uncommon in strategy research, serve a valuable purpose to highlight the stability of results over time.

Overall, we believe that this research calls for renewed attention to large sample persistence trends once popular in empirical strategy research. Our findings raise more questions than we answer, but provide many avenues for further research into recent persistence that we hope are pursued further. The question of persistence is central to strategic management and the magnitude of unanswered questions suggests that this is an important area for further study.

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Figure 1: Arellano-Bover/Blundell-Bond dynamic panel estimates of convergence interval over time

Notes: Figure plots the 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, 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.

Figure 2: Convergence intervals for samples of high and low performing firms

Notes: This figure reproduces the ABBB estimates shown in Figure 1 across three subsamples: high performers, low performers and neither. See text for how each subsample is determined.

Figure 3: Rank persistence, 1970-2015

Notes: This figure plots the rank-rank elasticities of the percentile rank of a firm in year t , based on their rank in year $t-1$. The rankings are based on ROA across the whole population of firms. A higher number represents more stability in rankings and less churn between firms.

Figure 4: Persistence and related factors over time

Panel A: Industry concentration

Panel B: Hedonic Q

Notes: Panel A overlays convergence interval with industry concentration over time. Industry concentration is calculated as the positive sales Herfindahl-Hirschman Index of industries by 3-digit SIC code. Panel B overlays the same convergence interval with the average level of hedonic Tobin's Q by industry over time. See text for calculation of hedonic Tobin's Q.

Figure 5: Changes in the percentage of firms mentioning “software” in 10-K filings over time

Panel A: Trends over time

Panel B: By industry

Notes: Panel A shows the trends over time in the software penetration of industries, as measured by the percent of firms mentioning the word “software” in their 10-K filings to the SEC on an annual basis. Panel B shows this breakdown by industry sector (at the 1-digit SIC level) at the beginning (1985) and end (2015) of our sample.

Figure 6: Convergence interval and Anti-trust enforcement

Notes: This figure shows the convergence interval shown in Figure 1 overlaid with number of Sherman Act anti-trust cases annually.

Figure 7: Mean absolute deviation of manager salaries and convergence interval

Notes: This figure shows the convergence interval shown in Figure 1 overlaid with the mean absolute deviation of non-CEO manager salaries.

Table 1: Summary statistics

Variables	Mean	Std Dev	1	2	3	4	5
1 Convergence interval	4.30	2.45	1.00				
2 Rank persistence	0.601	0.260	0.13	1.00			
3 Concentration	0.215	0.144	0.04	0.02	1.00		
4 Software	0.368	0.276	0.04	0.11	0.12	1.00	
5 Firms in industry	44	74	-0.09	-0.01	-0.30	-0.02	1.00

Notes: Please refer to text for variable definitions.

Table 2: Change in persistence around 2000

Persistence measure:	Convergence interval		Rank persistence	
	(1)	(2)	(3)	(4)
Year * Post 2000	0.0483 (0.1015)	0.0675 (0.0211)	0.0066 (0.0008)	0.0062 (0.0014)
Year	-0.0490 (0.0090)	-0.0601 (0.0013)	-0.0018 (0.1330)	-0.0016 (0.1621)
Post 2000	-96.5640 (0.1020)	-134.8770 (0.0212)	-13.1787 (0.0008)	-12.3195 (0.0014)
Constant	101.9759 (0.0064)	124.2398 (0.0009)	4.1396 (0.0813)	3.8485 (0.1002)
Observations	4573	4573	4573	4573
Industry FE	N	Y	N	Y
Adjusted R-squared	0.007	0.017	0.012	0.010

Notes: Please refer to text for variable definitions. Industry fixed effects are defined at the corporate 3-digit level SIC level.

Table 3: Industry concentration and performance persistence

Dependent variable:	Convergence interval		Rank persistence	
	(1)	(2)	(3)	(4)
Concentration * Post 2000	1.9965 (0.0790)	1.8748 (0.0743)	0.0576 (0.6178)	0.1568 (0.1195)
Year * Post 2000	0.0435 (0.1429)	0.0760 (0.0134)	0.0065 (0.0009)	0.0061 (0.0033)
Concentration	-0.9094 (0.3524)	-1.9118 (0.0346)	-0.0228 (0.7629)	-0.1067 (0.2314)
Year	-0.0479 (0.0104)	-0.0658 (0.0006)	-0.0018 (0.1400)	-0.0016 (0.1829)
Post 2000	-87.2966 (0.1417)	-152.1480 (0.0132)	-13.0207 (0.0009)	-12.1139 (0.0032)
Constant	100.0707 (0.0073)	135.7108 (0.0004)	4.1157 (0.0860)	3.8737 (0.1145)
Observations	4573	4573	4573	4573
Industry FE	N	Y	N	Y
Adjusted R-squared	0.019	0.022	0.012	0.011

Notes: See text and figure footnotes for definition of *Concentration*. All specifications also control for number of firms in each industry.

Table 4: Software penetration, industry concentration, and performance persistence

Dependent variable:	Concentration		Convergence interval		Rank persistence	
	(1)	(2)	(3)	(4)	(5)	(6)
Software penetration	0.0387 (0.0172)	0.0300 (0.0235)				
Concentration (software) * Post 2000			54.0038 (0.0136)	31.3243 (0.1184)	3.5452 (0.0150)	3.9269 (0.0582)
Concentration (other) * Post 2000			1.6870 (0.1478)	1.6331 (0.1327)	0.0376 (0.7454)	0.1370 (0.1698)
Year * Post 2000			0.0421 (0.2639)	0.0824 (0.0154)	0.0053 (0.0372)	0.0043 (0.1003)
Concentration (software)			-0.7138 (0.9606)	-0.6012 (0.9624)	-0.5209 (0.5890)	-1.1019 (0.3365)
Concentration (other)			-0.8921 (0.3859)	-1.9473 (0.0438)	-0.0224 (0.7674)	-0.0996 (0.2674)
Year			-0.0526 (0.0838)	-0.0735 (0.0034)	-0.0010 (0.5959)	-0.0003 (0.8902)
Post 2000			-95.2678 (0.1951)	-171.0710 (0.0112)	-11.3378 (0.0228)	-9.4055 (0.0639)
Constant	0.2135 (0.0000)	0.2157 (0.0000)	109.5270 (0.0612)	150.9023 (0.0019)	2.6962 (0.4600)	1.3779 (0.7269)
Observations	4573	4573	4573	4573	4573	4573
Industry FE	N	Y	N	Y	N	Y
R-squared	0.111	0.032	0.027	0.025	0.014	0.012

Notes: See text for definition of *Software*, *Concentration (software)* and *Concentration (other)*. All specifications also control for number of firms in each industry.

Table 5: Chinese import penetration, HHI, and convergence interval

Dependent variable:	Concentration		Convergence interval		Rank persistence	
	(1)	(2)	(3)	(4)	(5)	(6)
Chinese import penetration	0.0034 (0.4677)	0.0089 (0.0789)				
Concentration (import) * Post 2000			28.5731 (0.8969)	22.2085 (0.1305)	-4.3690 (0.5662)	1.0275 (0.1182)
Concentration (other) * Post 2000			2.0440 (0.6094)	2.4518 (0.5026)	-0.0579 (0.6471)	-0.1370 (0.2870)
Year * Post 2000			0.0456 (0.7245)	0.1633 (0.2506)	0.0191 (0.0053)	0.0162 (0.0090)
Concentration (import)			239.6129 (0.0285)	-15.2955 (0.6674)	4.7297 (0.1165)	-0.4990 (0.6804)
Concentration (other)			4.0099 (0.0809)	-5.9749 (0.2573)	0.1353 (0.2239)	-0.0759 (0.6332)
Year			0.1093 (0.1475)	-0.0083 (0.9266)	0.0045 (0.2932)	0.0026 (0.6074)
				- 332.092		
Post 2000			-98.3860 (0.7269)	5 (0.2411)	-37.3254 (0.0087)	-32.5991 (0.0085)
Constant	0.2660 (0.0000)	0.3006 (0.0000)	-262.0150 (0.0942)	24.0845 (0.8916)	-9.3471 (0.2719)	-4.5268 (0.6518)
Observations	988	988	988	988	988	988
Industry FE	N	Y	N	Y	N	Y
R-squared	0.168	0.036	0.051	0.011	0.029	0.018

Notes: See text for definition of *Chinese import penetration*, *Concentration (import)* and *Concentration (other)*. All specifications also control for number of firms in each industry.