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L.G. Thomas and Richard D'Aveni

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ARTICLES

The changing nature of competition in the US manufacturing sector, 1950–2002

L. G. Thomas Emory University, USA

Richard D'Aveni Dartmouth College, USA

Abstract

Recent work in several disciplines has established that the volatility of performance for US firms has greatly increased over the last 50 years. Yet, it is the differences in durable performance of firms that have been the primary focus of inquiry in competition and business strategy. This study documents the sharply increased within-industry heterogeneity of returns in the US manufacturing sector from 1950 to 2002, and links these changes to the documented increases in volatility. The evidence supports a broad, monotonic shift towards a new, more dynamic form of competition, which some have called hypercompetition.

Key words • financially unstable firms • heterogeneous performance • hypercompetition • temporary performance

Introduction

An important stream of literature has documented the increased volatility of performance for American firms. In macroeconomics, studies have demonstrated the steadily increased magnitude of firm-level variance for growth in employment, sales, earnings, capital expenditures and total factor productivity since 1950 (Comin and Mulani, 2006; Comin and Philippon, 2006). In finance, research has documented an increase in abnormal returns for US equity prices since the 1930s (Campbell et al., 2001; Irvine and Pontiff, 2009).

While this increase in firm volatility is important, studies of business strategy are more interested in the heterogeneity of durable firm performance than its perhaps transient volatility. Oddly, the strategic management literature has been largely silent on any trends in performance heterogeneity. The central studies of the heterogeneity of performance across industries ('industry effects') and within industries ('firm effects') are static, documenting presumably stable cross-sectional differences rather than trends over time (Brush et al., 1999; McGahan and Porter, 1997, 2002; Roquebert et al., 1996; Rumelt, 1991; Schmalensee, 1985).

This article integrates these currently separate literatures on volatility and heterogeneity of firm performance. We document basic trends over time for performance heterogeneity (both industry effects and firm effects) and link these increases to the associated trend of volatility in a common measurement framework. But more importantly, we also document steady changes over time in the relationships between heterogeneity across industries, heterogeneity within industries and volatility. The basic trends of increasing heterogeneity and volatility, as well as the increasing correlations between these constructs indicate that the nature of competition within industries of the US manufacturing sector has profoundly changed over the last five decades.

Theory and hypotheses

Numerous studies in strategic management have posited that a fundamental shift has occurred for the nature of competition in the modern American economy. Traditional competition and stable industry structures have been undermined by disruptive technology, aggressive competitive behavior, globalization, deregulation and other factors (Bettis and Hitt, 1995; Brown and Eisenhardt, 1998; Christensen, 1997; D'Aveni, 1994; Hamel, 2000; Slywotzky, 1996). These studies all predict a shift toward another type of competition, involving Schumpeterian 'gales of creative destruction' characterized by 'Austrian School' competitive behavior (Jacobson, 1992; Kirzner, 1997; Roberts and Eisenhardt, 2003; Schumpeter, 1950), including the rapid deterioration and replacement of competitive advantages.

Recently, these more theoretical works have been joined by empirical studies in macroeconomics and finance. Comin and Philippon (2006), Comin and Mulani (2006), Campbell et al. (2001) and Irvine and Pontiff (2009) all provide evidence of large increases over time in the volatility of short-term firm performance around long-run values. These studies also find stability over time in the economy-average performance for US firms. The documented increases in volatility therefore represent ever-greater dispersion around stable means. These increases are consistent with a shift from traditional to a new, more dynamic competition.

Not every recent study supports the notion of a pervasive change in competition. McNamara et al. (2003) documented several shifts in some aspects of competition, but found that these changes were cyclical around recessions rather than constituting any secular trend. Davis et al. (2007) found significant evidence of increased volatility in employment for large, publicly traded firms, but also found that small, private firms are largely immune to these shocks and have even enjoyed decreased volatility (which they link to improved inventory management). The debate over the extent and importance of changes in competition in the American economy recalls a much older controversy over the extent and importance of monopoly, collusion and exclusion. Hundreds of empirical studies contributed to an extensive literature on this topic. Arguably the most useful contributions to that debate were provided by a series of non-parametric studies, originating with Schmalensee (1985), followed by Rumelt (1991), and later by Roquebert et al. (1996), McGahan and Porter (1997, 2002) and Brush et al. (1999). These studies decomposed the total variance for firm performance into key components, notably at the industry and firm level.

The impact of these studies rests on the generation of simple descriptive statistics for the relative magnitudes of various types of competition. None of these studies document actual collusion or exclusion at the industry level, nor do they measure resources creating efficiency differences at the firm level. In a comparable manner, we do not document here the destruction and creation of competitive advantages over time that would characterize the new competition. Rather, our study adapts the techniques from this prominent literature to examine the plausible rise and extent of more dynamic competition in the US manufacturing sector.

Traditional competition

Traditional, static competition is characterized by equilibrium: stable sustained performance for individual firms and a fixed competitive landscape across firms. The established literature distinguishes two important mechanisms that create superior, durable performance in traditional competition. We label the first type *oligopolistic*, though Schmalensee (1985, 1987) initially called it 'classical', and subsequently labeled it the 'differential collusion hypothesis'. In the economics literature, the canonical reference is Bain (1959). In oligopolistic competition, firms successfully collude to raise prices above competitive levels and exclude potential entrants that might compete away high prices.

The conduct of firms to collude and exclude benefits all existing firms in an industry. The underlying industry structure that enables this conduct is also experienced in common by all existing firms. Thus successful collusion and exclusion represent 'shared assets' for established firms (Porter, 1979, 1980). If oligopoly is the *predominant* mechanism for the superior performance of firms, then across-industry heterogeneity (so-called 'industry effects') should comprise the largest share of the overall variance in firm returns.

The second mechanism for creating competitive advantage in traditional competition is the static version of the *resource-based view* (Barney, 1991; Peteraf, 1993; Prahalad and Hamel, 1990). Resource-based competition represents an extensive advance on the early work of Demsetz (1973) and Peltzman (1977), work that Schmalensee (1985, 1987) initially labeled 'revisionist' and later called the 'differential efficiency hypothesis'. In resource-based competition, profits arise through efficiency differences across firms, due either to lower costs or to superior products. Profits under this type of competition represent rents to resources, or the inimitable intangible assets that create the firm's lower costs or price premiums for superior products. When firms in an industry hold significantly different levels of resources, the efficiency rents across firms can be quite large.

The performance advantage of static resources is specific to individual firms. If static resources provide the *predominant* mechanism for the superior performance of firms, then across-firm within-industry heterogeneity (so-called 'firm effects') should comprise the largest share of the overall variance in firm returns.

In traditional competition then, volatility, across-industry heterogeneity (industry effects) and within-industry heterogeneity (firm effects) are independent phenomena caused by logically separate and unrelated mechanisms. Industry effects are based on shared industry structure and coordinated actions among firms associated with oligopoly. Firm effects are based on internal efficiency differences of individual firms. By the very nature and definition of static competition, volatility is transient noise with no lasting impact on industry effects or firm effects. This independence provides a null hypothesis against any new, more dynamic competition.

The new competition

Several scholars have argued that a new form of competition has widely supplanted the traditional type. The competitive landscape is less stable and firm advantages are less durable. Shocks to underlying conditions of demand, supply, technology, credit, information and the institutions underlying business activity occur more frequently and more extensively (Bettis and Hitt, 1995; Brown and Eisenhardt, 1998; D'Aveni, 1994, 1995; Hamel, 2000; Slywotzky, 1996). These scholars have also argued that endogenous shocks created by firm conduct through new business models, more rapid and more fundamental innovation and more aggressive behavior in pursuit of growth occur more frequently.

Shocks to the underlying structure of industries and firms feed into variance for individual firm performance. These performance effects can be measured with different metrics: sales growth rates, employment growth rates, profit rates and stock market returns. For this study, we focus on accounting profit rates, defining volatity as the difference between the annual profit rate and the underlying, long-run profit rate of a firm. Increases over time for this short-run profit volatility are the first effects of the new competition, as other studies have posited.

HYPOTHESIS 1 Volatility for profits around the long-run performance for firms has increased over time.

Multiple mechanisms have been suggested in the literature that cause this increased volatility, and it is an open issue as to the relative importance of these mechanisms. Studies have separately demonstrated an empirical association between the short-run volatility for firms in an industry and the deregulation of that industry, the research intensity of firms in that industry, the relative access to debt and equity from capital markets and increased foreign competition (Comin and Philippon, 2006; Irvine and Pontiff, 2009). Formal microeconomic models have predicted ties between increased volatility and greater research intensity (Comin and Mulani, 2005), greater use of information technology (Brynjolfsson et al., 2007) and declining brand loyalty of consumers (Irvine and Pontiff, 2009). Both these empirical and theoretical investigations of the causes of increased volatility indicate that its rise is not uniform across industries, but clustered by industry. Some industries experience large increases in volatility, while others retain their traditional stability.

Most studies of increased volatility focus on its magnitude. Yet what differs between traditional and new competition is really the nature of this volatility. Volatility has no effect on industry structure in traditional competition. In the new competition, volatility is created and continued precisely by shocks to the underlying competitive landscape. Such shocks to industry structure will not only increase short-run volatility in an industry, but also will increase the heterogeneity of long-run performance in that industry. The first impact of structural shocks on the within-industry heterogeneity for long-run performance arises from the differential impact of these shocks on incumbent firms. The incentives for incumbents to migrate from established to new advantages are asymmetric and negatively correlated with existing advantage (as demonstrated in the formal theoretical models cited immediately above). Firms that are historically less successful are most incentivized to take advantage of possible new competitive positions, while historically successful firms are less so. Additional increases in heterogeneity derive from new firms entering the industry. Structural shocks produce great uncertainty regarding which competitive positions will be successful in the new environment. Research has shown that this uncertainty makes the initial positions of entrants into an extremely diverse set of experiments or bets on the evolving competitive landscape (Henderson and Clark, 1990; Tushman and Anderson, 1986). An additional effect on heterogeneity derives from the inherent differences between entrants. Simple details such as the timing of entry (Mitchell, 1989; Walker et al., 2002), network position (Baum et al., 2000) and pre-founding experience (Klepper, 2002; Klepper and Simmons, 2000) strongly affect the individual performances of new firms and further accentuate within-industry heterogeneity. This diversity of responses to structural shocks creates greater performance heterogeneity alongside increases in volatility.

HYPOTHESIS 2 Within-industry heterogeneity for long-run performance for firms has increased over time.

The total variance for corporate performance for all firms decomposes into volatility around the long-run performance of firms (with the latter labeled 'firm effects' by Schmalensee [1985], Rumelt [1991] and others), within-industry heterogeneity of this long-run firm performance around the industry mean (with the latter labeled an 'industry effect') and across-industry heterogeneity for industry means. For a formal derivation of this decomposition, see Appendix A. If volatility and within-industry heterogeneity increase substantially, then the share of total variance accounted for by industry effects will probably fall over time.

HYPOTHESIS 3 Across-industry heterogeneity for long-run performance for firms has decreased as a share of total variance in firm performance over time.

Our hypotheses so far concern upward trends in the magnitudes of key variables. A distinctive contribution of our study is to also examine changes over time in the relationships between these variables. The shift from traditional to the new competition should be marked not just by increases in volatility and within-industry heterogeneity, but also by increasing correlation between these two measures. This increased correlation provides separate, important confirmation of the rise of the new competition alongside the predicted increases in magnitudes. A common process of structural shocks jointly creates volatility and within-industry heterogeneity in the new competition. As discussed earlier, recent research has established that the new competition spreads asymmetrically across industries, extensively in some and minimally in others (Comin and Philippon, 2006; Irvine and Pontiff, 2009). Industries extensively impacted by the new competition should have high levels of both volatility and within-industry heterogeneity, while industries still experiencing traditional competition should have lower levels of both together.

HYPOTHESIS 4 The correlation across industries of an industry's volatility (in short-run profit) with the industry's heterogeneity of long-run profits will increase over time.

This hypothesis suggests a significant change in our conception of within-industry heterogeneity. The strategy literature emphasizes valuable, durable performances of firms as the source of heterogeneity (Helfat et al., 2007;

Hoopes et al., 2003). Our hypothesis raises the possibility that as an empirical matter, many of the contemporary differences between firm performances in an industry may instead be due to short-run instability and structural turbulence.

The shift from traditional to the new competition also should create correlations for volatility and within-industry heterogeneity with the industry effects that are the basis for across-industry heterogeneity. These new correlations may seem surprising at first pass. The large, sustained increases in volatility predicted in this study would expectedly reduce the static advantages of industries in traditional competition, thereby shrinking the heterogeneity of industry effects. If across-industry heterogeneity becomes smaller in magnitude, it is difficult as a practical matter for correlations between industry effects and other variables to increase.

Large, sustained levels of volatility limit and erode the practice of oligopoly. Successful oligopolies are created and sustained by deliberate strategic action, facilitated by favorable industry structure (Porter, 1980; Scherer, 1980; Tirole, 1988). Collusion and exclusion require information exchange between firms and coordination of their strategic activity. Volatility in an industry obstructs this coordination and undermines explicit and implicit bargains between rivals. Indeed, some of the strategic actions of firms in oligopolies seek to alter basic industry processes to dampen volatility. Scholars have long expected that a central aspect of industry structure enabling successful oligopoly is its stability and predictability over time (Ghemawat, 1997).

Large, sustained levels of volatility also limit and erode the static resources of firms. Static resources are created and sustained through the deliberate strategic action of firms. Resources are formed with significant internal coordination to adapt to the external environment. The collective resources of a successful firm thus 'fit' together in a consistent and mutually reinforcing whole (Milgrom and Roberts, 1990, 1995; Porter, 1996), both internally and externally, which makes them valuable and also difficult to imitate. The very concept of 'fit' presumes stability over time. Additionally, the valuable resources of profitable firms are accumulated over time through a steady process (Diereckx and Cool, 1989). The static resources of successful firms remain valuable and rare because of the constancy and predictability of this accumulation process. Resources are also sustained because their deployment often requires the presence of complementary resources (Dosi, 1982; Helfat, 1997; Klepper and Simmons, 2000). This complementarity has strategic significance precisely because it is fixed over time. The mechanisms that underlie firm efficiency differences (internal and external fit, the accumulation process and complementary assets) all presume an environment that is reasonably stable.

In sum, industry effects for firm performance due to traditional sources of oligopoly and static resources should decline in magnitude over time with the rise of the new competition. But any shift to the new competition should also create new differences across industries, based on the extent of turbulence and structural shock in each industry. Taken together, these offsetting trends suggest that it is not the magnitude of across-industry heterogeneity that has changed over time, but rather its nature. Over time, the principal source of industry effects will move from whatever stable structural differences once existed to the presence or absence of dynamic competition, along with its associated volatility and within-industry heterogeneity. At that point, industry effects themselves then should cease to be independent of volatility and within-industry heterogeneity, as in traditional competition, since a common process creates all.

HYPOTHESIS 5A Industry effects are increasing codetermined along with the within-industry volatility of temporary profits and the within-industry heterogeneity of long-run profits.

This hypothesis suggests a significant change in our conception of across-industry heterogeneity. The strategy literature emphasizes stable differences in structure as the source of industry effects (McGahan and Porter, 1997; Schmalensee, 1985, 1987). Our hypotheses raise the possibility that as an empirical matter, much of contemporary differences between industry average performances may be due to the susceptibility of industry structures to turbulence and shock.

Structural shocks for an industry should be negatively related to average firm performance, at least in the short run (D'Aveni, 1994). Industries with higher levels of within-industry volatility should therefore exhibit lower profit rates.

HYPOTHESIS 5B The effect of the within-industry volatility of temporary profits on the industry average for long-run profits for firms in that industry (the industry effect) is negative.

As within-industry heterogeneity becomes more correlated across industries with within-industry heterogeneity, both become proxies for the new competition and its associated structural shocks. Industries with higher levels of within-industry heterogeneity should therefore exhibit lower profit rates.

HYPOTHESIS 5C The effect of within-industry heterogeneity of long-run profits on the industry average for long-run profits of firms in that industry (the industry effect) becomes more negative over time.

Method and estimation

Our study examines patterns of financial returns in order to understand the nature of competition that generates these returns. We first separate financial performance of each firm into long-run and temporary components. The temporary component is used to measure performance volatility, and the long-run components are used to measure performance heterogeneity. We then create industry-level constructs based on these components. And we examine trends over time in and between these constructs. Comparable empirical studies of performance volatility and heterogeneity have used a variety of different data sets and empirical measures. We note in the following the central measurement issues among these studies, and place our own study in the context of previous research.

Population of firms

The population for our study is drawn from every publicly listed manufacturing firm in the US economy from 1950 to 2002. Each observation is a firm in a year. The primary source of data is the Compustat compilation of accounting data. However, Compustat is comprehensive only after 1980, and omits roughly 300 firms in the early 1970s, 500 firms in the 1960s and 300 firms in the 1950s. Compustat failed to collect historic data for many firms that ceased to exist before 1980, either through merger or bankruptcy. Were we to ignore these omitted firms in our analysis, we might improperly minimize the volatility and heterogeneity of US manufacturing firms in the 1950s, 1960s and 1970s, and thereby exaggerate any rise over time of these traits. We utilized the Wharton matching of the CRSP data set of publicly traded firms and the Compustat database to identify firms omitted from Compustat, and the years of their omission. Accounting data for these missing firms (sales, assets, net income and interest expense) were then collected from Moody's (various years). Our statistical analyses rely on this augmented data set.

The earliest studies in this literature examined the US manufacturing sector (Mueller, 1986; Rumelt, 1991; Schmalensee, 1985; Waring, 1996). More recent studies in strategy have examined firms in the entire US economy, including the service sector but excluding financial service firms (McGahan and Porter, 1997, 1999, 2003; McNamara et al., 2003; Ruefli and Wiggins, 2003; Wiggins and Ruefli, 2002). Studies in macroeconomics (Comin and Mulani, 2006; Comin and Philippon, 2006) and in finance (Campbell et al., 2001; Irvine and Pontiff, 2009) rely on an even broader sample of all publicly traded firms.

This article returns to the focus on the manufacturing sector. The laborious collection of data from the Moody's Manuals to supplement the Compustat database makes it unfeasible to examine the entire US economy. Since we had to choose one sector for our empirical work, we selected manufacturing for continuity with the literature, both with the original empirical analyses cited immediately above and with the literature on the changing nature of competition that predominantly focuses on manufacturing for its theory development.

We tested the robustness of our results by including and excluding the hand-collected data on firms missing from Compustat. These empirical results were very similar. The much smaller volatility and heterogeneity for firm performance before 1980 (a central finding of this study) make the actual impact of these missing firms to be minor.

Firms deleted from the study

Analysis of the competitive landscape for an industry draws from experiences of direct competitors. Some firms may indeed occupy a different 'strategic group' and not compete directly with most firms. These fundamentally different firms are appropriately segregated. The studies of Schmalensee (1985) and Rumelt (1991) exclude business units with less than 1 percent sales share and those with only one year of data. McGahan and Porter (1997, 1999, 2003) and McNamara et al. (2003) omitted from their analyses business units with sales or assets of less than US$10 million and those with fewer than six years of data. They also deleted firms with the absolute value for return on assets in excess of 100 percent, to exclude potential outliers. Studies in macroeconomics and finance tend to include more firms. Comin and Mulani include firms that have positive sales in any year of a 10-year window, though they exclude firms that do not record sales in all years of the window. The latter tactic effectively excludes all newly formed firms. Campbell et al. (2001) and Irvine and Pontiff (2009) use all firms, though the latter study additionally conducts careful tests excluding firms that might be outliers.

We use the McGahan–Porter screen of firms with sales or assets of less than US$10 million in inflation-adjusted 1995 dollars and those with fewer than six years of data. We deflate sales and assets using the US GDP deflator from the International Monetary Fund. We compute the age of each firm by treating the birth year of the firm as the first year that its equity was publicly traded. The birth years are taken from the CRSP data set, matched to Compustat by Wharton's WRDS. Our exclusion of small and new firms represents a conservative approach that will understate the phenomena we study. When we rerun our analyses including small and new firms, the estimated volatility for transient shocks for the manufacturing sector increases by 140 percent and the estimated within-industry heterogeneity for the sector increases by 230 percent. We obtain comparably stronger results for other hypotheses as well.

A few studies have taken a more extreme approach to this issue. These studies reject the standard argument that the competitive landscape, thus the nature of competition, is best assessed by the experiences of every direct competitor. Instead, these new studies exclude firms based on the dependent variable of performance, for theoretical rather than statistical reasons. Hawawini et al. (2003) delete the two best performing and the two worst performing firms in every industry. Their rationale is that the competitive landscape is revealed by the experiences of the average firms in an industry, rather than the industry as a whole. Unfortunately, their extreme tactic deletes 'outliers', such as 'Wal-Mart, Microsoft, and Coke'. Taking an opposite position, Wiggins and Ruefli (2002, 2005) argue that only the heights of the competitive landscape, the very 'outliers' that Hawawini et al. (2003) exclude, matter for analysis. For Wiggins and Ruefli, the competitive landscape is revealed by the experiences of the superior firms in an industry or the frontier of firms. Our response to these studies is that they represent a complement to the bulk of the literature rather than a substitute for that literature.

Estimation of the long-run performance for firms

Our study examines changes in the competitive landscape, based on the durable profit performances of firms in an industry. We must first separate out durable profits from temporary deviation. We label the durable profit rate as LRP, for long-run performance. The annual profit deviation for firm i in year t is the difference between the reported accounting return on assets (ROA) for that firm and year and the LRP for the firm.

(1) $$\text{Annual Temporary Profit}_{it} = \text{ROA}_{it} - \text{LRP}_i$$

ROA is measured as the sum of net income plus interest divided by total assets, the standard definition in the literature. These data are taken from Compustat, supplemented by Moody's.

Like Comin (Comin and Mulani, 2005; Comin and Philippon, 2006), we trace the evolution of LRP for a firm over time by using a series of overlapping 10-year windows. Comin computes the arithmetic mean of ROA in each 10-year window and uses that mean for LRP. We adopt the predominant approach in the strategic management literature of estimating a difference equation for annual ROA for a firm during each 10-year window. The details for this estimation of LRP are given in Appendix B. Cubbin and Geroski (1987), Geroski and Jacquemin (1988), McGahan and Porter (1999), Mueller (1986, 1990) and Waring (1996) previously used this approach. LRP for each firm is computed as the solution to the estimated difference equation, with that solution being the firm fixed effect divided by 1 minus the persistence rate from the difference equation. In practice, our approach and that of Comin have very similar results, as confirmed by Comin and Philippon (2006). The reason for this similarity is that the estimated persistence rate is specified as the same for all firms in our estimation, is never large (at most .35) and declines toward zero in recent years. The estimated LRP is thus mostly the estimated firm-specific fixed effect over the 10-year window, which is effectively the 10-year average.

Construction of variables

We compute the short-run volatility for a firm i as the variance of annual temporary profits from Equation 1 during the 10-year window for that firm.

(2) $$\text{Volatility}_i = \sum_T (\text{ROA}_{it} - \text{LRP}_i)^2$$

We compute volatility for an industry by aggregating for all firms in that industry the volatility of each firm during a given 10-year window. Volatility for the sector as a whole is the sum across industries of the industry volatility.

The within-industry heterogeneity for LRP is the variance around the mean LRP for all firms i in an industry s during a 10-year window, with the industry mean denoted IMLRP_s.

(3) $$\text{Within-Industry Heterogeneity}_s = \sum_I (\text{LRP}_{is} - \text{IMLRP}_s)^2$$

The across-industry heterogeneity for the sector is the variance of industry-mean-LRP for each industry s around the sector-mean-LRP, with the latter denoted as SMLRP.

(4) $$\text{Across-Industry Heterogeneity} = \sum_S (\text{IMLRP}_s - \text{SMLRP})^2$$

Our final hypotheses posit that in the new competition a common process jointly causes the above variables. Industries with high levels of volatility will also have high levels of heterogeneity. As some industries experience extensive shocks from the new competition, the principle determinant of industry performance will be the joint presence of these features. We specify an OLS regression across S industries in the sector with error term ε_s.

(5) $$\text{IMLRP}_s = \beta_0 + \beta_1 {*}\begin{array}{l}\text{Within-}\\\text{Industry}\\\text{Volatility}_s\end{array} + \beta_2 {*}\begin{array}{l}\text{Within-}\\\text{Industry}\\\text{Heterogenity}_s\end{array} + \varepsilon_s$$

We expect the independent variables in Equation 5 to become positively intercorrelated over time, but not sufficiently severely to bias the coefficient estimates. In any case, such correlation will not bias the overall goodness of fit for the regression equation. Consistent with previous studies, we delete from analysis of Equation 5 industries with three or fewer firms as such small industries provide potentially distorted measures of volatility and heterogeneity.

Statistical tests for trends

All of our hypotheses examine linear trends over time of the form:

(6) $$Y_t = \theta_0 + \theta_1{}^*t + \omega_t$$

where the null hypothesis is that θ_1 is zero. For most of these trends, time is measured across a sequence of overlapping 10-year windows, beginning in 1950–9 and ending in 1993–2002. Therefore, we test our hypotheses for θ_1 on time series data where the error term ω_t may exhibit large and potentially complex serial correlation. We follow the examples in the finance literature of Campbell et al. (2001) and Irvine and Pontiff (2009), and employ tests proposed by Vogelsang (1998) that are robust to even very severe autocorrelation. The details of these tests are given in Appendix C.

Statistical findings

Figures 1 and 2 report trends in the three components for the decomposition of variance of performance of firms in the manufacturing sector into volatility for temporary profits, within-industry heterogeneity for long-run profits and across-industry heterogeneity for long-run profits. Figure 1 reports the levels of these variances. Two of the three sources of variance, within-industry heterogeneity and volatility, increase enormously and steadily over time and these increases are statistically significant (formal statistical tests for trends are

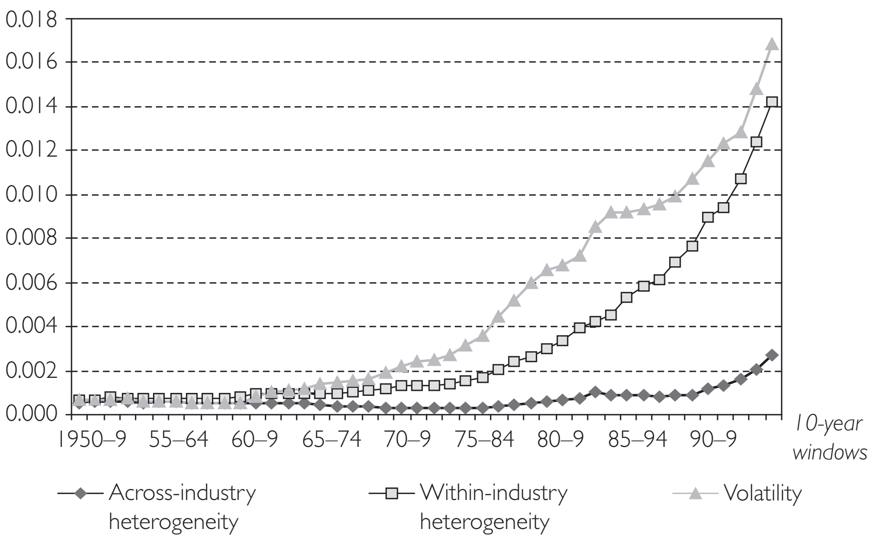


Figure 1 Decomposition of variance for firm ROA into volatility of temporary profit, within-industry heterogeneity for long-run profit and across-industry heterogeneity for long-run profit

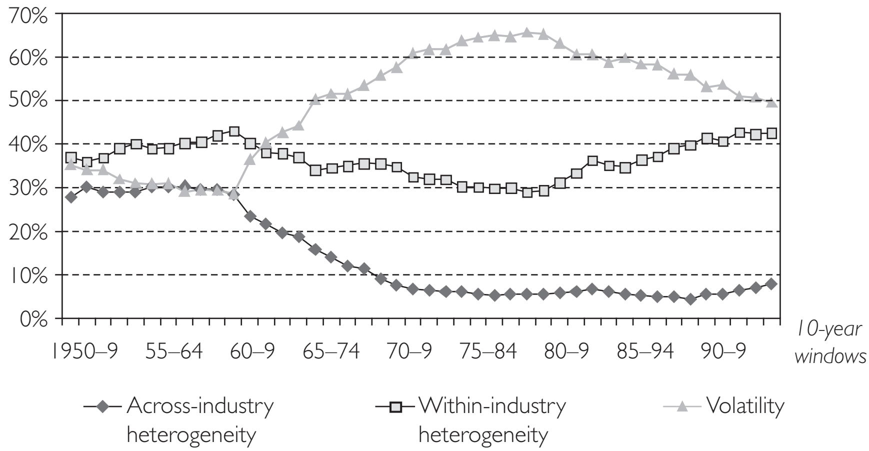


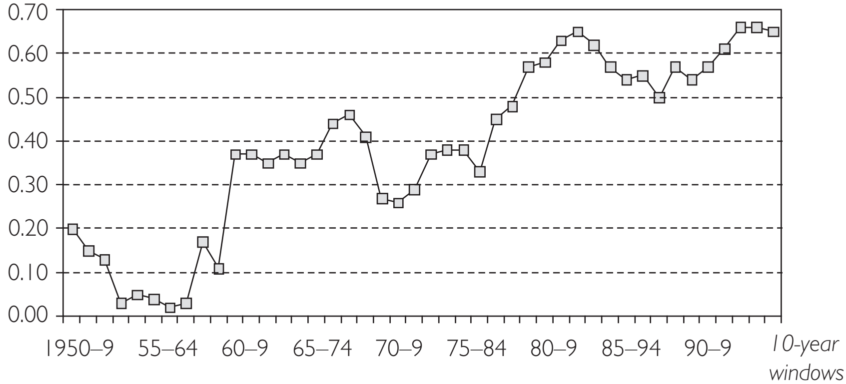
Figure 2 Decomposition of variance for firm ROA by percentages into volatility, within-industry heterogeneity for long-run profit and across-industry heterogeneity for long-run profit

given in Appendix C). These findings provide confirmation for hypotheses 1 and 2. In contrast, the across-industry variance in LRP has increased only a little and only quite recently, so that there is no statistically significant trend.

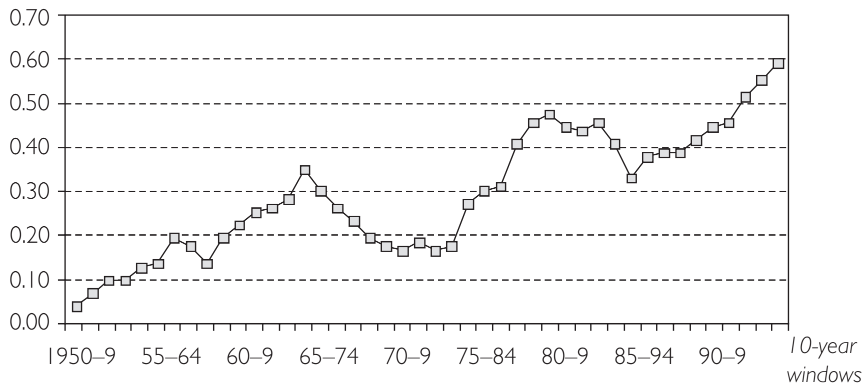
Figure 2 reports the percentage of total variance in firm performance for the sector that is accounted for by each of the three components of variance. Here, in contrast to the trends in levels, it is only the trend for the across-industry variance in LRP that is statistically significant. Industry effects decreased as a share of total variance over time, although that share has stabilized in recent years. This decline is statistically significant, providing confirmation for hypothesis 3.

Our remaining hypotheses examine the relationships between the components of variance. There are over 210 four-digit SIC industries in the US manufacturing sector. For traditional, static competition there is no expected relationship between the industry effect (mean performance across firms) and the volatility or interfirm heterogeneity in that industry. In contrast, these constructs are all jointly affected by the new, dynamic competition. As industries shift to this dynamic competition, these constructs become intercorrelated. Panel A of Figure 3 reports the simple correlation across the more than 210 manufacturing industries for volatility and within-industry heterogeneity in each 10-year window. We know from Figure 1 that both of these constructs steadily increase over time. We see in Figure 3 that the correlation between these constructs also steadily increases over time, confirming hypothesis 4. Industry volatility and within-industry heterogeneity were independent phenomena before 1960, and are now highly correlated. This trend is statistically significant.

Panel A: Correlation across industries for within-industry heterogeneity of long-run profit with within-industry volatility of temporary profit



Panel B: R^2 statistics for Equation 5: industry effects as a function of within-industry volatility of temporary profit and within-industry heterogeneity of long-run profit



Panel C: Estimated coefficients for Equation 5: industry effects as a function of within-industry heterogeneity of firm effects (long-run profits)

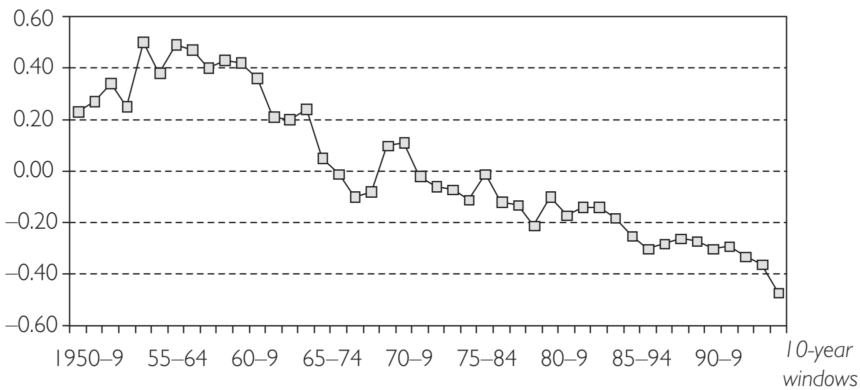


Figure 3 (Continued)

Panel D: Estimated coefficients for Equation 5: industry effects as a function of within-industry volatility of annual temporary profit

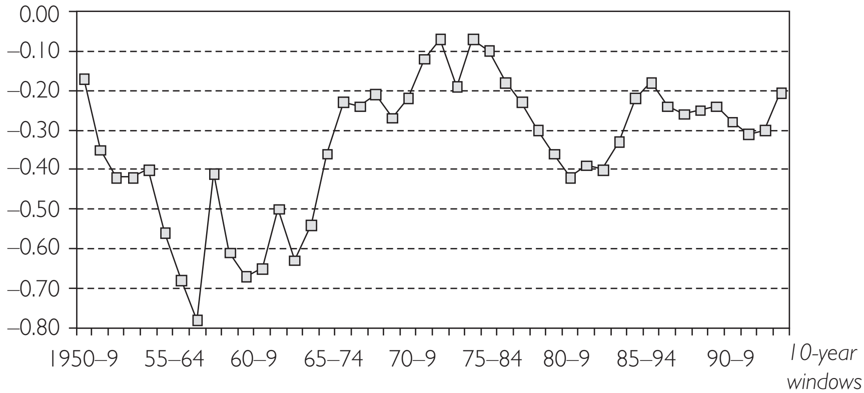


Figure 3 Structural change among components of variance for manufacturing industries

Finally, we estimate a regression of calculated industry effects for each of the more than 210 four-digit SIC manufacturing industries on within-industry volatility, within-industry heterogeneity and the extent of financial instability in that industry. This regression specification was given in the earlier section as Equation 5, and the estimation results are reported in Table 1. The R^2 statistic for that regression in each 10-year window is plotted in Panel B of Figure 3, and indicates the extent to which these once distinct phenomena are now interrelated. Note that in the 1950s, industry effects are only very weakly associated with firm effects and volatility. Yet, by the 1990s, 50 percent of industry effects are 'explained' by these supposedly separate and distinct phenomena. The trend over time for this R^2 statistic is positive and statistically significant, confirming hypothesis 5a. Panel C of Figure 3 traces the estimated coefficient from these regressions for within-industry heterogeneity as an independent variable in Equation 5. In the 1960s, interfirm heterogeneity is significantly positively associated with average industry profit. This historic result is consistent with this heterogeneity being driven by stable, valuable resources for firms with associated efficiency rents. By the 1990s, this coefficient is significantly negatively associated with average industry profits, even controlling for the direct effects of within-industry volatility. This finding for the more recent years is consistent with within-industry heterogeneity driven by strategic disequilbrium and failing firms. The trend over time is positive and statistically significant, confirming hypothesis 5c. Surprisingly, there is no trend over time for the estimated coefficient for the independent variable of within-industry volatility in Equation 5. Panel D of Figure 3 traces this estimated coefficient over the various 10-year windows. That coefficient is always negative, and particularly large in the 1960s.

Table 1 Relationships among industry attributes

	Equation 5: Regression coefficients for industry mean LRP on within-industry variables			Correlations across industries
A: 10-year window	B: Within-industry heterogeneity in LRP	C: Within-industry volatility	D: R^2 statistic	E: Heterogeneity in LRP with volatility
1950–9	.23	–.17	.02	.16*
1951–60	.27	–.35**	.05	.15
1952–61	.34*	–.42**	.08	.13
1953–62	.25*	–.42***	.08	.03
1954–63	.50**	–.40**	.11	.05
1955–64	.38**	–.56**	.12	.04
1956–65	.49**	–.68**	.18	.02
1957–66	.47***	–.78**	.16	.03
1958–67	.40***	–.41***	.12	.17
1959–68	.43***	–.61***	.18	.11
1960–9	.42***	–.67**	.21	.37***
1961–70	.36**	–.65**	.24	.37***
1962–71	.21*	–.50**	.25	.35***
1963–72	.20*	–.63**	.27	.37***
1964–73	.24*	–.54**	.34	.44***
1965–74	.05	–.36**	.29	.46***
1966–75	–.01	–.23**	.25	.51***
1967–76	–.10	–.24**	.22	.41***
1968–77	–.08	–.21**	.18	.27***
1969–78	.10	–.27**	.16	.26***
1970–9	.11	–.22**	.15	.29***
1971–80	–.02	–.12*	.17	.37***
1972–81	–.06	–.07	.15	.38***
1973–82	–.07	–.19***	.16	.58***
1974–83	–.11	–.07	.26	.33***
1975–84	–.01	–.10*	.29	.34***
1976–85	–.12	–.18***	.30	.45***
1977–86	–.13*	–.23***	.40	.48***
1978–87	–.21**	–.30***	.45	.57***
1979–88	–.10*	–.36***	.47	.58***
1980–9	–.17***	–.42***	.46	.63***
1981–90	–.14***	–.39***	.44	.65***
1982–91	–.14***	–.40***	.45	.62***
1983–92	–.18***	–.33***	.40	.57***
1984–93	–.25***	–.22***	.32	.54***
1985–94	–.30***	–.18***	.37	.55***
1986–95	–.28***	–.24***	.38	.50***
1987–96	–.26***	–.26***	.38	.57***

Table 1 (Continued)

	Equation 5: Regression coefficients for industry mean LRP on within-industry variables			Correlations across industries
A: 10-year window	B: Within-industry heterogeneity in LRP	C: Within-industry volatility	D: R^2 statistic	E: Heterogeneity in LRP with volatility
1988–97	–.27***	–.25***	.41	.54***
1989–98	–.31***	–.24***	.43	.57***
1990–9	–.29***	–.28***	.45	.61***
1991–2000	–.33***	–.31***	.50	.66***
1992–2001	–.36***	–.30***	.55	.66***
1993–2002	–.47***	–.20***	.59	.65***

* Significant at 5 percent; ** Significant at 1 percent; *** Significant at 0.1 percent.

Extensions of findings

We examine the robustness of our findings by considering three additional phenomena: financial stability of firms, entry into industries and diversification of firms across industries. Each of these phenomena changes over time and these changes might account for the trends we report and analyze in the previous section. These changes thus provide potential alternative explanations for our reported trends, and our examination of them provides robustness checks for our study findings.

We are interested in the extent to which financial stability, entry and diversification impact the focal variables of our study: volatility of temporary performance, within-industry heterogeneity of long-run performance and the industry average for long-run performance. In the spirit of the initial studies of Schmalensee (1985) and Rumelt (1991), we examine simple associations rather than formal models of causation. For each of the three potential alternate explanations, we first document aggregate changes over time in the phenomena for US manufacturing firms. Then we examine the association of these changes at the industry level with the focal variables of our study. To preview the results, we find that changes in financial stability, entry and diversification indeed each have expected associations with the focal variables. But the core results of our study do not change with inclusion of these additional associations, the estimated magnitude of these additional associations is never large and their direction and statistical significance sometimes change in interesting and potentially important ways. In the end, these results provide further confirmation for our basic findings.

In the interest of brevity, we provide a single pass at statistical analysis including at once all three additional phenomena. The intercorrelations between measures of financial stability, entry and diversification are small and stable. There is thus no benefit in separate analyses, though we conducted such separate analyses to validate our findings; these separate analyses are not reported here. Our method is first to extend Equation 5 by adding measures for all three additional phenomena. The mean of LRP for firms in industry s has the following form.

$$(7)\quad \text{IMLRP}_s = \beta_0 + \beta_1{*}\text{Within-Industry Volatility}_s + \beta_2{*}\text{Within-Industry Heterogenity}_s + \beta_3{*}\text{Industry Percentage of Firms that Are Financially Unstable}_s + \beta_4{*}\text{Percentage of New Firms in Industry}_s + \beta_5{*}\text{Industry Mean Herfindahl for Firm Diversification}_s$$

We add an OLS regression equation for within-industry heterogeneity in long-run performance as a function of within-industry volatility and the additional variables.

$$(8)\quad \text{Within-Industry Heterogenity}_s = \alpha_0 + \alpha_1{*}\text{Within-Industry Volatility}_s + \alpha_2{*}\text{Industry Percentage of Firms that Are Financially Unstable}_s + \alpha_3{*}\text{Percentage of New Firms in Industry}_s + \alpha_4{*}\text{Industry Mean Herfindahl for Firm Diversification}_s$$

The coefficients α_1, β_1, and β_2 represent the findings that we reported earlier in Panels A, C and D of Figure 3 respectively. We hope that these coefficients will maintain the trends over time and the magnitudes as previously reported, indicating that our findings are robust to consideration of additional variables.

Financial instability of firms

Firms are in financial equilibrium when they repeatedly invest in the same established, successful business positions. Each investment generates a stream of immediate costs followed by subsequent positive cashflows, all patterned in a profile associated with the established business position. The profile over time of investment costs followed by positive cashflows generates the true economic rate of return for the firm (Fisher and McGowan, 1983).

A great expansion of financial markets over the last several decades has enabled firms increasingly to fund investment with infusions of external capital rather than internal cashflows. One outcome of this increased external funding is that firms may bet on creation of new competitive advantages. Increasingly in recent years, these bets are from new firms that suffer large financial losses and have significant risk of ultimate failure (Fama and French, 2004). These firms are financially unstable in the sense that indefinite continuation of their existing performance must lead to exit. In addition, structural change has destroyed the historic position of some established firms, pushing them also into financial instability. Both the new entrants and the delayed exits suffering financial instability are currently in competitive disequilibrium. But their existence provides opportunity for reconfiguration and eventual success.

Financial instability for firms is presumably associated with the structural shocks that underpin the new competition, hence industry volatility. However, the increased availability of external capital itself may be the catalyst for our documented changes in competition. Worse, the apparent changes in competition may be instead merely the results of the disaggregation of firms due to vertical disintegration and corporate spinoffs. Investments that were once made inside an established firm in financial equilibrium (such as in pharmaceuticals) might now be made by new firms that are financially unstable (such as in biotechnology). The simple disaggregation of basic investments (such as drug research) across multiple firms might well exaggerate any real increase in volatility and heterogeneity in an industry.

We examine the extent of financial instability for US manufacturing firms and the association between this financial instability and the trends documented earlier. We identify a firm as suffering financial instability if it exhibits at least one of the following three conditions: (1) technical bankruptcy, or firms with negative common equity; (2) operation below breakeven performance, or firms with selling, general and administrative expenses in excess of sales; and (3) insolvency, or firms with current liabilities exceeding current assets. Each of these financial conditions is not sustainable for firms in the long run, and as such is an indication of a lack of fully formed competitive position. We compute the percentage of firms in each industry that suffer any one of these measures of financial instability. Figure 4 reports the aggregate proportion of financially unstable firms for our study population of large, established firms in the US manufacturing sector. This proportion has increased steadily, reaching 15 percent in the 1990s. This positive trend is statistically significant. We report separately in Figure 4 the percentages of financial instability for small, young firms in the sector alongside those for our study population. By the 1990s, 75 percent of small, new firms in the US manufacturing sector experience at least one of our three measures of financial instability.

The trend of median ROA for the study population of firms is plotted in Figure 5. Foreshadowing the statistical findings immediately below, there is no decline in median ROA even as the percentage of financially unstable firms greatly increases. However, this independence of performance and financial instability is not true for small, new firms, underscoring the need for this particular robustness check. The large difference in performance since 1980 between our study population and small, new firms suggests that the latter might well operate in a different strategic group, justifying their exclusion from our study population. We computed data comparable to those in Figures 4 and 5 for other sectors of the US economy and find similar results to manufacturing for every single sector (not reported here).

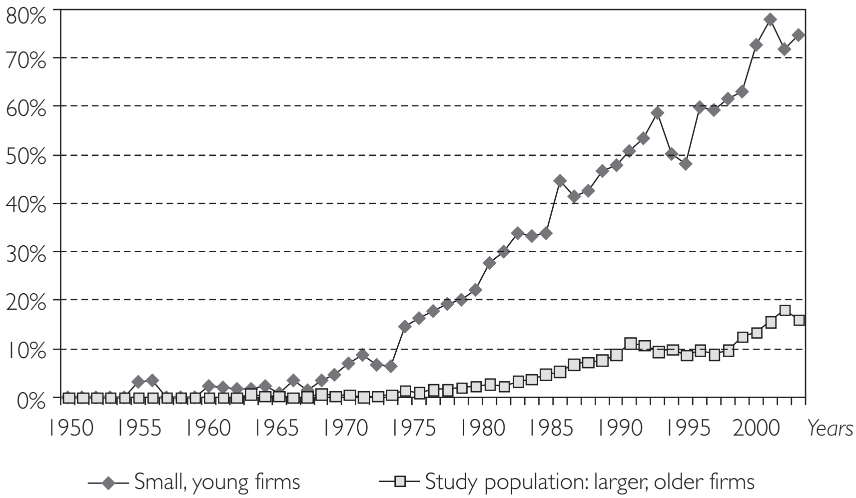


Figure 4 Financially unstable firms as a percentage of all firms, by year

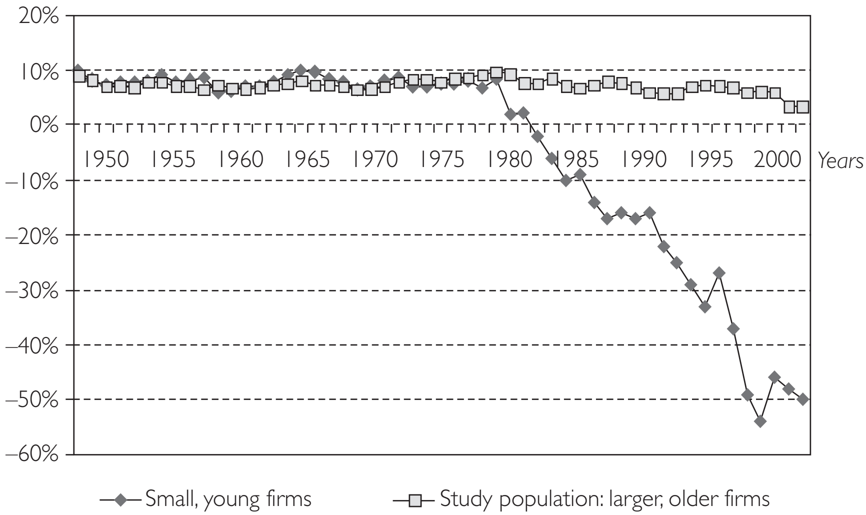


Figure 5 Median ROA across firms, by year

Figure 6 presents the average duration for spells of financial instability for firms in the manufacturing sector. Each spell is a continuous period of one of the three forms of financial distress for a particular firm, and each spell is formally assigned to the end year of that period. The average duration for spells of financial instability has more than doubled since the 1970s, when these spells began occurring regularly.

The results of estimating Equations 7 and 8 are given in Table 2, along with correlations across industries for within-industry volatility and the three

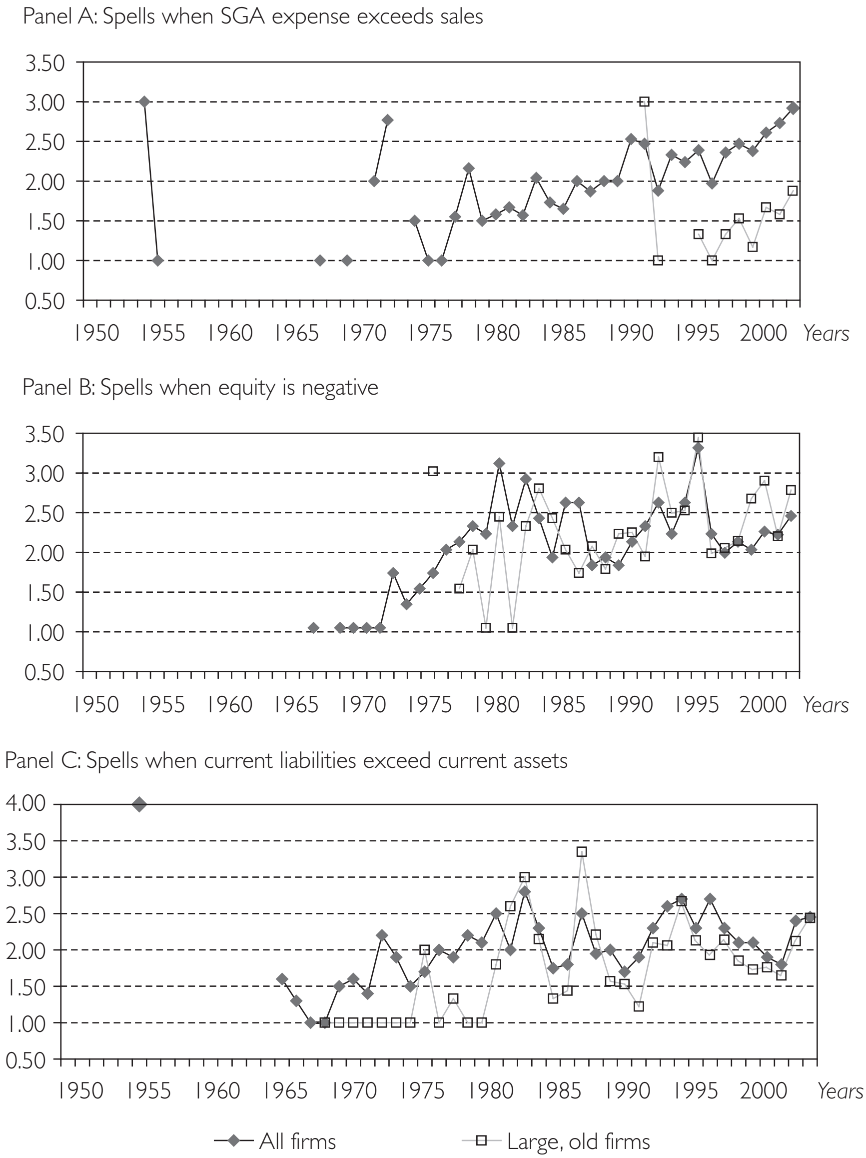


Figure 6 Average duration for spells of financial instability, by year

alternative variables. We first examine the effects of financial instability. The effects of this measure on the industry mean for long-run performance (in column D of Table 2) are negative, significant and of important magnitude during the 1960s. Then, the effect fades away and is completely gone by the 1990s. There is never any consistent effect on within-industry heterogeneity (in column I), and while the correlation between the extent of financial instability and volatility for an industry is positive and statistically significant, as would be expected, it is never large (in column M).

Table 2 Robustness checks for relationships between industry attributes: financial instability, extent of competitive fringe and corporate diversification

	Equation 7: Regression coefficients for industry mean long–run performance as a function of within–industry attributes						Equation 8: Regression coefficients for within–industry heterogeneity in long–run performance as a function of within–industry attributes					Correlations between within–industry volatility and other within–industry attributes		
A: 10-year window	B: Within–industry heterogeneity in LRP for industry	C: Within–industry volatility around LRP for industry	D: Percentage of firms suffering financial instability	E: Ratio of small, young firms to study firms for industry	F: Mean Herfindahl for multi–segment assets for industry	G: R^2 statistic	H: Within–industry volatility around LRP for industry	I: Percentage of firms suffering financial instability	J: Ratio of small, young firms to study firms for industry	K: Mean Herfindahl for multi-segment assets for industry	L: R^2 statistic	M: Percentage of firms suffering financial instability	N: Ratio of small, young firms to study firms for industry	O: Mean Herfindahl for multi-segment assets for industry
1950–9	.20	–.17	.13	.004*		.02	.23**	.080	.001		.05	.01	.02	
1951–60	.25	–.31**	.01	.005*		.08	.13*	.01	.001		.02	.08	–.10	
1952–61	.32**	–.40**	–.44	.004		.10	.12	.37	.001		.01	.10	–.08	
1953–62	.26*	–.39**	–.14	.006*		.11	.02	.18	.000		.00	.10	–.18	
1954–63	.50***	–.49**	–.07	.003		.14	.24*	–.01	–.000		.03	.24**	.17*	
1955–64	.41**	–.64***	–.09	.007***		.25	.01	.03	.000		.00	.18*	–.00	
1956–65	.49***	–.64***	–.10	.007***		.26	–.04	.02	.000		.00	.14	–.10	
1957–66	.46***	–.71**	–15	.002**		.26	–.04	.01	.000		.00	.18*	–.09	
1958–67	.42***	–.52**	–09	.002**		.22	.22*	–.06	.000		.02	.21**	–.10	
1959–68	.41***	–.61***	–.08	.002*		.22	.18*	–.16*	.001		.03	.42***	–.03	
1960–9	.32***	–.67***	–.18**	.002		.29	.37***	–.07	.001		.16	.45***	.18	
1961–70	.40**	–.71***	–.28***	.002*		.29	.32***	.03	.000		.18	.31***	.03	
1962–71	.25**	–.52***	–.36***	.002*		.31	.27***	.04	.000		.18	.37***	–.02	
1963–72	.18*	–.50***	–.36***	.002*		.34	.22***	.14*	.001		.25	.27***	.13	
1964–73	.16*	–.44***	–.36***	.001		.38	.25***	.13*	.000		.30	.34***	.18*	

Table 2 (Continued)

A: 10-year window	Equation 7: Regression coefficients for industry mean long–run performance as a function of within–industry attributes						Equation 8: Regression coefficients for within–industry heterogeneity in long–run performance as a function of within–industry attributes					Correlations between within–industry volatility and other within–industry attributes		
	B: Within–industry heterogeneity in LRP for industry	C: Within–industry volatility around LRP for industry	D: Percentage of firms suffering financial instability	E: Ratio of small, young firms to study firms for industry	F: Mean Herfindahl for multi–segment assets for industry	G: R^2 statistic	H: Within–industry volatility around LRP for industry	I: Percentage of firms suffering financial instability	J: Ratio of small, young firms to study firms for industry	K: Mean Herfindahl for multi-segment assets for industry	L: R^2 statistic	M: Percentage of firms suffering financial instability	N: Ratio of small, young firms to study firms for industry	O: Mean Herfindahl for multi-segment assets for industry
1965–74	.14	–.36***	–.22***	.000		.32	.31***	–.06	.000		.29	.47***	.34***	
1966–75	–.01	–.23***	–.13**	.000		.27	.41***	–.08	.000		.31	.48***	.18*	
1967–76	–.07	–.34***	–.09*	.000		.24	.34***	–.02	.002		.24	.48***	.25***	
1968–77	–.05	–.20**	–.11**	.000		.19	.34***	–.09*	.000		.23	.41***	.34***	
1969–78	.12	–.28***	–.05	.000		.14	.39***	–.02	.000		.27	.37***	.18*	
1970–9	.12	–.23***	–.10*	.000		.15	.32***	–.05	–.000		.21	.36***	.06	
1971–80	.02	–.15**	–.09*	.001		.16	.30***	.01	–.000		.25	.30***	.11	
1972–81	–.03	–.17**	–.10*	.002*		.15	.39***	.00	–.000		.27	.25***	.11	
1973–82	–.07	–.19**	–.06	.003		.16	.39***	–.00	.000		.38	.23***	–.02	
1974–83	.03	–.19***	–.08*	.000		.24	.26***	.02	.000		.20	.25***	.06	
1975–84	–.24**	–.20**	–.05	.000		.30	.23***	.09**	.004***		.22	.29***	.05	
1976–85	–.23**	–.19**	–.06	.000		.34	.31***	.03	.005***		.25	.28***	.07	
1977–86	–.23**	–.23***	–.07*	–.001		.41	.30***	.03	.005***		.31	.31***	.10	
1978–87	–.18**	–.28***	–.07*	–.002*		.47	.32***	.01	.005***		.35	.35***	.09	
1979–88	–.11*	–.34***	–.04	–.002	.02	.48	.31***	–.01	.000	.05***	.31	.32***	.09	.14*

Table 2 (Continued)

	Equation 7: Regression coefficients for industry mean long–run performance as a function of within–industry attributes						Equation 8: Regression coefficients for within–industry heterogeneity in long–run performance as a function of within–industry attributes					Correlations between within–industry volatility and other within–industry attributes		
A: 10-year window	B: Within–industry heterogeneity in LRP for industry	C: Within–industry volatility around LRP for industry	D: Percentage of firms suffering financial instability	E: Ratio of small, young firms to study firms for industry	F: Mean Herfindahl for multi-segment assets for industry	G: R^2 statistic	H: Within–industry volatility around LRP for industry	I: Percentage of firms suffering financial instability	J: Ratio of small, young firms to study firms for industry	K: Mean Herfindahl for multi-segment assets for industry	L: R^2 statistic	M: Percentage of firms suffering financial instability	N: Ratio of small, young firms to study firms for industry	O: Mean Herfindahl for multi-segment assets for industry
1980–9	–.04	–.41***	–.01	–.002*	.01	.47	.38***	–.01	.000	.05**	.31	.27***	.00	.15*
1981–90	–.18**	–.38***	–.01	–.003*	.02	.45	.44***	–.02	.000	.04**	.31	.23***	.06	.17*
1982–91	–.16**	–.35***	–.04	–.007**	.01	.49	.43***	–.02	.000	.05***	.41	.32***	.14*	.18**
1983–92	–.19**	–.30***	–.02	–.005**	.01	.41	.45***	–.05*	.000	.03*	.31	.32***	.18*	.13*
1984–93	–.25***	–.22***	–.01	–.004*	.00	.32	.40***	–.05	.000	.04*	.23	.30***	.13	.12
1985–94	–.28***	–.29***	.00	–.005**	–.01	.37	.45***	.03	.01*	.03	.32	.24***	.09	.16*
1986–95	–.24***	–.24***	.01	–.007***	–.01	.40	.42***	.03	.01**	.04*	.29	.24***	.09	.19**
1987–96	–.20***	–.27***	.00	–.007***	–.02	.41	.45***	.01	.01***	.05**	.32	.24***	.06	.17*
1988–97	–.20***	–.27***	.00	–.007***	–.02	.41	.45***	.01	.01***	.05**	.38	.24***	.06	.17*
1989–98	–.21***	–.25***	.02	–.006***	–.02	.43	.42***	.03	.01**	.06***	.37	.25***	.10	.14*
1990–9	–.26***	–.26***	.02	–.009***	–.03	.47	.46***	.01	.01**	.05**	.40	.24***	.14*	.20*
1991–2000	–.26***	–.20***	.01	–.015***	–.03	.50	.51***	.01	.01***	.05***	.48	.18**	.33***	.22**
1992–2001	–.30***	–.30***	.02	–.017***	–.03	.55	.50***	.01	.02***	.08***	.50	.17*	.34***	.22**
1993–2002	–.40***	–.21***	.02	–.028***	.03	.61	.47***	.01	.03***	.03***	.50	.13*	.32***	.23**

* Significant at 5 percent. ** Significant at 1 percent. *** Significant at .1 percent.

Our finding of essentially no impact from the quite large expansion in external finance and the dramatic spread of financial instability for firms is surprising. To verify that this finding is not an artifact of mismeasurement or outliers, we directly examined several industries in detail. We report one here as typical: SIC 2111 covers cigarette firms. During the decade 1990–9, cigarettes had the highest industry mean LRP for the manufacturing sector (over 16 percent) while over 30 percent of the firm-years in the same period exhibited financial distress. This unexpected pairing of variable outcomes is in fact valid, and derives from a turbulent industry with extensive financial and strategic restructuring. For example, the Vector Group (the modern incarnation of the old Liggett Group) exhibited volatile sales and extremely volatile earnings during the 1990s. This firm had both the lowest and the highest single year ROA for the industry, the latter achieved after Vector slashed its assets by 75 percent over two years. This firm had negative equity in every year of the decade due to its financial restructurings, though its long-run performance rate of 24 percent enabled it to return finally to positive equity in 2000.

Financial instability has always indicated an absence of fit between the firm and its environment. In a static industry, poor fit indicates poor performance. However, in a dynamic or turbulent industry, poor fit with current industry conditions often indicates restructuring, innovation and experimentation, or some other repositioning to take advantage of new or emerging conditions. Today, financial instability is as often associated with good long-run financial performance as poor, at least at the industry level. For this reason, the spread of financial instability does not account for or distort the core findings of our study. Rather, this spread appears to be an independent measure of restructuring and strategic experimentation.

Entry and the new competitive fringe

Our second robustness check is to examine the impact of entry on the basic findings of our study. Figure 7 gives the sector-level entry and exit rates for the large, established firms of our study population. 'Entry' into this population, by definition, means that the firm has been publicly traded for six or more years and has sales and assets of US$10 million or more. As can be easily seen in Figure 7, entry into the study population has been vigorous and quite stable over time. The expansion of the New York and the American Stock Exchanges in the 1960s, and the formation of NASDAQ in 1971 led to a steady listing of new firms during 1960–74. As these newly listed firms age and expand, they move into our study population. We estimated the impact of this entry in OLS regressions similar to Equations 7 and 8. The estimated impact was small and statistically insignificant, largely because the entry rate itself is highly episodic and skewed, making the pure entry rate itself a poor measure. These results are not reported.

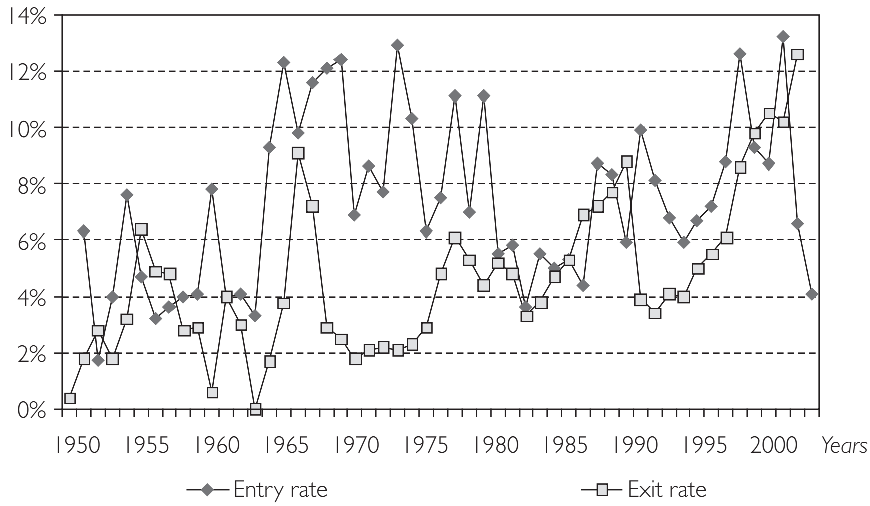


Figure 7 Sector entry and exit rates for study population of large, established firms

Instead, we consider the effect of cumulative entry using two measures. First, we compute for each 10-year window the ratio of the number of firms aged six to 10 years old against the total number of large, established firms in an industry. This measure captures recent entrants into the study population. Second, we compute the ratio of the number of small, new firms in an industry (as defined above) against the same denominator of total large, established firms in that industry. This second measure captures entrants into the competitive fringe, but not yet the study population. These cumulative measures are far better behaved than the simple entry rate. While neither measure of cumulative entry changes extensively over time, we have seen from Figures 4 and 5 that the nature of the competitive fringe dramatically changes after 1980.

We estimated Equations 7 and 8 using both cumulative measures of entry. The most important result of this estimation is that the core findings of our study (coefficients α_1 in Equation 8 and β_1 and β_2 in Equation 7) are unaffected. The effects of greater entry themselves should be to reduce the industry mean LRP ($\beta_4 < 0$ in Equation 7), increase the heterogeneity in industry LRP across firms ($\alpha_3 > 0$ in Equation 7) and increase industry volatility. The estimated coefficients on the measure of cumulative entry into the study population all take these correct signs, but are statistically significant in fewer than six of 43 10-year windows each for β_4 and α_3. The results for this first entry measure are thus not reported. The estimated coefficients on the second measure of cumulative entry (into the competitive fringe) are reported in Table 2. These estimates are frequently statistically significant, but contribute little to the overall goodness of fit and the estimated magnitude of effect at variable means are small relative to those for the core measures of our

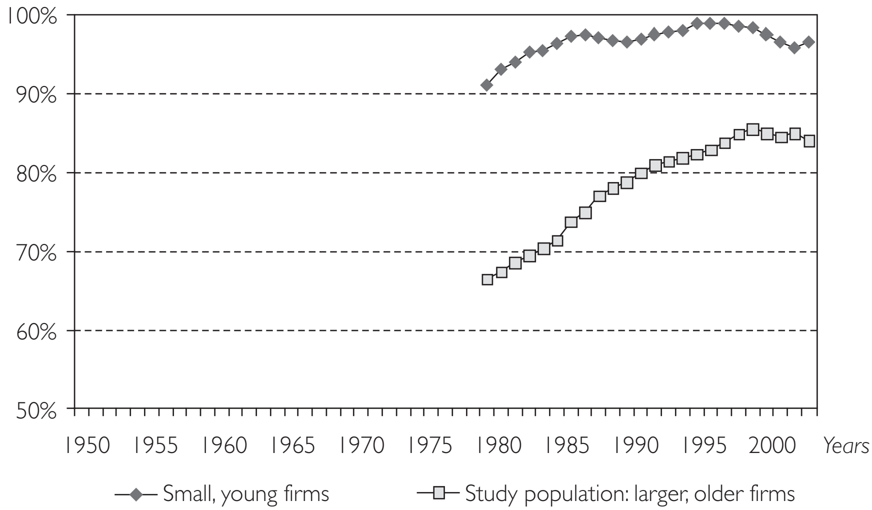


Figure 8 Diversification: Average firm Herfindahl index for assets across business segments

study. Interestingly, entry into the competitive fringe of small new firms is positively associated with average industry LRP during the 1950s (in column E of Table 2). In recent years, entry indeed depresses average industry LRP (in column E) and increases within-industry heterogeneity (in column J). In the last four 10-year windows, these effects are sharply larger. Perhaps these increased impacts are due to the steady change in the nature of entry in the competitive fringe shown earlier in Figures 4 and 5. But there are too few years for these very recent trends to sensibly test for this possibility.

Diversification of firms

A third possible alternate explanation for our findings is that firms have diversified across industries increasingly over time. In this study, we measure performance at the firm level, rather than at the line of business level. Therefore, our findings potentially confuse heterogeneity in an industry due to different diversification strategies of firms with actual performance heterogeneity among lines of business in that industry.

We examine this possibility by computing for each firm i in our study population in each year t a Herfindahl index over the assets of its total of B business segments.

$$\text{SegHerf}_{it} = \sum_{B} (\text{Segment Assets}_{bit}/\text{Firm Assets}_{it})^2 \tag{9}$$

Note that a firm with only one business segment would have a value for SegHerf of 1.0, while a firm with two equally sized business segments would have a value of 0.5. We then compute for the mean for the study population of firms for these Herfindahl indices, and plot the value of that mean in Figure 8. The data for these computations are from Compustat, and are available only since 1979. Note that US manufacturing firms have become steadily less diversified since 1979, rather than more, though this trend toward increased focus moderates after 1998.

To test the extent to which firm diversification affects the reported results of this study, we compute the average segment asset Herfindahl index for each industry and each 10-year window. That industry average is employed in OLS regression Equations 7 and 8, with results reported in Table 2. We find that diversification indeed increases heterogeneity (column K of Table 2). But our study findings are unchanged and the magnitude of the estimated impact of diversification at variable means is small compared to that of industry volatility (column H).

Discussion of findings

Our study has provided evidence that the nature of competition in the US manufacturing sector has significantly changed over the last 50 years. The volatility of temporary performance, and the within-industry heterogeneity across firms for durable performance have increased steadily and enormously since 1950. Also, these constructs have become increasingly intercorrelated over time and their joint presence accounts for an increasingly large share of performance differences across industries.

These changes have occurred around basic stability for the average performance of US firms (see Figure B2 in Appendix B; see also Comin and Mulani, 2006). To give a sense of the trends using the data from this study, the median long-run performance is about 6 percent in the 1990s, little changed from just over 7 percent in the 1950s. Meanwhile, the median standard deviation for annual profit shocks around long-run performance has steadily risen from 2 percent in the 1950s to over 8 percent today. The median standard deviation for within-industry heterogeneity of performance has risen from under 2 percent to 6 percent today.

The modern strategy literature offers two different responses to these trends in corporate experience, both incorporating more dynamic aspects for strategy. Many scholars have modernized the original resource-based view of the firm to examine dynamic capabilities (Eisenhardt and Martin, 2000; Helfat et al., 2007; Teece et al., 1997; Zollo and Winter, 2002). Other scholars have taken a different approach, emphasizing transient advantages and disruptive strategic moves (Bettis and Hitt, 1995; Brown and Eisenhardt, 1998; Christensen, 1997; D'Aveni, 1994, 1995; Hamel, 2000; Quinn et al., 1997; Slywotzky, 1996). The former scholarship focuses on the exploitation and preservation of some established and valuable capability, while the latter emphasizes the flexibility to pursue new and disruptive positions that are highly risky and will often fail. While there are obvious similarities between these two literatures, there is also an important strategic and organizational boundary between them. At some level of volatility and frequent episodes of poor performance, that boundary is crossed and durable advantage becomes transient experiment (Brown and Eisenhardt, 1998).

Our empirical characterization of the experiences of US firms facilitates and forces discussion of this boundary. We note that for most firms, the standard deviation of temporary profits around stable long-run performance (volatility) became larger than the long-run performance itself during the 1980s. We suggest that the study of performance for most firms today is then appropriately and predominantly a study of disequilibrium and transience. We note that interfirm heterogeneity for an industry has been significantly, negatively associated with the average performance of firms in an industry, also since the 1980s. We suggest that the study of interfirm heterogeneity for most industries today is then appropriately and predominantly a study of experimentation and short-run failure, not long-term success. Finally, we note that while the 1980s represented a turning point for these two phenomena, both are the product of trends that continue a steady rise over time for the last 50 years and will presumably do so for years to come.

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Appendix A: Decomposition of total variance in ROA for sector

Consider N firms (indexed by f) over P periods (indexed by t). Firms are segregated into M industries (indexed by i), with N_i firms in industry i. We have the following sum, where the last term gives the number of industries times the average number of firms per industry:

(A1) $N = \Sigma_I N_i = M \Sigma_I (N_i / M)$

The total number of observations is NP.

The annual return for each firm and period is denoted R_{ift}. We have the following means. The mean return for firm f in industry i over all periods is:

(A2) $$L_{if} = (1/P)\Sigma_T R_{ift}$$

The mean return over for industry i over all periods is λ_i:

(A3) $$\lambda_i = (1/N_i)\Sigma_{Fi} L_{if}$$

The mean return for the sector over all periods is denoted μ:

(A4) $$\mu = (1/M)\Sigma_I \lambda_i$$

We can decompose the return for each firm into a stable and temporary effect, making no assumption as to the distribution of E_{ift}:

(A5) $$R_{ift} = L_{if} + E_{ift}$$

Consider now the variance of performance across all N firms and over all P periods:

(A6) $$\begin{aligned}
&(1/NP)\, \Sigma_I \Sigma_{Fi} \Sigma_T (R_{ift} - \mu)^2 = (1/NP)\, \Sigma_I \Sigma_{Fi} \Sigma_T (L_{if} + E_{ift} - \mu)^2 \\
&= (1/NP)\, \Sigma_I \Sigma_{Fi} \Sigma_T [(L_{if})^2 + (E_{ift})^2 + \mu^2 + 2L_{if}E_{ift} - 2L_{if}\mu - 2\mu E_{ift}] \\
&= (1/NP)\, \Sigma_I \Sigma_{Fi} \Sigma_T [(L_{if})^2 - 2L_{if}\mu + \mu^2 + 2L_{if}E_{ift} - 2\mu E_{ift}] + (1/NP)\, \Sigma_I \Sigma_{Fi} \Sigma_T [E_{ift}]^2 \\
&= (1/NP)\, \Sigma_I \Sigma_{Fi} \Sigma_T [(L_{if})^2 - 2L_{if}\mu + \mu^2 + 2L_{if}E_{ift} - 2\mu E_{ift}] + \text{volatility} \\
&= (1/NP)\, \Sigma_I \Sigma_{Fi} \Sigma_T [(L_{if})^2 - 2L_{if}\mu + \mu^2] + (1/NP)\, \Sigma_I \Sigma_{Fi} \Sigma_T [2L_{if}E_{ift} - 2\mu E_{ift}] + \text{volatility} \\
&= (1/NP)\, \Sigma_I \Sigma_{Fi} [P[(L_{if})^2 - 2L_{if}\mu + \mu^2]] + (2/NP)\, \Sigma_I \Sigma_{Fi} \Sigma_T [(L_{if} - \mu)E_{ift}] + \text{volatility} \\
&= (1/N)\, \Sigma_I \Sigma_{Fi} [(L_{if})^2 - 2L_{if}\mu + \mu^2] + 2\text{Cov}[(L_{if} - \mu), E_{ift}] + \text{volatility}
\end{aligned}$$

Examine next the remaining terms:

(A7) $$\begin{aligned}
&(1/N)\, \Sigma_I \Sigma_{Fi} [(L_{if})^2 - 2L_{if}\mu + \mu^2] \\
&= (1/N)\, \Sigma_I \Sigma_{Fi} [(L_{if})^2 - 2L_{if}\lambda_i + (\lambda_i)^2 + 2L_{if}\lambda_i - (\lambda_i)^2 - 2L_{if}\mu + \mu^2] \\
&= (1/N)\, \Sigma_I \Sigma_{Fi} [(L_{if})^2 - 2L_{if}\lambda_i + (\lambda_i)^2] + (1/N)\, \Sigma_I \Sigma_{Fi} [2L_{if}\lambda_i - (\lambda_i)^2 - 2L_{if}\mu + \mu^2] \\
&= (1/N)\, \Sigma_I \Sigma_{Fi} [L_{if} - \lambda_i]^2 + (1/N)\, \Sigma_I \Sigma_{Fi} [2L_{if}\lambda_i - (\lambda_i)^2 - 2L_{if}\mu + \mu^2] \\
&= \text{Within-Industry Variance} + (1/N)\, \Sigma_I \Sigma_{Fi} [2L_{if}\lambda_i - (\lambda_i)^2 - 2L_{if}\mu + \mu^2]
\end{aligned}$$

Finally, examine the still remaining terms:

(A8) $$\begin{aligned}
&(1/N)\, \Sigma_I \Sigma_{Fi} [2L_{if}\lambda_i - (\lambda_i)^2 - 2L_{if}\mu + \mu^2] \\
&= (1/N)\, \Sigma_I \Sigma_{Fi} [2L_{if}\lambda_i - (\lambda_i)^2 - 2L_{if}\mu + \mu^2] \\
&= (1/N)\, \Sigma_I [\Sigma_{Fi}\, 2L_{if}\lambda_i - \Sigma_{Fi} (\lambda_i)^2 - \Sigma_{Fi} (2L_{if}\mu) + \Sigma_{Fi}\, \mu^2] \\
&= (1/N)\, \Sigma_I [2\lambda_i \Sigma_{Fi} L_{if} - N_i\lambda_i^2 - 2\mu\Sigma_{Fi} L_{if} + N_i\mu^2] \\
&= (1/N)\, \Sigma_I [2\lambda_i N_i\lambda_i - N_i\lambda_i^2 - 2\mu N_i\lambda_i + N_i\mu^2] \\
&= (1/N)\, \Sigma_I [N_i\lambda_i^2 - 2\mu N_i\lambda_i + N_i\mu^2] \\
&= (1/N)\, \Sigma_I [Ni(\lambda_i - \mu)^2] \\
&= \text{Weighted Across-Industry Variance}
\end{aligned}$$

Appendix B: Estimation of firm-specific long run performance (LRP)

Our examination of volatility leads us to decompose the financial performance of firms into stable and temporary components – an approach adopted by Mueller

(1986, 1990), Cubbin and Geroski (1987), Geroski and Jacquemin (1988), Waring (1996) and McGahan and Porter (1999). Their approach estimates a basic difference equation for the profit rate (return on assets) of firm f in time t in a particular window of time T:

$$R_{f,t} = \alpha_f + \beta^* R_{f,t-1} + \varepsilon_{ft} \tag{B1}$$

Specific details of this difference equation are the sector-wide persistence rate β, the firm-specific intercept term α_f, and the $\varepsilon_{f,t}$ error term for each firm in each time period. The sustained profit rate for the firm is its permanent component of the solution to this difference equation, or:

$$LRP_f = \alpha_f / (1 - \beta) \tag{B2}$$

Note that long run performance (LRP) is independent of time during the window T, though it varies across firms. We employ LRP as a measure of sustained competitive performance. The deviation around LRP represents the annual volatility:

$$R_{f,t} = LRP_f + Volatility_{f,t} \tag{B3}$$

We illustrate the decomposition of financial performance into LRP and volatility in Figure B1. Panel A of that figure reports the annual return on assets during 1950–2002 for Briggs and Stratton, a US manufacturer of small motors. We choose this firm, as it was one of the handful of firms used for illustration by Mueller (1986) in his seminal study. In Panels B and C of Figure B1, we split the ROA data for Briggs and Stratton into two subperiods, 1950–76 and 1977–2002. For each subperiod, we estimate Equation B1 above, with results reported in each panel. LRP for 1950–76 is 0.162, calculated as 0.11 divided by (1.0–0.33), while LRP for 1977–2002 is 0.074, calculated as 0.06 divided by (1.0–0.21). The volatility for each year is ROA minus the appropriate LRP. The variance for this volatility in each subperiod is computed and also reported in Figure B1. Note that LRP declines between the two subperiods, while the average variance of volatility rises. This latter change is directly visible in the raw data in Panel A, and foreshadow findings in this study.

The start of the statistical analyses for our article is estimation of Equation B1 for each window of time. This estimation is complicated by the fact that the error terms $\varepsilon_{i,t}$ in Equation B1 are not independently, identically normal in distribution. In particular, the error terms are highly skewed, meaning that the predicted values and residuals are positively correlated. Also, the error terms are heteroskedastic, varying greatly across observations. We also expect the error terms to be higher for younger and smaller firms. While we exclude the smallest and youngest firms from our study population, we still expect significant heteroskedasticity even among the large, established firms in our study population.

The estimation methodology is pseudo-maximum likelihood, a version of iteratively weighted least squares (Carroll and Ruppert, 1988). We estimate the following extension of Equation B1, adding year effects, for each 10-year window for 1950–2002:

$$R_{f,t} = \alpha_f + \delta_t + \beta^* R_{f,t-1} + \varepsilon_{f,t} \tag{B4}$$

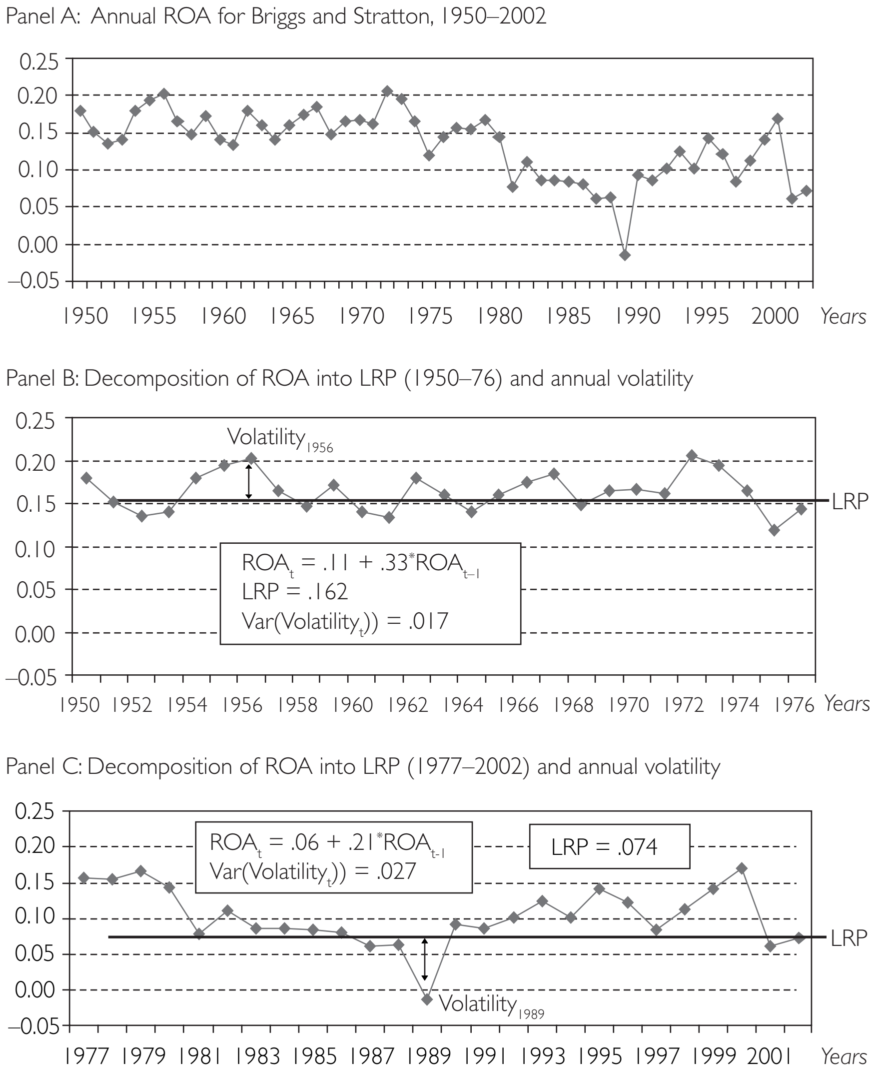

Figure B1 Decomposition of performance into long-run and temporary components, Briggs and Stratton, 1950–2002

The fixed effects for firms are given by the α_f, the fixed effects for year are given by the δ_t and the persistence rate is given by β. To deal with non-normality and heteroskedasticity of the $\varepsilon_{f,t}$ error terms, we weight each observation with the inverse of the following variance term:

(B5) $$(R_{f,t} - \text{pred}(R_{f,t}))^2 = v_0 + v_1{*}\text{pred}(R_{f,t-1}) + v_2{*}\ln(\text{Sales}_{f,t}) + v_4{*}\ln(\text{Age}_{f,t}) + \mu_{f,t}$$

Note that the variance for each observation is a linear function of the predicted value (the v_1 parameter), consistent with a non-normal distribution for the error term. We also expect the variance to decrease with the scale of the firm (measured by sales, the

v_2 parameter) and with the age of the firm (the v_3 parameter). The error term for the variance equation is denoted $\mu_{f,t}$.

We initiate estimation with start values for parameters of Equations B4 and B5, obtained through OLS regression. We next estimate parameters for Equation B4, weighting each observation with the inverse of the variance term from Equation B5, based on the start values. We then take the estimates for the predicted values from our newly estimated Equation B4 and estimate Equation B5 with OLS. We take the parameter estimates from Equation B5, compute new weights for each observation and re-estimate Equation B4. Then, we take the predicted values from Equation B4 and re-estimate Equation B5. We continue this process until there are no changes in our parameter estimates for either equation.

The results of this estimation are reported in Table B1 for the difference equation B4 and Table B2 for the variance equation B5. The fixed effects for year are quite small, though statistically significant, and are not considered in this study. For each 10-year window, we take the fixed effect for each firm and the sector-wide persistence rate and compute the LRP for the firm. The quartiles across resulting LRPs are reported in Figure B2. For example, in the 1985–94 window, there are 2517 large, established US manufacturing firms. The median LRP among these firms is 0.061. One-quarter of the firms have LRPs above the upper quartile of 0.088. Another quarter of the firms have LRPs below the lower quartile 0.029.

These long-run performance rates are relatively stable over time, a result also reported by Comin and Mulani (2006) and Comin and Philippon (2006). Estimation and statistical tests of trends for the quartiles in Table B2 are given in Appendix C, Table C2. There is no statistically significant trend for the upper quartile of LRP during the study period. The trend for the median is negative and significant or not depending on the chosen test statistic. What truly has changed is the lower quartile, which has steadily dropped since the 1970s, increasing the dispersion of LRPs across firms. The decline in the lower quartile is statistically significant.

Some earlier studies have focused on the persistence rate β in Equations B1 and B2. In particular, Waring (1996) defined β as a measure of the 'sustainability' of performance for firms. Waring estimated β in a fixed panel for 1970–89. He thus produced a time-invariant estimate of the persistence rate, comparable to our estimates for a single 10-year window in Table B1. In contrast, we examine the trend over time for estimated βs from multiple 10-year windows. These estimates are reported in Table B1 and plotted in Figure B3. The estimated βs decline over time, and this decline is statistically significant (Table C2 of Appendix C). However, the trend for β flattens out in later years, a finding which is not inconsistent with the stability for β reported in McNamara et al. (2003) for their study period 1978–97. Note that since the upper quartile and median for the estimated LRPs are essentially stable over time, the estimated firm fixed effects α_f must be rising over time for most firms to offset the decline in β (see Equation B2 for the calculation of firm LRP). This simultaneous movement across 10-year windows for both the persistence rate β and the firm fixed effects α_fs makes difficult interpretation of any trend in the persistence rate alone.

Detailed analysis of the persistence rate is a distinct line of inquiry not pursued in this article. We estimate a sector-wide persistence rate only to calculate long-run performance for firms. We find, along with Comin and Mulani (2006), that simple arithmetic averages of ROA in 10-year windows as estimates of LRP produce similar findings in the aggregate, rendering minimal any benefits from even more complex estimation than we already pursue. And estimations of firm-specific persistence rates offer costs of estimation difficulty and complexity of interpretation. Convergence of pseudo-maximum likelihood estimation for Equations B4 and B5 while allowing the β to vary by firms becomes difficult as performance becomes more volatile for many firms in recent years.

An alternate though related approach is to examine the correlation of performance rates for firms in an industry in one period versus another. Such correlations provide a more direct measure of the stability over time for the competitive landscape. Comin and Philippon (2006) and Brynjolfsson et al. (2007) both document that these correlations decline over time. Wiggins and Ruefli (2002, 2005) provide a

Table B1 Estimates for basic difference equation B4

10-year window	Estimate of β	t-statistic for β	R^2 statistic	Number of observations
1950–9	.23	7.1	.73	2780
1951–60	.24	8.4	.72	2953
1952–61	.26	10.9	.73	3129
1953–62	.28	11.9	.77	3297
1954–63	.28	16.3	.77	3497
1955–64	.29	18.2	.77	3646
1956–65	.26	16.5	.79	3889
1957–66	.24	15.7	.82	4186
1958–67	.30	19.9	.80	4522
1959–68	.27	18.5	.76	4912
1960–9	.34	26.4	.78	5334
1961–70	.38	28.4	.78	5791
1962–71	.38	27.3	.76	6310
1963–72	.31	24.2	.77	6881
1964–73	.26	20.9	.77	7556
1965–74	.26	19.4	.73	8171
1966–75	.22	18.6	.84	8771
1967–76	.22	15.6	.70	9407
1968–77	.29	26.3	.74	10,086
1969–78	.30	28.0	.73	10,718
1970–9	.31	28.4	.70	11,390
1971–80	.27	24.6	.63	12,109
1972–81	.26	25.1	.57	12,596
1973–82	.17	17.8	.77	13,106
1974–83	.19	18.7	.60	13,369
1975–84	.16	15.7	.61	13,653
1976–85	.14	11.6	.51	13,842
1977–86	.12	13.2	.76	13,896

Table B1 (Continued)

10-year window	Estimate of β	t-statistic for β	R^2 statistic	Number of observations
1978–87	.15	18.1	.76	13,964
1979–88	.15	19.7	.87	13,945
1980–9	.19	22.3	.74	13,878
1981–90	.19	20.9	.80	13,877
1982–91	.10	8.9	.79	13,977
1983–92	.09	11.5	.88	14,112
1984–93	.06	7.6	.72	14,300
1985–94	.05	8.5	.60	14,583
1986–95	.07	10.2	.83	14,961
1987–96	.10	12.4	.84	15,345
1988–97	.12	18.4	.88	15,887
1989–98	.10	13.2	.87	16,545
1990–9	.08	15.3	.84	16,935
1991–2000	.09	9.7	.72	17,412
1992–2001	.13	13.8	.62	29,601
1993–2002	.12	19.1	.70	29,276

Table B2 Estimates for variance equation B5

10-year window	Intercept	Predicted value of ROA	Log(sales)	Log(age)	R^2 statistic
1950–9	–8.7 (–36.5)	–1.0 (–1.1)	–.02 (–0.8)	–.06 (–1.5)	.02
1951–60	–9.7 (–31.8)	–2.0 (–2.2)	–.03 (–1.6)	.18 (2.7)	.03
1952–61	–9.5 (–29.3)	–2.1 (–7.2)	–.03 (–2.3)	.08 (2.3)	.03
1953–62	–9.0 (–36.5)	–4.2 (–4.0)	–.05 (–3.3)	.11 (1.6)	.04
1954–63	–8.8 (–38.2)	–4.3 (–4.3)	–.05 (–3.5)	–.00 (–0.5)	.05
1955–64	–8.7 (–42.0)	–4.3 (–4.6)	–.05 (–2.8)	–.09 (–1.6)	.06
1956–65	–8.8 (–44.2)	–6.4 (–6.9)	–.07 (–3.7)	–.00 (–0.4)	.07
1957–66	–8.9 (–46.4)	–6.8 (–7.5)	–.08 (–4.5)	.06 (1.0)	.07
1958–67	–8.8 (–49.4)	–4.3 (–5.3)	–.08 (–4.5)	–.00 (–0.1)	.07
1959–68	–8.8 (–46.5)	–5.6 (–8.3)	–.08 (–4.5)	–.03 (–0.6)	.07
1960–9	–8.7 (–49.2)	–7.7 (–11.2)	–.07 (–4.3)	–.09 (–1.7)	.06
1961–70	–8.7 (–52.2)	–8.5 (–12.9)	–.05 (–5.0)	–.07 (–1.4)	.07
1962–71	–8.1 (–51.8)	–3.3 (–5.3)	–.07 (–4.3)	–.08 (–1.5)	.08
1963–72	–7.8 (–50.5)	–8.6 (–13.4)	–.17 (–9.1)	–.05 (–0.9)	.07
1964–73	–7.3 (–49.6)	–11.9 (–18.3)	–.16 (–8.7)	–.15 (–3.0)	.09
1965–74	–7.1 (–51.0)	–11.0 (–18.3)	–.15 (–7.5)	–.15 (–3.4)	.08
1966–75	–6.6 (–48.3)	–11.8 (–20.1)	–.13 (–6.5)	–.33 (–6.9)	.08
1967–76	–6.4 (–48.5)	–14.0 (–24.1)	–.17 (–8.5)	–.26 (–5.4)	.10
1968–77	–6.3 (–50.1)	–12.2 (–23.1)	–.19 (–10.2)	–.23 (–5.0)	.09
1969–78	–6.2 (–49.9)	–12.1 (–24.4)	–.26 (–14.2)	–.18 (–4.0)	.10
1970–9	–7.0 (–60.3)	–5.1 (–11.5)	–.12 (–7.5)	–.11 (–2.7)	.11
1971–80	–6.7 (–58.1)	–6.8 (–15.2)	–.16 (–9.9)	–.14 (–3.3)	.11

Table B2 (Continued)

10-year window	Intercept	Predicted value of ROA	Log(sales)	Log(age)	R^2 statistic
1972–81	–6.7 (–58.0)	–7.1 (–16.3)	–.18 (–11.6)	–.07 (–1.8)	.10
1973–82	–6.2 (–53.3)	–10.8 (–23.8)	–.23 (–14.7)	–.03 (–0.8)	.11
1974–83	–6.0 (–50.3)	–12.5 (–26.8)	–.26 (–17.2)	–.02 (–0.4)	.12
1975–84	–5.8 (–50.2)	–13.6 (–31.0)	–.25 (–17.0)	.00 (0.1)	.12
1976–85	–5.8 (–49.5)	–14.0 (–33.7)	–.26 (–18.1)	.04 (1.0)	.13
1977–86	–5.7 (–49.1)	–13.6 (–35.8)	–.26 (–18.4)	.04 (0.8)	.13
1978–87	–5.6 (–49.3)	–12.1 (–35.8)	–.22 (–16.4)	.01 (0.3)	.14
1979–88	–5.6 (–49.4)	–13.7 (–41.4)	–.24 (–17.9)	.03 (0.8)	.16
1980–9	–5.7 (–50.5)	–12.5 (–40.5)	–.23 (–17.6)	.03 (0.8)	.16
1981–90	–5.6 (–98.0)	–5.9 (–50.2)	–.31 (–35.5)	.01 (0.4)	.26
1982–91	–5.5 (–96.6)	–5.9 (–51.0)	–.31 (–35.1)	–.01 (–0.3)	.26
1983–92	–5.5 (–97.0)	–5.8 (–50.7)	–.28 (–33.3)	.00 (0.1)	.25
1984–93	–5.5 (–97.0)	–5.7 (–50.6)	–.29 (–34.4)	.03 (1.4)	.25
1985–94	–5.5 (–98.9)	–5.5 (–49.3)	–.30 (–35.8)	.06 (2.6)	.24
1986–95	–5.5 (–98.7)	–5.4 (–48.1)	–.31 (–37.2)	.07 (3.4)	.24
1987–96	–5.4 (–96.5)	–5.4 (–49.3)	–.30 (–36.9)	.03 (1.4)	.24
1988–97	–5.4 (–97.2)	–5.2 (–49.7)	–.31 (–38.5)	.04 (2.0)	.24
1989–98	–5.3 (–93.7)	–5.3 (–51.5)	–.28 (–35.4)	.01 (0.4)	.24
1990–9	–5.2 (–92.1)	–5.3 (–52.0)	–.29 (–35.6)	–.034 (–1.4)	.23
1991–2000	–5.1 (–92.1)	–5.1 (–52.0)	–.29 (–35.6)	–.04 (–2.6)	.24
1992–2001	–5.0 (–86.8)	–5.1 (–52.9)	–.27 (–33.0)	–.11 (–5.5)	.25
1993–2002	–5.0 (–82.9)	–4.9 (–52.9)	–.26 (–31.5)	–.12 (–6.1)	.25

Note: t-statistics in parentheses.

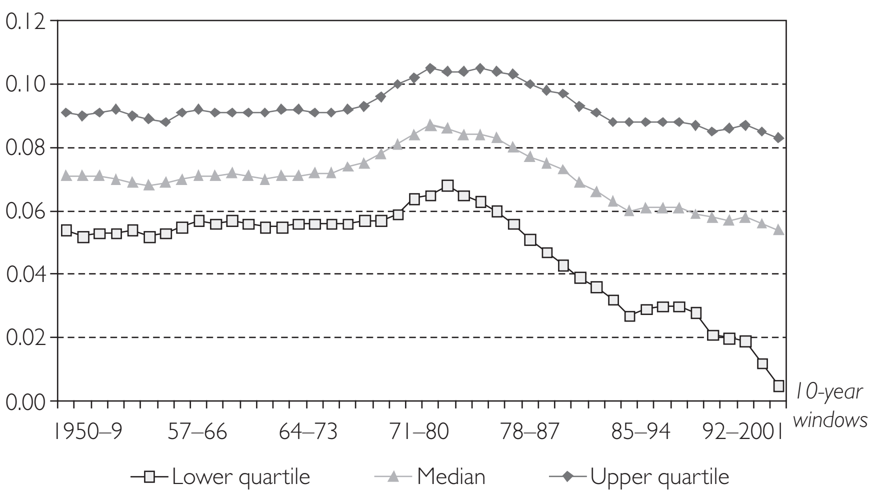

Figure B2 Quartiles across population of large, established firms for long-run performance (LRP, from Equation B2)

Figure B3 Trend over time for persistence rate (β in Equation B1)

different technical approach to the same end that examines only the positions for leading performers in an industry. They also find increased structural change over time.

Appendix C: Statistical tests for trends

All of our hypotheses examine trends. We test these hypotheses on time series data with large and potentially complex serial correlation. Our use of overlapping 10-year windows inherently accentuates any existing autocorrelation. We address this problem by using recent tests by Vogelsang (1998) that are robust to even severe autocorrelation.

We test various null hypotheses that θ_1 equals zero as follows:

(C1) $$Y_t = \theta_0 + \theta_1 t + \omega_t$$

where ω_t is a mean zero error process with important time series structure. Were we to ignore this time series structure and to estimate Equation C1 with OLS, we would obtain an artificially low standard error for our estimate of θ_1, as is well known. We would thus face potentially severe overstatement of the statistical significance of the θ_1 estimate. We deploy two tactics to correct for this problem. First, since we expect a high degree of autocorrelation, we estimate a one-period autoregressive or 'AR(1)' lag for the ω_t error process and remove this simple autocorrelation. This first tactic achieves a so-called 'pre-whitening' of the data. If this tactic fully accounts for the entire time series structure for the ω_t error process, then the remaining error term would be 'white noise' with no time series structure. Unfortunately, it is not likely that the time series structure for the ω_t error process is anything as a simple as a one-period autoregressive lag. Our second tactic, therefore, is to use conservative statistical tests for the significance of the θ_1 estimates that are 'robust' to the potential remaining time series structure of the pre-whitened data.

We pre-whiten the basic data for each trend, using a standard Prais and Winsten (1954) transformation. Specifically, we treat ω_t as following an AR(1) process:

(C2) $$\omega_t = \rho\ \omega_{t-1} + \eta_t$$

The original time series is transformed as:

(C3) $$Z_t = Y_t - \rho^*\ Y_{t-1}\ \textit{when } t > 1 \quad \text{and} \quad Z_t = \sqrt{1 - \rho^{*2}}\ Y_t\ \textit{when } t = 1$$

where ρ^* is a consistent estimate of ρ. If the ω_t error process is indeed precisely AR(1), this transformation will render the new η_t error process to be white noise. All our test statistics for time trends will be executed on these transformed data.

The underlying ω_t error process is probably far more complex than AR(1), hence the η_t error process will not in fact be white noise. Vogelsang (1998) offers several Wald-type tests for the significance of trends that are robust to complex forms of serial correlation, including non-stationary errors and lengthy lags for error autocorrelation. Vogelsang emphasizes his PS1 statistic in his work. However, this PS1 statistic is not appropriate for our study. First, when the ω_t error process is not stationary, the PS1 statistic is not powerful. Second, the PS1 statistic is additionally not powerful if the slope θ_1 changes over time. Yet, several papers on the changing nature of competition suggest an acceleration of change after 1980 (including Thomas, 1996). For both reasons, we compute and report for each time trend alternate Wald-type tests suggested by Vogelsang. There is no consensus as to which test is superior, so we will be conservative and implement two: (1) t-HAC, the heteroskedasticity and autocorrelation consistent statistic from Newey and West (1987) and Andrews (1991), and (2) t-Star, a cointegration robust statistic from Keifer et al. (2000). We also compute the J-test for unit roots proposed by Park (1990). We rely on Park's J-test for non-stationary errors for intellectual consistency since Vogelsang's test statistics frequently incorporate the computational formula for the J-test. We use these J-tests for our series to demonstrate that the expected high autocorrelation is indeed present. We supplemented the J-test with the more common Dickey and Fuller (1979) statistic – the Dickey–Fuller tests produced findings comparable to the Park J-tests, and are not reported.

These various statistical tests are performed for the hypothesized trends of the article with results reported in Table C1, and for central trends discussed in Appendix B with results reported in Table C2.

Table C1 Trend significance tests for study hypotheses

A: Time series	B: Depiction location	C: θ_1 trend estimate	D: Estimated AR(1) ρ	E: t-HAC statistic	F: t-Star statistic	G: J-test for unit root	H: Number of observations
1. Sector level total variance in annual profit deviations around firm LRPs	Figure 1	0.0014	–0.81	5.9**	13.4**	10.8	44
2. Sector level total within-industry variance for firm LRPs	Figure 1	0.0013	–0.83	5.6**	11.5**	11.4	44
3. Sector level total variance across industries in industry mean LRP	Figure 1	0.0000	–0.71	0.1	0.3	6.7	44
4. Percentage of sector total variance due to annual profit deviations around firm LRPs	Figure 2	0.0053	–0.87	1.3	1.8	19.8	44
5. Percentage of sector total variance due to within-industry differences in firm LRPs	Figure 2	0.0012	–0.91	0.9	2.0	25.1	44
6. Percentage of sector total variance due to across-industry differences for industry mean LRP	Figure 2	–0.0068	–0.85	–3.5*	–5.2*	9.9	44
7. R2 statistic for industry mean LRP as a function of within-industry traits	Figure 3, Panel A	0.0105	–0.80	4.8**	26.8**	2.0	44
8. Partial correlation across industries of industry mean LRP with within-industry heterogeneity across firm LRPs	Figure 3, Panel B	–0.0139	–0.74	–3.8**	–15.4**	2.1	44
9. Partial correlation across industries of industry mean LRP with within-industry profit shocks around firm LRPs	Figure 3, Panel C	–0.0025	–0.82	–.06	2.0	5.3	44
10. Correlation across industries of within-industry profit shocks around firm LRPs with within-industry heterogeneity across firm LRPs	Figure 3, Panel D	0.0130	–0.74	5.1**	28.7**	3.1	44

* Significant at 5 percent. ** Significant at 1 percent.
Test critical values are from Vogelsang (1998) for column E, Keifer et al. (2000) for F and Park (1990) for G.

Table C2 Significance tests for trends in Appendix B

A: Time series	B: Depiction location	C: θ_1 trend estimate	D: Estimated AR(1) ρ	E: t-HAC statistic	F: t-Star statistic	G: J-test for unit root	H: Number of observations
1. Sector persistence rate (β)	Figure B3	–0.0051	–0.62	–4.5**	–12.4**	0.9*	44
2. Sector upper quartile for firm LRPs	Figure B2	–0.0002	–0.89	–1.3	–3.5	3.7	44
3. Sector median for firm LRPs	Figure B2	–0.0004	–0.86	–2.4*	–4.8	1.6	44
4. Sector lower quartile for firm LRPs	Figure B2	–0.0011	–0.93	–5.5**	–6.8*	18.5	44

* Significant at 5 percent. ** Significant at 1 percent.
Test critical values are from Vogelsang (1998) for column E, Keifer et al. (2000) for F and Park (1990) for G.

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L. G. Thomas, III is Professor of Organization and Management at the Goizueta Business School of Emory University. Prior to joining Emory in 1991, he was on the faculty of the University of Illinois, the Graduate School of Business at Columbia University and the Stern School of Business at New York University. His research focuses on construction of the competitive advantage of firms from external factors, including technology, social forces and politics. His research has been published in *Strategic Management Journal*, *Organization Science*, *Management Science*, *Rand Journal of Economics*, *Industrial and Corporate Change* and *The Journal of Law and Economics*. His most recent book is *The Japanese Pharmaceutical Industry: The New Drug Lag and the Failure of Industrial Policy* (Edward Elgar, 2001). *Address:* Goizueta Business School, Emory University, 1300 Clifton Road, Atlanta, GA 30322-2710, USA. [email: LG_Thomas@bus.emory.edu]

Richard D'Aveni is Professor of Strategic Management at the Tuck School of Business at Dartmouth College. He has been a World Economic Forum Fellow and listed as one of the topic strategic thinkers in the world by The Thinker 50 list published by CNN, *The London Times* and *Times of India*. He has published articles in the *Academy of Management Journal*, *Administrative Science Quarterly*, *Harvard Business Review*, *Organization Science*, *Management Science*, as well as numerous other journals and major newspapers. *Address:* Tuck School of Business, Dartmouth College, Hanover, NH 03755, USA. [email: Richard.A.Daveni@dartmouth.edu]