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Published in:
Long Range Planning

DOI:
10.1016/j.lrp.2023.102328

Publication date:
2023

Document Version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
Lindskov, A., Sund, K. J., Dreyer, J. K., & Yu, J. (2023). The Regional and Temporal Nature of Hypercompetition. *Long Range Planning*, *56*(4), [102328]. https://doi.org/10.1016/j.lrp.2023.102328

Long Range Planning 56 (2023) 102328

Contents lists available at ScienceDirect

Long Range Planning

journal homepage: www.elsevier.com/locate/lrp

The regional and temporal nature of hypercompetition

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ARTICLE INFO

Keywords:
Hypercompetition
Sustainable competitive advantage
Dynamic competition
Technology-intensive sectors
Performance

ABSTRACT

Numerous scholars have suggested that the global technology-intensive sector has become hypercompetitive, yet few have tested this empirically. Those that have find seemingly conflicting evidence. Applying commonly used measures, we explore whether this could be due to hypercompetition being more time and context specific than previously thought. Based on data from the United States, Europe, Japan, and China covering 1980–2018, we find no indication of a generalized increase in business performance volatility in this sector across regions. We do find a declining stability in the performance of Japanese firms over the study period, but in US firms only leading up to the burst of the dotcom bubble. A structural break analysis helps us conclude that hypercompetition is a phenomenon limited in both location, time, and industry, linked to industry breakpoints across its life cycle.

1. Introduction

A hypercompetitive environment is associated with market instability, uncertainty, and aggressive competition (Andrevski and Ferrier, 2019). This environmental state makes it difficult for firms to sustain competitive advantages and superior performance over time (Bettis and Hitt, 1995; D'Aveni, 1994; Ilinitch et al., 1996; Wiggins and Ruefli, 2005). The central hypercompetition thesis is that a combination of technological breakthroughs and globalization trends since the 1980s have led to a rise in this kind of competition (Bettis and Hitt, 1995; D'Aveni, 1994, 1998; D'Aveni and Dagnino, 2010; Nault and Vandenbosch, 1996; Schmalensee, 2000; Thomas, 1996). Technology-intensive sectors, such as the technology hardware and equipment sectors, are among those most commonly associated with this rise in the management literature. Studies on the hypercompetition phenomenon have typically focused on investigating macroeconomic and institutional contexts within which it is said to arise (Loayza and Palacios, 1997), and to an even greater extent on the effects of hypercompetition on the organization and its strategy (e.g. Dagnino et al., 2017; Kapur et al., 2003). In uncertain, dynamic, and hypercompetitive environments, dynamic capabilities (Bragge et al., 2019; Grant,1996; Malhotra and Majchrzak, 2004), business model exploration (Egfjord and Sund, 2020; Khan and Azmi, 2005; Jensen and Sund, 2017), and increased organizational flexibility (Gallo and Gardiner, 2007; Gómez et al., 2022; Karuppan and Kepes, 2006) are said to gain in importance. But where is the evidence for hypercompetition?

Despite the notion of hypercompetition having existed for a quarter of a century, a careful examination of the literature yields a very mixed bag of empirical evidence for its existence, some consistent (Thomas, 1996; Thomas and D'Aveni, 2009; Wiggins and

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https://doi.org/10.1016/j.lrp.2023.102328
Received 7 July 2021; Received in revised form 9 May 2023; Accepted 16 May 2023
Available online 17 May 2023

Ruefli, 2005) and some inconsistent (Castrogiovanni, 2002; Lindskov et al., 2020; McNamara et al., 2003; Vaaler and McNamara, 2010) with the thesis of increasing hypercompetition. In particular, some of the foundational studies have investigated only the US manufacturing sector, and using substantially different methodologies, making it difficult to compare results (Lindskov et al., 2020). This is somewhat surprising, as so much theoretical progress has been made on strategies to survive in a hypercompetitive environment, often focused on high tech industries. Have industry-level dynamics, particularly in technology-intensive sectors, really changed towards a hypercompetitive state, as some scholars defend? And if we do not find evidence of hypercompetition, what does this mean for the growing literature theorizing about this type of competition?

In this paper, we attempt to reconcile the mixed findings by asking whether we can observe regional differences in the level of competition over time. We know that industry sectors evolve over time, and firms therefore go through different stages of competition, that may affect the performance and growth of firms (Gallo and Gardiner, 2007; Klepper, 1996; Klepper and Simons, 2000; Ozcan, 2018). Furthermore, regional differences may exist. For example, despite the global nature of the technology sector (Man et al., 1997), this sector may differ in terms of the level of competition at the regional level, because of the timing of when firms in a region entered the sector (Klepper and Simons, 2000; Man et al., 1997; Gray, 1991; Wang, 2007), and because some regions may contain firms more specialized in hardware, others in software, yet others in services. Furthermore, in the global technology-intensive industries that we examine, some firms have become meta-multinationals, for which "*country-specific advantages often have little impact on (differentiated) firm-level competitive advantage*" (Lessard et al., 2016, p. 213). However, many others remain more traditional multinational, regional, or even local firms.

Exploring evidence for the thesis of increasing hypercompetition by methodologically quasi-replicating Vaaler and McNamara (2010), we look for longitudinal trends within our sample of over 1600 firms in the sector from 1980 to 2018 in the United States, Europe, Japan, and China. These four regions have been the main contributors to the development of the technology industries (Borrus, 1982; Henisz and Macher, 2004; Kim and Kogut, 1996; Rho et al., 2015). Our results yield a mix of general and region-specific trends that are important for scholars debating the thesis of hypercompetition. On one hand, the results from our general cross-regional study reveal no general trend of increasing hypercompetition over the almost 40-year period. On the other hand, considered separately, we observe some significant regional differences. Furthermore, when searching for structural breaks in our sample, we find strong evidence of structural changes in business returns around the turn of the millennium, related to the burst of the dotcom bubble. In Japan, we find evidence of increasing competition across the entire study period. In the United States, we find evidence of declining performance stability from 1981 to 2000, indicating possible hypercompetition during that period, but not thereafter. For Europe and China, we find insufficient evidence of hypercompetition. Although we uncover a general increase in business mortality, we find no general evidence of increasing dynamism or decreasing munificence, as would be expected during hypercompetition. Overall, we therefore find it difficult to support the idea that this sector has been experiencing a systematic trend toward hypercompetition, but find some evidence of distinguishable periods of hypercompetition.

We conclude that the hypercompetition thesis, even in technology-intensive sectors, may well apply to only very specific circumstances and time periods. Similar to previous research that have examined other sectors (Lindskov et al., 2020; McNamara et al., 2003; Vaaler and McNamara, 2010), if we were asked the question of whether these technology-intensive sectors have become increasingly hypercompetitive, our general answer would therefore be “no”, but on a regional level and for shorter time periods, perhaps “yes”. This helps reconcile the conflicting results in existing studies and allows us to conclude that future studies of the phenomenon need to treat it as local and time-bound, not universal.

2. Hypercompetition and technology sectors

A hypercompetitive market is characterized by a lesser ability to sustain abnormal profits, a greater rate of firm mortality, greater industry dynamism and complexity, and lower industry munificence (Lindskov, 2022; McNamara et al., 2003; Vaaler and McNamara, 2010). Studies on hypercompetition thus suggest that competitive advantages become temporary as environmental disruptions and competitor moves become more frequent and intense (Craig, 1996; D’Aveni, 1994, 1998). The central thesis of hypercompetition scholars is that this form of competition has grown over time, making it “*increasingly difficult for firms to remain competitive due to intense rivalry, rapid technological change, and high rates of knowledge obsolescence*” (Hoisl et al., 2017, p. 1455).

This supposed shift towards hypercompetition has consequences at both the firm and industry levels, as traditional sources of competitive advantage become less durable (e.g. Andrevski and Ferrier, 2019; Bettis and Hitt, 1995; Craig, 1996; Shay and Rothaermel, 1999). Foremost, hypercompetition decreases the ability of firms to sustain superior performance (McNamara et al., 2003; Ruiz et al., 2017; Vaaler and McNamara, 2010; Wiggins and Ruefli, 2005). This thesis appears difficult to reconcile with the central premise of the resource based view of the firm that firms can build sustainable competitive advantages by identifying and developing valuable and inimitable resources (for evidence in favor of this premise see, e.g. the meta-analysis of Crook et al., 2008). Finding evidence for the existence of hypercompetition is therefore an important step not just in determining the validity of this theoretical environmental state, but also in establishing the boundaries of one of the central modern theories of strategy. Thomas (1996) suggests that hypercompetition implies a more dynamic view of resources, in which the firm rapidly develops new firm-specific resources over time.

2.1. *Existing evidence*

Table 1 outlines the few studies that have empirically investigated the thesis of increasing hypercompetition directly (Castrogiovanni, 2002; Hermelo and Vassolo, 2010; Lindskov et al., 2020; McNamara et al., 2003; Thomas, 1996; Thomas and D’Aveni, 2009; Vaaler and McNamara, 2010; Wiggins and Ruefli, 2005). Most use data from the United States. These measure variables associated with hypercompetition at firm and industry levels, such as firm performance volatility, abnormal business returns, rivalry, industry dynamism, and munificence. Findings are mixed. Thomas (1996) reports evidence of a hypercompetitive shift occurring in the manufacturing sector in the US economy from 1958 to 1991. Similarly, Wiggins and Ruefli (2005) finds evidence supporting the notion of increasing hypercompetition reflected in the decreasing ability to sustain superior financial performance for several industries over the 1978 to 1997 period. One of the more recent studies (Thomas and D'Aveni, 2009) finds an increase in within-industry heterogeneity of business returns and greater volatility in the long-run performance of publicly traded US firms in the manufacturing sector from 1950 to 2002 (Thomas and D'Aveni, 2009). These three studies indicate support for claims of increasing hypercompetition. A study by Hermelo and Vassolo (2010) suggests a trend towards hypercompetition in the emerging economies of Latin America over the 1990 to 2006 period.

Other studies are more skeptical. Castrogiovanni (2002) investigates U.S. firms in the manufacturing sector over the period 1967 to 1992 and finds only limited support for increasing dynamism and complexity over time. He observes that newer manufacturing industry environments exhibit greater dynamism and complexity compared to established industries. McNamara et al. (2003) test several performance-related hypotheses for a wide sample of U.S. firms and find no general evidence of increasing hypercompetition from 1978 to 1997. Even though the results of McNamara et al. (2003) provide no general support for the assumption of increasing hypercompetition in US firms, the authors recognize that hypercompetition could be more industry and time specific. Lindskov et al. (2020) find a lack of evidence in a smaller sample of Danish firms.

Based on the hypothesis that hypercompetition might exist mainly in technology-intensive industries, Vaaler and McNamara (2010) extend the study of McNamara et al. (2003) using both technology-intensive industries and a broader sample of non-technology-intensive industries. Their results are also inconsistent with the claims of universal increasing hypercompetition, showing no general difference between technology-intensive industries and non-technology-intensive industries. However, they do find some evidence of increasing dynamism for high-performing technology-intensive firms. Similarly, Lindskov et al. (2020) find no general evidence of increasing hypercompetition in Denmark across industries, but some industry-specific differences. In this case, the authors show that the financial and real estate sectors, as well as the retail industries, experience a higher level of competition compared to others (such as the mining industry).

The overall evidence suggests that industry dynamics of competition may be much more time, region, and industry specific than stipulated by the hypercompetition thesis. This questions D'Aveni's (1998, p. 183) argument that hypercompetition has spread to many industries such as "*the airline, pharmaceutical, financial services, health care, consumer electronics, telecommunications, broadcasting, auditing, automotive, and computer industries among many others*". Others have claimed that industries ranging from hairstylists to motorsports have become hypercompetitive over time (see e.g. Hoisl et al., 2017; Mahto et al., 2018; Mattila, 2001; Thomas and D'Aveni, 2009). The argument is not yet settled. Examining regional and time period differences may help shed important light onto the reasons behind the apparently mixed findings of existing studies.

Table 1
Studies exploring the existence of hypercompetition.

Author	Sample	Key Variables(s)	Key Findings
Castrogiovanni (2002)	U.S., manufacturing industries, 1967-92	Environmental munificence; Dynamism; Complexity.	Munificence decreases over time; Dynamism and Complexity does not increase over time; New industries do not face greater environmental munificence than established industries; New industries face greater dynamism and complexity than established industries.
Hermelo and Vassolo (2010)	Latin America, multiple industries, 1990–2006	Persistence of business returns (return on assets) of firms and industries	More persistent returns in Latin America than US; A hypercompetitive shift in the last decades; The development of institutions increases firms' rate of exit from superior performance stratum
Lindskov et al. (2020)	Denmark multiple industries, 1980–2017	Abnormal business returns; Firm survival; Industry dynamism; Munificence	No general trend of increasing hypercompetition across industries, but some industry differences.
McNamara et al. (2003)	U.S., multiple industries, 1978-97	Abnormal business returns; Business mortality; Industry dynamism; Munificence	No general evidence of increasing hypercompetition but decreasing performance from late-70s to late-80s; Trend reverses again and performance and market stability increases.
Thomas (1996)	U.S., manufacturing industries, 1958-91	Industry resourcefulness; Intra-industry performance variance; Rivalry; Growth in industry shipments and prices	Increasing industry rivalry is associated with lower market performance; Growth in shipment has no significant impact on firm value; Increased market concentration is associated with decreasing variance in performance.
Thomas and D'Aveni (2009)	U.S., manufacturing industries, 1950–2002	Volatility of profits; Industry heterogeneity	Increase in within-industry heterogeneity of business returns; Increase in volatility of firm profit; Industry effects have decreased over time; Industry volatility and within-industry heterogeneity are becoming highly correlated.
Vaaler and McNamara (2010)	U.S., multiple industries, 1978-97	Abnormal business returns; Market leadership; Business mortality; Industry dynamism	No general evidence of increasing hypercompetition, but intra-industry-specific trends. For high-performing TI firms performance stability declines over time.
Wiggins and Ruefli (2005)	U.S., multiple industries, 1978-97	Persistence of performance over time; Industry differences in the level of competition	Persistency of performance decreases over time; Hypercompetition has spread to several industries; Performance patterns have become more prevalent over time.

Although many studies name technology-intensive industries as hypercompetitive, to our knowledge only two empirically investigate and search for the phenomenon in a technology-intensive context (Vaaler and McNamara, 2010; Wiggins and Ruefli, 2005). These studies vary in their results, where one provides evidence of a decreasing ability to sustain above average business performance (Wiggins and Ruefli, 2005), while the other does not find evidence of greater performance instability over time (Vaaler and McNamara, 2010). Both only explore the US. Therefore, before labelling this sector as hypercompetitive, it is important to extend samples to cover other regions, and with more up-to-date data. Vaaler and McNamara's (2010) approach to hypercompetition, in addition to being itself based on the seminal approach to industry dynamics of Dess and Beard (1984), has the advantage of focusing on trends in real variables over time, such as ROA or survival. We thus focus on time trends in: (1) the sustainability of abnormal business performance, (2) the survival probability of firms, (3) industry dynamism, and (4) munificence.

2.2. *Unsustainable abnormal performance*

Management scholars tend to view sustainable superior economic performance as abnormal profits (Jacobsen, 1988; McNamara et al., 2003; Ruiz et al., 2017; Vaaler and McNamara, 2010), "*above-average performance in the long run*" (Porter, 1985, p. 11), or "*long-term profitability*" (Porter, 1985, p. 1), when they describe the consequences of sustained competitive advantage (Jacobsen, 1988; Porter, 1985; Ruiz et al., 2017; Wiggins and Ruefli, 2002). These profits will be affected if indeed "*competitive industries experience a constantly changing hierarchy of rates of return and therefore a less persistent return*" (Jacobsen, 1988, p. 417). Abnormal business returns thus tend to decrease and regress to the mean over time as a consequence of pressures in the competitive industry environment (Jacobsen, 1988; Mueller, 1986). Economic theory dictates that conditions such as low barriers to entry and exit, undifferentiated products, and factor mobility need to be met in such a scenario. If technology-intensive industries become hypercompetitive over time, the competitive advantages of firms become temporary, and the ability to sustain abnormal business performance will tend to decrease. This leads to a first hypothesis to be tested as follows.

Hypothesis 1. **(H1).** The ability to sustain abnormal business performance in the technology-intensive sector decreases over time

2.3. *Lower survival probability*

Why do some firms survive, while others die? Changes in the task environment has long been recognized as affecting the population density of an industry (Klepper, 2002; Utterback and Suárez, 1993). The population density reflects underlying driving forces such as technological change, level of competition, attractiveness of entry, and the structure of the industry (D'Aveni, 1998; Klepper, 2002; Utterback and Suárez, 1993). Turbulence and intensifying competition (as in hypercompetition) lead to reduced collaboration and has a negative effect on firm survival (D'Aveni, 1994; Saridakis et al., 2022; Selsky et al., 2007). As industries evolve, some firms will become stronger and adapt to the environment. Others may start to merge or leave the industry altogether (Hannan and Freeman, 1988). Anderson and Tushman (2001) find that lower survival rates are associated with dynamic environments, whereas firms can more easily survive fluctuations in munificence and increases in complexity. With the thesis of increasing hypercompetition, we expect therefore to find a decreasing survival probability over time.

Hypothesis 2. **(H2).** The survival rate of firms in the technology-intensive sector decreases over time

2.4. *Higher dynamism and lower munificence*

Three popular descriptors of industry environments are closely linked to the idea of hypercompetition. These are dynamism, munificence, and complexity (Dess and Beard, 1984). Anderson and Tushman (2001) find that lower survival rates are associated with dynamic environments, whereas firms can more easily survive fluctuations in munificence and increases in complexity. Environmental dynamism refers to the unpredictability and lack of continuity of the environment (Dess and Beard, 1984; Oliva and Suarez, 2007). Hypercompetitive industry environments are generally considered to be more turbulent, dynamic, unpredictable, and uncertain (D'Aveni, 1994; D'Aveni and Dagnino, 2010; Huff et al., 2016; King, 2013; Mahto et al., 2018; Wirtz et al., 2007). In such an environment firms must deal with constant changes. Demand is likely to fluctuate, and firms compete more intensely for customers (D'Aveni, 1998). Fast-paced technological evolution makes it more difficult for firms to sustain any kind of first mover advantage, as product categories evolve, patent advantages become limited in time, and experience curve benefits disappear (Suarez and Lanzolla, 2007). Following this rationale, as well as the lead of McNamara et al. (2003), we hypothesize that increasing hypercompetition will be associated with higher levels of dynamism but will decrease slack resources and thus munificence within the industry. The greater unpredictability brought forward by hypercompetition should thus be associated with dynamism of the industry environment (market instability).

Hypothesis 3. **(H3).** Dynamism in the technology-intensive sector increases over time

Environmental munificence refers to the capacity of the environment to support and sustain growth (Dess and Beard, 1984; Oliva and Suarez, 2007). With D'Aveni's (1998, p. 186) argument of hypercompetitive environments having an "*ever-escalating level of hostility, turbulence and uncertainty*", and firms responding with aggressive tactics, any resource and profit pools will be seized by competing firms. Therefore, our last hypothesis links the hypercompetitive environment with reducing munificence of the industry environment.

Hypothesis 4. **(H4).** Munificence in the technology-intensive sector tends to decrease over time

3. Methodology

We based our analysis on data collected from the Refinitiv Eikon (formely Thomson Reuters) database and restrict ourselves to the Technology Hardware and Equipment sector, which in this database includes the semiconductor, mobile telecommunications, and computer manufacturing industries. We relied on the industry classification in Eikon, recognizing that some very large firms in this sector are actually diversified and could possess income sources from outside the sector. We collected data for China, Japan, Europe, and the United States. Our observations of China were collected from the stock exchanges of Hong Kong, Shanghai, and Shenzhen. For Japan, we collected data from the Osaka and Tokyo stock exchanges. To represent the European region, we collected data from all possible stock exchanges in the Euro Area, including Deutsche Börse, Easdaq, Euronextlife, Xetra and SEAQ Int. Exchange. Finally, for the US, we collected data from all possible stock exchanges including NYSE and NASDAQ. The non-US observations were collected in HK Dollar, Yuan, Yen, and Euro, and these were converted into US Dollars. Although, the sector is older than this (Borrus, 1982), we were only able to collect data from 1980 onwards in this database. We thus collected 28,544 annual observations representing financial data of 1605 publicly listed firms from 1980 to 2018. We cleaned this data according to McGahan and Porter (1997), McNamara et al. (2003) and Lindskov et al. (2020) by eliminating firms with less than 6 years of data on return on assets (ROA) and those with absolute ROAs exceeding 100 percent, and we removed duplicates so each firm would only appear once. Once we had cleaned our data, we achieved a base sample of 18,918 observations representing 9406 observations from the United States, 2681 observations from Europe, 3452 observations from Japan, and 3379 observations from China.

In our methodological approach, we quasi-replicate the seminal study of Vaaler and McNamara (2010). Quasi-replication refers to a study assessing the robustness and/or generalizability of previous findings to a new population. According to Bettis et al. (2016) “these types of studies hold especially strong promise for the field of strategic management, because quasi-replications inform us about how well results hold up in multiple settings, using a variety of measures and methods”. Contrary to effects from behavioral experiments, that are often difficult to replicate in independent laboratories using the same methods, archival findings lend themselves well to quasi-replication studies such as ours, applying similar methods but to new time periods and contexts (Delios et al., 2022; Keum, 2021).

3.1. Unsustainable abnormal performance

To investigate the durability of abnormal business performance across the 39 years of our data, we use ROA, a commonly used measure (see e.g. Etiennot et al., 2019; McNamara et al., 2003; Thomas and D’Aveni, 2009; Vaaler and McNamara, 2010). In the Refinitiv Eikon datastream, Worldscope calculates ROA as the sum of net income plus interest expenses, divided by the average between the total assets of the previous and current years. We estimate a pooled regression model, where we test whether abnormally higher or lower annual business performance measured by ROA decays to the mean over time (Jacobsen, 1988; Lindskov et al., 2020; Mueller, 1986).

To test hypothesis 1, we employ a year-to-year autoregressive analysis to model ROA. We regress our dependent variable ($ROA_{i,t}$) on a constant, a one-year lagged value of our dependent variable ($ROA_{i,t-1}$), a year counter ($Year_t$) ranging from 2 (1981) to 39 (2018), a control variable representing the world economic growth ($GDPG_t$) and an error term $\varepsilon_{i,t}$. Since technology firms are strongly dependent on global demand, and to control for any international pattern in the development of competitive environment, we collected data on the world’s real Gross Domestic Product in US Dollars, calculating its yearly growth rates in percentage terms. Contrary to Vaaler and McNamara (2010), we have not included the Herfindahl-Hirschman Index (HHI) in our autoregressive model as an industry control variable, given that we are looking only at one industry, albeit a wide one. Thus, our base model to measure performance can be written as:

$$ROA_{i,t} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 YEAR_t + \beta_3 GDPG_t + \varepsilon_{i,t} \tag{1}$$

With this model, we expect the coefficient estimate of the one-year lagged ROA ($ROA_{i,t-1}$) to fall between 0 and 1.00 with a value 1.00 indicating little if any decay in the ROA from the prior year to the current year, and a value above 1 indicating an explosive time series.

We build a second model to measure whether the durability of abnormal business returns has decreased over time. This model includes a new independent variable that captures the interaction between our one-year lagged ROA and the year counter ($ROA_{i,t-1}$*$Year_t$). The interaction model can be written as:

$$ROA_{i,t} = \beta_0 + \beta_1 ROA_{i,t-1} + \beta_2 YEAR_t + \beta_3 GDPG_t + \beta_4 \left(ROA_{i,t-1} * YEAR_t\right) + \varepsilon_{i,t} \tag{2}$$

Consistent with our hypothesis 1, we predict that the interaction term ($ROA_{i,t-1} * YEAR_t$) would exhibit a negative and significant coefficient estimate, indicating an increase in the rate of decay in abnormal business returns over the 1981–2018 period. In other words, we expect a firm’s ROA in the prior year to explain less of the firm’s ROA for the current year over time. To test for regional differences, we re-estimate equations (1) and (2) with regional industry dummies, and then for each region independently.

During the past 50 years the technology-intensive sectors have seen many developments, not only technological evolutions, but also many economic and political events that may have affected both the structural level of business performance, and its stability in subsequent periods. Examples include the Asian financial crisis, the burst of the dotcom bubble, and more recently the global financial crisis in the late-2000s. A long-term analysis of performance could oversee trends in hypercompetition within different sub-periods. Therefore, we test whether the structural level of business performance of technology-intensive sectors have changed over the 38 years. If structural breaks in ROA appear, we can then redo the analysis of stability in abnormal performance accounting for this feature.

3.1.1. Identifying structural breaks

We follow Bai and Perron (1998) and test for structural stability of the mean of ROA across regions over time by fitting a constant to the mean of ROA across regions for every period of time. We use the classical empirical fluctuation CUSUM test for structural changes in the coefficients (Chambers and Hastie, 1992; Ploberger and Krämer, 1992; Wilkinson and Rogers, 1973). The time series model and the null hypothesis of the structural break test ("no break") can be written as:

$$\boldsymbol{\overline{ROA}_{it}} = \boldsymbol{\beta_t x_t'} + \boldsymbol{\varepsilon_t} \quad (\mathrm{t} = 1, \ldots, \mathrm{n})\ \boldsymbol{H_0} : \boldsymbol{\beta_t} = \boldsymbol{\beta_0} \tag{3}$$

where $\overline{ROA}_{it}$ is the mean of ROAs across regions in time period t, β_t is a vector of coefficients, x_t is a vector indicating each time period, β_0 is the constant (intercept), and ε_t is the residual.

The null hypothesis for the structural stability test is of "no structural break" against the alternative that the regression coefficient varies over time. If significant, we identify the break dates. We use the ordinary least squares (OLS) procedure proposed by Bai and Perron (1998, 2003) to determine both the number of breaks and their dates in the coefficient of our regression. Suppose there are m breaks n $(n_1, \ldots, n_m)$ in the 38-years of ROA. In this case, the problem is to identify the "optimal" breakpoints $(\widetilde{n}_1, \ldots, \widetilde{n}_m)$ that minimize our OLS-based residual sum of squares:

$$(\widetilde{n}_1, \ldots, \widetilde{n}_m) = \arg\min\ (n_1, \ldots, n_m)\ RSS_n(n_1, \ldots, n_m) \tag{4}$$

where arg min $(\mathrm{n}_1, \ldots, \mathrm{n}_\mathrm{m})$ is the argument of the minimum m breaks, and RSS_n is the resulting OLS-based residual sum of squares based on the m-regressions. This computes an arbitrary m-segment model based on Bai and Perron's (2003) *RSS* triangular matrix. The selection procedure of m breakpoints is based on the minimization of the Bayesian Information Criteria (BIC) (Bai and Perron, 2003; Zeileis et al., 2003).

In order to test for regional differences in the structural levels of the business returns, we re-run the structural break analysis for each of the regions. In this case, the same exercise is done, but with the following time series models and null hypothesis for each region j:

$$\overline{ROA}_{i_t}^{j} = \beta_t^j x_t' + \varepsilon_t^j \quad (\mathrm{t} = 1, \ldots, \mathrm{n})\ H_0 : \beta_t^j = \beta_0^j \tag{5}$$

where now $\overline{ROA}_{i_t}^{j}$ is the mean of ROA in region j in time period t and the intercept is region-specific.

3.2. Survival probability regression

To test hypothesis 2, we resort to a survival probability regression model, investigating the probability of a firm surviving the following year. We construct a dummy variable to identify when a firm exits the industry the following year (excluding the observations in the final year (2018), as we cannot determine whether the firm has survived in 2019). As a preliminary step for our regression model, we run the Kaplan-Meier probability estimate to construct our dependent variable, the survival probability. The model can be written as:

$$S_t = \frac{\mathrm{n}_t - \mathrm{Exit}_t}{\mathrm{n}_t} \tag{6}$$

where n_t is the total number of firms existing across regions in year t and $Exit_t$ is the number of firms that exit the industry in the following year. With this equation, we measure the survival probability at any given time in the study period. We regress our dependent variable (S_t) in percentage terms, on a constant, a year counter ranging from 1 (1980) to 38 (2017), an independent variable representing world economic growth (GDPG_t), and two control variables, industry density ($\mathrm{DENSITY}_\mathrm{t}$) and its quadratic form ($\mathrm{DENSITY}_\mathrm{t}^2$), and an error term $\varepsilon_{i,t}$ ... The survival probability model can be written as:

$$Survival\ Prob_t = \beta_0 + \beta_1 Year_t + \beta_2 GDPG_t + \beta_3 Density_t + \beta_4 Density_t^2 + \varepsilon_t, \tag{7}$$

where *Year* is the respective year counter, GDP is the real world GDP growth rate, DENSITY is the number of firms in year t, and $\mathrm{DENSITY}^2$ is the quadratic transformation of density used to account for nonlinear inverted U-shaped density effects on firm survival, as preconized by McNamara et al. (2003). If hypercompetition is associated with decreasing firm survival (increasing firm exit), we predict that the estimate of our year counter ($Year_t$) will be significant and negative. To check for regional differences in the survival probability, we re-estimate equation (7) for each of the regions.

3.3. Industry dynamism and munificence models

To test Hypotheses 3 and 4, we follow previous research and use a within-subjects approach to investigate dynamism and munificence using region dummies (Dess and Beard, 1984; McNamara et al., 2003; Vaaler and McNamara, 2010). We are dealing with a single industry and study the dynamism and munificence across firms within each region.[1] This leads to two regression models of (1) dynamism and (2) munificence, on regional dummies and time dummies (seven of eight possible time periods) for comparison of the overall regional dynamism and munificence scores. We start by calculating dynamism and munificence for each of our four regions and divide our sample into 8 different 5-year panels (1980-84, 1985-89, 1990-94, 1995-99, 2000-04, 2005-09, 2010–2014 and 2015–2019). We regress firm revenues, total assets and capital expenditures within a region on a year counter representing each of the five years in a panel. Total assets are defined as the sum of the current total assets, investments, net loans and other assets. Revenues are defined as the total revenues and other revenues minus the discounts, and capital expenditures are the funds used to acquire fixed assets other than acquisitions. The regressions are given by the following equations:

$$Revenues_{i,t}^{j,s} = \beta_{0,Rev}^{j,s} + \beta_{1,Rev}^{j,s} Year_t + \varepsilon_{i,t}^{j,s} \tag{8}$$

$$Total\ Assets_{i,t}^{j,s} = \beta_{0,TOA}^{j,s} + \beta_{1,TOA}^{j,s} Year_t + \varepsilon_{i,t}^{j,s} \tag{9}$$

$$Capital\ Expenditures_{i,t}^{j,s} = \beta_{0,CapEx}^{j,s} + \beta_{1,CapEx}^{j,s} Year_t + \varepsilon_{i,t}^{j,s} \tag{10}$$

where i represents each firm in the individual region j, t represents the years of our 5-year panel in each of the 8 subsamples s, Rev represents the annual revenues, TOA the annual total assets, and $CapEx$ the annual capital expenditures.

For industry dynamism, we divide the standard error of each regression by the mean of each of the dependent variables. We use the resulting value to construct a composite dynamism score for each of the regions j in each of the eight 5-year panels being examined.

$$Dynamism\ Score_t^{j,s} = \frac{\frac{\sigma_{res,Rev}^{j,s}}{\frac{\sum_{i=1}^{n_{j,t}} Rev_{i,t}}{n_{j,t}}} + \frac{\sigma_{res,TOA}^{j,s}}{\frac{\sum_{i=1}^{n_{j,t}} TOA_{i,t}}{n_{j,t}}} + \frac{\sigma_{res,CapEx}^{j,s}}{\frac{\sum_{i=1}^{n_{j,t}} CapEx_{i,t}}{n_{j,t}}}}{3} \tag{11}$$

where $\sigma_{res,Rev}^{j,s}$, $\sigma_{res,TOA}^{j,s}$ and $\sigma_{res,CapEx}^{j,s}$ are the standard errors of equations (8)–(10) for each sub-sample s and region j. n represents the total number of firms in each region j in year t. With this model, we expect to capture the volatility of the industry.

To measure munificence, we use the regression coefficients of equations (8)–(10). As with industry dynamism, we take the mean of the coefficients for three dependent variables to construct a composite measure of the munificence score for each of the regions j in each of the eight 5-year panels examined.

$$Munificence\ Score_t^{j,s} = \frac{\frac{\beta_{1,Rev}^{j,s}}{\frac{\sum_{i=1}^{n_{j,t}} Rev_{i,t}}{n_{j,t}}} + \frac{\beta_{1,TOA}^{j,s}}{\frac{\sum_{i=1}^{n_{j,t}} TOA_{i,t}}{n_{j,t}}} + \frac{\beta_{1,CapEx}^{j,s}}{\frac{\sum_{i=1}^{n_{j,t}} CapEx_{i,t}}{n_{j,t}}}}{3} \tag{12}$$

where $\beta_{1,Rev}^{j,s}$, $\beta_{1,TOA}^{j,s}$ and $\beta_{1,CapEx}^{j,s}$ are the regression coefficients of each regression on revenues, total assets and capital expenditures for each subsample s and region j. Both the dynamism and munificence scores provide an indication of their respective growth or decline in the region over the study period. We run regressions for each of the dynamism and munificence scores including regional dummies to control for possible regional differences in each of our dependent variables. Then we add time-dummies representing seven of the eight sub-panels, using the final time period 2014–2019 as base. By regressing the annual dynamism and munificence score on the time dummy variable, we can compare the resulting coefficient estimates of each of the 7 periods to the omitted time period (2014–2019).

To support hypothesis 3, we would expect the coefficients for all the time dummies in our dynamism regression model to be negative and significant with the greatest negative coefficient in the first time period (1980-84), indicating a positive time trend in dynamism over the 1980–2018 period. To support hypothesis 4, we would expect the regression coefficients of our time dummies to be positive and significant with the largest estimate in sub-panel 1 (1980-84), thus indicating a negative time trend for industry munificence over the study period.

4. Findings

To facilitate reading, both standard errors and significance levels of 0.1, 1, 5 and 10% are reported in the tables and text. Given the

[1] Contrary to McNamara et al. (2003) and Vaaler and McNamara (2010) who conducted a multi-sector single country study, we measure within-industry dynamism and munificence, because we have a single-sector but multi-region study. Our approach is thus simpler, while still following the logic. Using firm sales was our best alternative, even if this potentially raises an issue of heterogeneity. What we end up with is a type of “coefficient of variation” for dynamism, that we assume to be higher when there is more dynamism. For munificence, the higher the slopes of the regressions (beta), the more munificence.

possibility of heteroscedasticity and autocorrelation of our residuals, there could be a possibility that our coefficients are consistent, but not efficient. This in turn could bias our inference tests. In order to account for this problem, we decided to adjust our standard errors and significance tests by using a heteroscedasticity autocorrelation consistent covariance matrix (HAC). Results for the cross-regional autoregressive analyses of equation (1) are reported in Table 2 in Columns 1 and 3. Consistent with previous research (Jacobsen, 1988; Lindskov et al., 2020; McNamara et al., 2003; Vaaler and McNamara, 2010), we find that the coefficients associated with the prior performance ($ROA_{i,\ t-1}$) are significant, positive, and with a coefficient ranging from 0.5272 to 0.5365. The linear time trend for ROA is not statistically significant, except when we include regional dummies. Thus, we find no evidence that global ROA in this sector decreases with time.

The coefficients associated with economic growth are statistically significant ($p < 0.001$) and positive, logically indicating that higher economic growth tends to be associated with higher business returns. The coefficients are between 0.8506 and 0.8618.

Recall that to support hypothesis 1, we need to identify a significant increase in the decay rate of abnormal business performance over the 38 years. This means that the coefficient associated with the interaction term ($ROA_{i,t-1}$*$Year_t$) needs to be significant and negative. Results from the analyses of equation (2) are reported in Table 2 in Columns 2 and 4. The interaction term is not significant independently of controlling for regional dummies. Therefore, we find no evidence of global decreasing durability in abnormal business performance over time. The re-estimations for each region independently are reported in Table A1in the Appendix. In line with the cross-regional results, the business performance in each of the regions is influenced by its past observation. Only Japan has a negative and significant interaction coefficient ($p = 0.0650$), indicating decreasing decay in abnormal business performance over time. We infer that we have insufficient evidence to support hypothesis 1. One could question the homogeneity of our technology sector sample, given recent evidence that value migrates between parts of this sector over time (Jacobides and Tae, 2015). As a test of robustness, we broke the sample down into 8 sub-sectors and re-ran our estimations. Results (available on request) do not deviate from our initial findings.

Probing further, we test for possible structural changes using the framework of Bai and Perron (1998, 2003) to test the stability of the time series of the mean of ROA across regions from 1981 to 2018. Equation (3) reveals highly significant evidence ($p < 0.001$) of structural changes in the parameter across the 38 years. We identify three breakpoints with dates in 1985, 1999 and 2004, reported in Table 3 with their 95 percent confidence intervals (see Figure A1 in the Appendix for illustration). These could be associated with new technological developments (Yu et al., 2020) such as the PC, portable CD player and similar products released in the early to mid-1980s, the Internet in the late 1990s and the launch of companies like Ebay and Amazon, and the advent of Web 2.0 applications (e.g. the birth of Facebook, Skype and others). In a few years at the end of the 1990s more than 10,000 dotcom firms were established (Wang, 2007). March 2000 was a turning point for this excitement as the dotcom bubble burst.

As a post hoc analysis, we follow Zeileis et al. (2003) and create a plot, using two linear models: (1) with the hypothesis of no structural break and (2) with 3 breakpoints. Fig. 1 depicts the two linear models together with our dependent variable ROA in year *t*.

We can observe in Fig. 1 that the structural level of ROA completely changed around the second breakpoint, indicating that the biggest change in the structural level of business performance happens around the new millennium. Before the burst of the dotcom bubble (1981–2000), the mean of ROA was ranging between 9.15 percent and −0.71 percent, while after the bubble (2001-18) ROA changed its levels to between 2.40 percent and −7.46 percent. One could claim that the collapse in spring 2000 had a severe impact on the structural level of business returns within this technology-intensive sector. Following the principle of BIC, our model should be divided into at least two-segments to get a lower BIC than with no breaks. Therefore, we chose to divide our cross-regional model into two: before and after the burst of the dotcom bubble. To test for any possible regional difference, we redo the exercise and test for multiple breakpoints in each of the regions (equation (5)).

Our tests show significant evidence of structural changes, but with different dates in each of the regions (Table 4). For illustration, Figure A2 in the Appendix depicts the suggested *(m+1)*-segment model, a linear model with no structural break and the fluctuation process of our dependent variable ROA. Like in our cross-regional analyses, we find that the structural level of ROA in Europe and the United States has changed completely after the burst of the dotcom bubble in spring 2000. Especially the United States was affected by

Table 2
Autoregressive models across regions.

	Models without region dummy		Models with region dummy	
	Control model	Interaction model	Control model	Interaction model
Constant	−2.7473*** (0.4480)	−2.7514*** (0.4482)	−2.9097*** (0.4645)	−2.9182*** (0.4648)
Prior performance (ROA_{it-1})	0.5365*** (0.0148)	0.5364*** (0.0148)	0.5273*** (0.0146)	0.5272*** (0.0146)
Year counter ($YEAR_t$)	−0.0041 (0.0012)	−0.0039 (0.0118)	−0.0440*** (0.0125)	−0.0438*** (0.0125)
World GDP growth rate (GDP_G_t)	0.8511*** (0.0913)	0.8506*** (0.0912)	0.8618*** (0.0910)	0.8614*** (0.0910)
Interaction term (ROA_{it-1} *$YEAR_t$)		0.0002 (0.0002)		−0.0003 (0.0002)
Control variable				
Europe			2.3026*** (0.4092)	2.3073*** (0.4092)
Japan			2.2410*** (0.2871)	2.2527*** (0.2881)
China			2.3706*** (0.3666)	2.3616*** (0.3567)
F	2541.15***	1906.24***	1294.63***	1109.96***
R^2	0.2945	0.2945	0.2984	0.2985
N	18,269	18,269	18,269	18,269
n	1210	1210	1210	1210

Significance levels: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; •$p < 0.1$.
[a] Standard error terms appear in parentheses.

Table 3
OLS-based CUSUM process and *F* statistics with the corresponding test of breakpoints (Cross-regional analyses).

	Number of breakpoints	Estimated break dates	95% confidence intervals for break dates	Test statistics		Sample period
				OLS-based CUSUM process	*F*Statistics	
Across regions	3	1985 1999 2004	[1982–1986] [1997–2000] [2003–2010]	2.882***	48.186***	1981–2018

Significance levels: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; •$p < 0.1$.

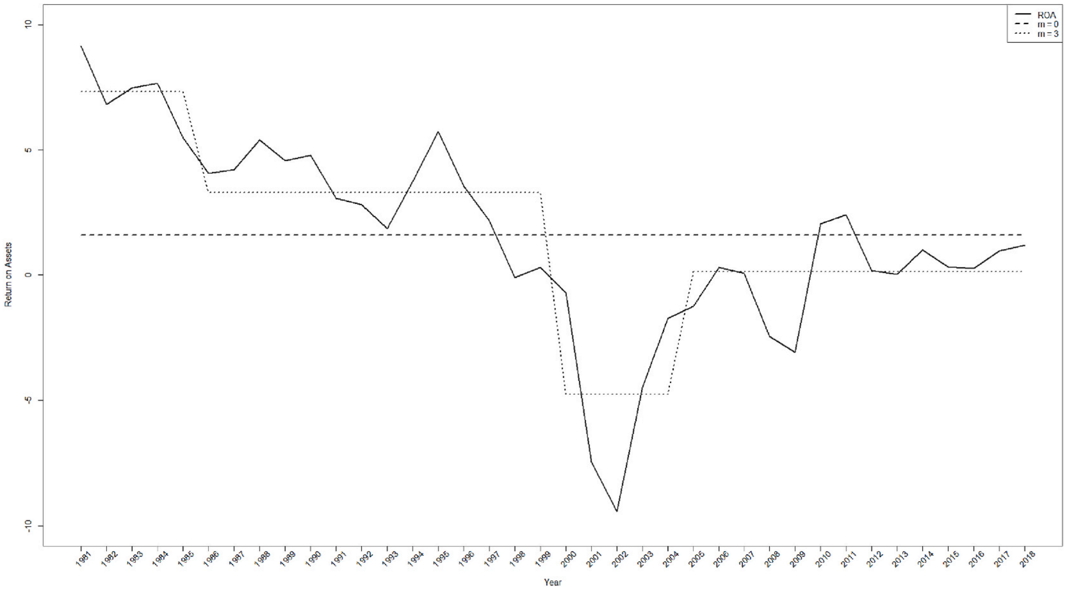

Fig. 1. The fitted models of ROA across regions.

Table 4
OLS-based CUSUM process and *F* statistics with the corresponding test of breakpoints for each region independently.

Market	Number of breakpoints	Estimated break dates	95% confidence intervals for break dates	Test statistics		Sample period
				OLS-based CUSUM process	*F*Statistics	
United States	3	1995 2000 2005	[1993–1997] [1996–2001] [2003–2012]	2.4188***	63.892***	1981–2018
Europe	2	1999 2004	[1996–2000] [2002–2010]	1.6038*	13.867**	1981–2018
Japan	4	1985 1991 2008 2013	[1984–1986] [1987–1992] [1999–2010] [2012–2017]	1.9402**	35.237***	1981–2018
China	1	1990	[1989–2001]	1.5224*	20.675***	1984–2018

Significance levels: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; •$p < 0.1$.

this collapse, as the structural level of the average of ROA changed from 4.10 percent in the 1981–2000 period to −4.30 percent in the 2001–2018 period. Japan and China were not affected in the same way as the two western regions. After several years of high growth in the 1980s, Japan was hit by a stock market and real estate bubble in the early-1990s, and the Japanese market has declined markedly ever since. Internet penetration was also lower in the late 1990s than in the US and (parts of) Europe. Thus, there is no breakpoint around the dotcom crisis. Similarly, internet penetration was very low in China at that time, although the Chinese government made reforms to boost the technology sector at that time. Over all, we find evidence of at least one structural break in each of the four regions, indicating that the structural level of ROA changes over time.

We re-estimated equations (1) and (2) for both cross-regional and regional specific samples with the dotcom bubble structural break. Results for the cross-regional analysis of equations (1) and (2) are reported in Table 5. Again, the coefficients associated with the lag of ROA for both time periods are significant, positive, and less than one, ranging from 0.4902 to 0.5335. This indicates little decay in the

Table 5
Autoregressive models for the Cross-regional sample (Estimations with Structural Breaks).

	Models without region dummy				Models with region dummy			
	Control models		Interaction models		Control models		Interaction models	
	Model 1 (1981–2000)	Model 2 (2001-18)	Model 1 (1981–2000)	Model 2 (2001-18)	Model 1 (1981–2000)	Model 2 (2001-18)	Model 1 (1981–2000)	Model 2 (2001-18)
Constant	3.0792*** (0.7330)	−11.1236*** (0.9025)	3.0791*** (0.7331)	−11.1210*** (0.9025)	3.0071*** (0.7485)	−11.4290*** (0.8981)	3.0076*** (0.7491)	−11.4290*** (0.8981)
Prior performance (ROA_{it-1})	0.4921*** (0.0250)	0.5335*** (0.0163)	0.4921*** (0.0250)	0.5335*** (0.0163)	0.4902*** (0.0250)	0.5214*** (0.0160)	0.4902*** (0.0250)	0.4661*** (0.0160)
Year counter ($YEAR_t$)	−0.2026*** (0.0341)	0.2514*** (0.0259)	−0.2025*** (0.0342)	0.2514*** (0.0259)	−0.2170*** (0.0352)	0.2098*** (0.0257)	−0.2170*** (0.0352)	0.2099*** (0.0257)
World GDP growth rate (GDP_G_t)	0.3356• (0.1886)	0.9629*** (0.0994)	0.3359• (0.1881)	0.9628*** (0.0994)	0.3463• (0.1899)	0.9628*** (0.0990)	0.3473• (0.1895)	0.9628*** (0.0989)
Interaction term (ROA_{it-1} *$YEAR_t$)			−0.00005 (0.0008)	0.0001 (0.0002)			−0.0001 (0.0008)	0.00009 (0.0002)
Control variable								
Europe					1.0678• (0.5886)	2.8841*** (0.4773)	1.0724• (0.5904)	2.8849*** (0.4775)
Japan					0.3623• (0.3441)	2.7986*** (0.3406)	0.3593 (0.3453)	2.7993 (0.3407)
China					4.2100*** (1.6651)	2.4068*** (0.3889)	4.2235*** (1.1666)	2.4002*** (0.3889)
F	513.893***	2020.6***	385.335***	1515.17***	258.8***	1035.05***	221.788***	887.154***
R^2	0.2554	0.3057	0.2554	0.3057	0.2569	0.3109	0.2569	0.3109
N	4498	13,771	4498	13,771	4498	13,771	4498	13,771
n	702	1158	702	1158	702	1158	702	1158

Significance levels: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; •$p < 0.1$.
[a] Standard error terms appear in parentheses.

return on assets from previous-to current years. For model 1 (1981–2000), we now observe negative linear time trends for ROA during the pre-bubble period ($p < 0.001$), whereas for the post-bubble period (2001-18) we observe positive linear time trends ($p < 0.001$). Coefficients associated to economic growth are like before significant and positive in both time periods ($p = 0.0752$ and $p < 0.001$).

Results for the estimation of the coefficient related to the interaction term ($ROA_{i,t\text{-}1}*Year_t$) of equation (2) are reported in Table 4 (Column 3, 4, 7 and 8). Once again, in contrast to hypothesis 1, the interaction term is not significant, showing no evidence of decay in abnormal business performance over time. We re-estimate equations (1) and (2) for the US and Europe. As there was no evidence of structural break for Japan and China during the burst of the dotcom bubble, we do not run new estimations for these two regions. Estimation results for the US and Europe individually are reported in Table A2 in the Appendix. We generally find similar results as for the cross-regional setting. However, for the US our estimate associated to the interaction term is negative and slightly significant ($p = 0.0762$), providing evidence for a decrease in the decay of abnormal business performance from 1981 to 2000. We consider this to be marginal significant evidence for the increasing hypercompetition thesis in the US during the period leading up to the dotcom bubble. Over all though, we conclude that we have insufficient support for hypothesis 1.

4.1. Survival probability models

To test for the existence of a time trend in the survival probability of firms across the four regions, we estimate equation (7). These results are reported in Table 6. Recall that to support hypothesis 2, we expect the year counter to be negative, indicating a decreasing likelihood of survival over the period.

The coefficient associated to the year counter is indeed negative and significant ($p < 0.001$), meaning that the risk of a firm exit within the industry across regions increases year-on-year by 0.15 percent. In line with previous research (Lindskov et al., 2020; McNamara et al., 2003; Vaaler and McNamara, 2010), the macroeconomic control variable representing economic growth ($GDPG_t$) is not significant. However, the industry density coefficient is positive and significant, indicating that when density increases by 1, the survival probability increases by 0.01 percent. This result is in line with Mazzucato's (2002) suggestion that new entries in the PC industry do not immediately upset the industry structure. We can conclude that our results suggest a sustained negative linear trend in the likelihood of survival in the technology-intensive sectors across regions. Re-estimations for equation (7) for each of the regions are reported in Table 7, showing decreasing survival rates for the United States, Europe, and Japan ($p < 0.001$). The survival probability of the United States has the strongest impact in time, which suggests that this region has a general higher level of competition relative to Europe, Japan and China. For China, the coefficient is negative, but not significant ($p = 0.1759$). As a post hoc analysis, we controlled for mergers and acquisitions. We calculated a relative M&A variable, defined as the annual worldwide dollar value of M&A, divided by the annual total world market capitalization. This approach avoids the problems of inflation and non-stationarity. The results of the new estimations including this M&A variable are available on request from the authors. The M&A variable is not statistically significant in any of our models and does not change the results of other variables.

To gain a better sense of trends in the survival during the 1980–2017 period, we use a structural break approach to plot the cross-regional survival probability from year-to-year in Fig. 2. Our plot reveals that the survival probability has three different structural levels: (1) 1980–1997, (2) 1998–2004 and (3) 2005–2017.

During the first period there were only 13 firm exits, while from 1998 to 2004 there were more than 100. The obvious reason to this increase in business mortality are the burst of the dotcom bubble in 2000, when many firms closed and NASDAQ fell significantly (Barbarino and Jovanovic, 2007; Wang, 2007). The later global financial crisis, the most severe since the Great Depression in the 1930s, also have an impact on the number of firm exits (Helleiner, 2011). The crisis generated a collapse in international trade, and the world economy took a downturn (Helleiner, 2011). Our results show that approximately 27 percent of the total number of firm exits happened during the 2007 to 2010 period. A majority of the firm exits in our sample are from the United States (75.24 percent), while China represents less than 2 percent. Overall, our plot reveals that the survival probability is decreasing over the 1980–2017 period, giving support to hypothesis 2.

4.2. Industry dynamism and munificence

Results from our analyses of dynamism and munificence are found in Table 8. Recall that to support our hypothesis of increasing

Table 6
Survival probability models of the cross-regional sample.

	Control model	Time model
	Cross-regional 1980–2017	Cross-regional 1980–2017
Constant	99.801*** (0.3581)	391.11*** (44.696)
Year counter ($YEAR_t$)		−0.1472*** (0.0226)
World GDP growth rate (GDP_G_t)	0.0356 (0.0338)	−0.0089 (0.0692)
Industry Density ($DENSITY_t$)	−0.0004 (0.0030)	0.0100*** (0.0024)
the quadratic trans. of the industry density ($DENSITY_t^2$)	−0.000004 (0.000003)	−0.00001*** (0.000002)
F	31.56***	60.34***
R^2	0.7357	0.8797
N	38	38

Significance levels: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; •$p < 0.1$.
[a] Standard error terms appear in parentheses.

Table 7
Survival probability models of the individual regions.

	Control models				Interaction models			
	US 1980–2017	Europe 1980–2017	Japan 1980–2017	China 1983–2017	US 1980–2017	Europe 1980–2017	Japan 1980–2017	China 1983–2017
Constant	103.77*** (2.4920)	100.31*** (0.4360)	99.43*** (0.2938)	100.6*** (0.0561)	844.46*** (91.564)	495.27*** (10.710)	283.17*** (44.331)	123.09*** (16.651)
Year counter ($YEAR_t$)					−0.3763*** (0.0464)	−0.1993*** (0.0541)	−0.0928*** (0.0224)	−0.0116 (0.0083)
World GDP growth rate (GDP_G_t)	0.1130 (0.3431)	−0.1023 (0.1226)	0.1097• (0.0585)	−0.0211 (0.0185)	0.0392 (0.1702)	−0.1201 (0.1154)	0.1088• (0.0569)	−0.0252 (0.0200)
Regional Industry Density ($DENSITY_{tk}$)	−0.0640• (0.0320)	−0.0021 (0.0304)	0.0161* (0.0063)	0.0023* (0.0011)	0.0350** (0.0101)	0.0819*** (0.0215)	0.0379*** (0.0061)	0.0038* (0.0018)
the quadratic trans. of the industry density ($DENSITY^2_{tk}$)	0.0001 (0.00006)	−0.0002 (0.0002)	−0.0001*** (0.00003)	−0.00002** (0.000006)	−0.00005** (0.00002)	−0.0005*** (0.0001)	−0.0002*** (0.00002)	−0.00002** (0.000006)
F	9.375***	12.4***	30.71***	7.788***	47.99***	18.82***	40.67***	6.041**
R^2	0.4527	0.5225	0.7305	0.4298	0.8533	0.6952	0.8313	0.4461
N	38	38	38	35	38	38	38	35

Significance levels: ***p < 0.001; **p < 0.01; *p < 0.05; •p < 0.1.
[a] Standard error terms appear in parentheses.

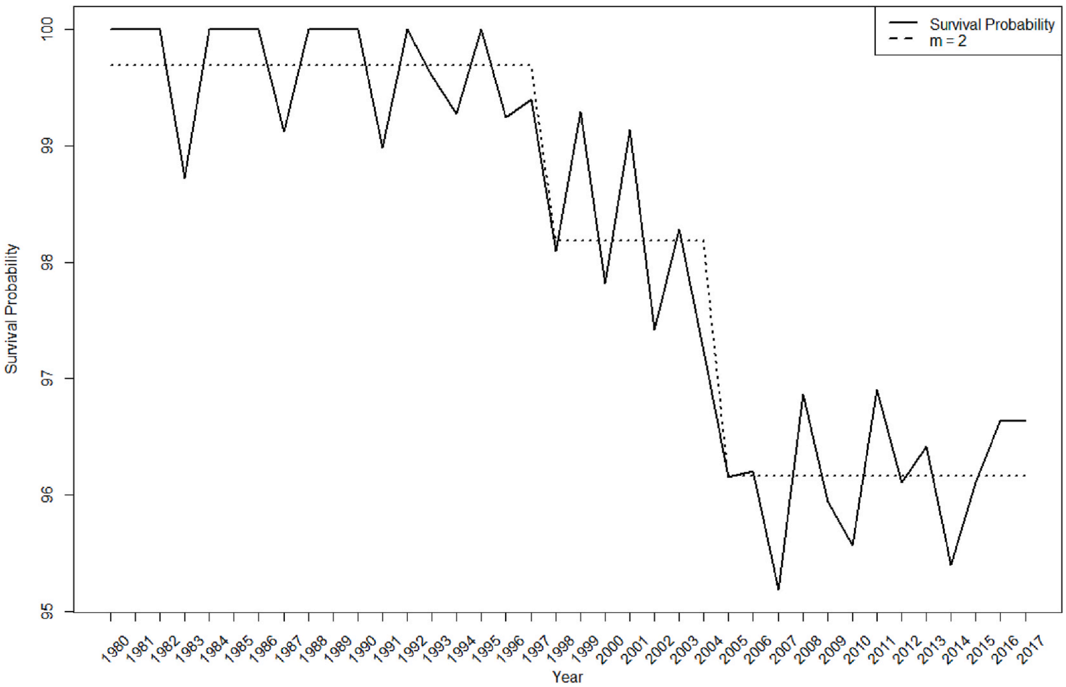

Fig. 2. Annual survival probability of firms across regions.

Table 8
The industry dynamism (instability) and munificence model.

Independent variable	Dynamism		Munificence	
	Controls only	Time model	Controls only	Time model
Constant	4.0236*** (0.000000004)	5.1958*** (0.3091)	0.0430*** (0.0000000002)	0.0843*** (0.0124)
Panel 1 (1980-84)		−3.5178*** (0.9059)		−0.0111 (0.0419)
Panel 2 (1985-89)		−2.9537** (0.8922)		−0.0210 (0.0702)
Panel 3 (1990-94)		−2.1897*** (0.5495)		−0.0608*** (0.0168)
Panel 4 (1995-99)		−1.2028*** (0.2482)		−0.0947** (0.0293)
Panel 5 (2000-04)		0.3392 (0.2527)		−0.1224*** (0.0357)
Panel 6 (2005-09)		0.0967 (0.2014)		−0.0267 (0.0270)
Panel 7 (2010-14)		0.2792*** (0.0182)		0.0042 (0.0268)
Control variable				
Europe	0.8072*** (0.00000004)	0.8080*** (0.0069)	−0.1014*** (0.0000000003)	−0.1000*** (0.0005)
Japan	−1.4686*** (0.000000004)	−1.4678*** (0.0069)	−0.0289*** (0.0000000002)	−0.0275*** (0.0005)
China	−0.8818*** (0.000000003)	−1.9523*** (0.3116)	0.0673*** (0.0000000002)	0.0760*** (0.0106)
F	12.99***	36.3554***	15.1291***	22.6687***
R^2	0.2227	0.7381	0.5398	0.3333
N	140	140	140	140

Significance levels: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; •$p < 0.10$.
[a] Standard error terms appear in parentheses.
[b] Observation 17 is excluded to correct for HAC and residual autocorrelation.

dynamism, we expect the coefficients to be negative and significant with the greatest negative estimate in the first time period (1980-84). As Column 2 of Table 8 indicates, the signs on the time period dummies from 1980 to 1999 are consistent with our predicted pattern, indicating increasing dynamism in the first 20 years studied. This trend stops in the 2000s, the coefficient becoming positive but not significant ($p = 0.1819$, $p = 0.6319$). In Time Period 7, the coefficient is again significant, but positive ($p < 0.001$), indicating a lower level of dynamism compared to the base level (2015-19). Thus, we find increasing dynamism from the 1980s to the late-1990s, but then the tendency stops, and in the early 2010s market stability increases (decreasing dynamism). Our results do not support a general trend of increasing dynamism over the entire study period and thus point to a lack of support for hypothesis 3.

Concerning hypothesis 4, our results in Column 4 of Table 8 on industry munificence yield no evidence of decreasing munificence. The largest coefficient is found in Time Period 7 (2010-14), and not in Time Period 1 (1980-84), as we anticipated for a negative time trend across the study period. The time dummy variable for Time Period 3, 4 and 5 are significant and negative ($p < 0.001$), indicating a lower level of munificence compared to the base level (2015-19). However, the magnitude for the parameter estimates are not what we anticipated for the predicted pattern of industry munificence. Over all, we are unable to conclude that there is any clear evidence of a negative time trend in munificence across the 1980–2018 period.

Looking at the regional industry differences in both dynamism and munificence, we find significant differences between regions. Europe has a significantly lower market stability ($p < 0.001$) compared to the United States, while both Japan and China have a positive and significant coefficient ($p < 0.001$), indicating a lower level of dynamism compared to the United States. Europe and Japan have a lower relative level of munificence ($p < 0.001$) than the United States, while China has a positive and significant ($p < 0.001$) coefficient, indicating a greater capacity to support growth than in the United States.

5. Discussion

The over-arching empirical conclusion of our study is that we do not find evidence to support the notion of a universal move towards hypercompetition, even in the case of the technology-intensive sector. Instead, we demonstrate that hypercompetition is a "local" phenomenon, contingent not just on specific industry contexts, but also on region, and time period. Hypercompetition cannot be assumed generalizable across time and space, even within the globalized technology sector. Where previous studies either advocate for (Hermelo and Vassolo, 2010; Thomas, 1996; Thomas and D'Aveni, 2009; Wiggins and Ruefli, 2005) or are skeptical of (Castrogiovanni, 2002; Lindskov et al., 2020; McNamara et al., 2003; Vaaler and McNamara, 2010) the existence of hypercompetition, our study to some extent helps to reconcile these opposing views. Indeed, we speculate that the industry breakpoints created by the transition from growth to maturity, to eventual decline, along the industry life cycle, as well as regional factors, will impact whether or not hypercompetition takes place. Thus, the industry life cycle stage matters to studies of competition (Karniouchina et al., 2013).

Our cross-regional findings indicate no general long-term decrease in the ability to sustain profit for firms, consistent with Lindskov et al. (2020), McNamara et al. (2003) and Vaaler and McNamara (2010). However, a closer look at the samples and time periods of previous studies shows that results could be consistent with other studies as well. If we compare our regional findings of the US with those reported by Thomas and D'Aveni (2009), Thomas (1996), and Wiggins and Ruefli (2005), there are similar patterns. These scholars find that the ability to sustain competitive advantage has decreased from the 1950s to the early-2000s in the United States. We find the same for the period before the structural break (1981–2000). However, our study of the US goes beyond the early-2000s when the evidence of increasing hypercompetition stops. Bettis and Hitt (1995, p. 8) argue that there was "*no definitive view of the landscape*" in the 1990s, as the competitive landscape was still changing. We can confirm that this was the case in this sector, and our findings indicate that a breakpoint, coinciding with the dotcom bubble, changed the structural level of business returns drastically.

Industry breakpoints are a well-known phenomenon, linked to the industry life cycle (Strebel, 1995). The technology sector as we know it today was up until the time of the structural break we identify in our analysis, in a growth stage of the industry's life cycle. Before the bubble, there was a period of decreasing ability to sustain business profit from 1981 to 2000 for US firms. The dot-com bubble represents an industry break point resulting in a shake-out (Demers and Lev, 2001). In the aftermath, the industry moved into another life cycle stage, characterized among others by M&A activity (Bauer et al., 2017) and growing standardization of products and services in the industry (Gómez et al., 2022). The evidence also points to consistently decreasing survival probability and a lower relative level of market stability in the US in the pre-breakpoint period, compared to Japan and China. Thus, the industry underwent a period of hypercompetition in the US before the turn of the millennium.

We do not find the same evidence of increasing hypercompetition in Europe, Japan, or in China, based on returns before and after the burst of the dotcom bubble. However, the survival probability analyses could support the hypothesis of decreases over time in survival rates in the US, Europe and Japan, but again with breaks as previously described. On the other hand, we see little basis for the claim of a universally increasing hypercompetition based on industry dynamism, as this increases from 1980 to 2000, but then the tendency stops, and even reverses in the early 2010s. This again suggests that hypercompetition is a local phenomenon bound in time and space, and consistent with a life cycle perspective.

Why is the breakpoint not as obvious outside the US? König et al. (2019) argue that in the period leading up to the dotcom bubble and subsequent economic recession, firms and investors poured money into untested business models, but that this behavior changed in the aftermath. Incumbents have in subsequent years played a greater role in new ventures (Egfjord and Sund, 2020; Snihur and Wiklund, 2019; Sund et al., 2021). The dotcom bubble was felt mostly in the United States, where the NASDAQ exchange exhibited a bubble from late 1998 (DeLong and Magin, 2006), that burst in a short period in early 2000. There was a spill-over effect on major European stock markets, but to a lesser extent on the Japanese market (Tsai, 2014). The subsequent recession had different effects as well. In the US, service sector productivity growth saw a dive after the dotcom bubble, while it remained stable (yet lower) in Europe (Uppenberg, 2011). The Japanese economy meanwhile exhibited low economic growth both before and after the bubble, while the Chinese economy was on a steadily increasing growth curve already before the bubble burst. In more general terms, regional industrial resilience to shocks differs according to a region's growth pattern and adaptive capability, and this is true also for the technology sectors (Holm and Østergaard, 2015). Thus, we would conclude that industry life cycle breakpoints may be experienced differently across regions.

6. Conclusion

We see several implications from our study for management research and practice. Our results demonstrate how hypercompetition is contingent on both the industry breakpoints inherent to the industry life cycle, and the local macroeconomic context. Such a contingency can help explain differences in the findings of existing studies. One of the fundamental aims of strategic management research is to investigate and explain the competitive advantage of firms and its intended results, superior economic performance. To reach and maintain such economic performance in hypercompetitive environments is said by many scholars to be difficult. Understanding the true nature of competition in an industry may be beneficial for researchers and managers alike. Some managers may start trying to fit their business model to a hypercompetitive environment, but if the market conditions are not hypercompetitive, their strategic effort to adapt to the environment may fail (Sund and Lindskov, 2022). Our results show that the technology-intensive sectors may have gone through different levels of competition both nationally and internationally through time. Short periods of volatility in firm performance and market instability should not mistakenly lead to the conclusion that this industry is hypercompetitive worldwide, and indefinitely. Equally, hypercompetition in one industry does not imply hypercompetition in another, as the theory of hypercompetition seems to predict. Therefore, we suggest that both researchers and managers stay alert to both national and international market conditions, rather than assuming a worldwide spread of hypercompetition across industries and regions.

A limitation of this research is that while one of the key characteristics of hypercompetition is temporary advantage, we are unable to directly measure the sustainability of competitive advantage, and instead measure its generally accepted consequence of abnormal profits over time. Another is that we were unable to control for mergers and acquisitions in the models, as this information was not available in the database. Therefore, in the survival probability models our dummy variable of firm exit might be overestimating the risk of firm exit. This overestimation favors the claim of increasing hypercompetition, as some firms that actually merged will appear as dead (firm exit). Thus our conclusions regarding evidence of hypercompetition in mortality data may be too optimistic.

It should also be noted that we investigate the development in the industry environment of four economies at the industry level, but we do not explore the institutional context of each. There may be further economic, political, or social differences between regions that affect competitiveness. For example, it could be that new policies or regulations implemented by the government have an impact on the firm's ability to compete both domestically and globally. In our study, we find significant evidence of regional trends, but whether these trends are triggered or influenced by the institutional context remains unanswered.

Going forward, we see different streams for future research on hypercompetition to follow. We will briefly note three. First, we see value in extending our study by including a new variable representing the R&D expenditures or a direct measure of technology and knowledge endowment. One could group the data into the R&D intensity level, and for example explore whether the survival probability of R&D-intensive firms is higher or lower than firms with low R&D expenditure. Second, there is the question of how managers of technology-intensive firms perceive the competitive environment. It may be that the nature of a hypercompetitive environment is more psychological or perceptual, as Makadok (1998) also argues. After all, the original conceptualization of hypercompetition developed during the 1990s, a time when increasing dynamism and firm mortality may have led both scholars and executives to look for an explanation of the growing difficulty in maintaining abnormal profits. The construct of hypercompetition provided such an explanation, regardless of its empirical validity.

Third, we see value in better understanding what causes a hypercompetitive environment. Our study examines the business performance implication of increasing hypercompetition from 1980 to 2018, but we do not examine the antecedents and factors causing a hypercompetitive environment. Scholars explicitly or implicitly assume that for example economic reforms, technological shifts, and globalization are the drivers of hypercompetition (Božič and Dimovski, 2019; Kulkarni and Sivaraman, 2019; Panigrahi, 2019), but the empirical evidence of what events actually trigger such a change in the environment are few. Therefore, we suggest future research to explore the important link between environmental change and hypercompetition.

We finish with a final word of caution to scholars using the hypercompetition construct, to only use this for industry contexts, locations, and time periods, when this state of the environment has been empirically established. Theorizing about a context without having established that this context really exists is misleading.

Author statement

Lindskov, Annesofie: Conceptualization, Methodology, Software, Validation, Formal Analysis, Investigation, Resources, Data Curation, Writing – Original Draft, Writing – Review & Editing, & Visualization.

Sund, Kristian J.: Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Writing – Original Draft, Writing – Review & Editing, Supervision, Project administration, and Funding acquisition.

Dreyer, Johannes K.: Methodology, Software, Formal analysis, Investigation, Resources, Data Curation, Writing – Review & Editing, Visualization, & Supervision.

Yu, Jiang: Writing – Review & Editing, Supervision, & Project Administration.

Data availability

The authors do not have permission to share data.

Acknowledgements

We are very grateful to the reviewers for their insightful comments. An earlier version was presented at the 2021 Academy of Management Conference and the Competitive Dynamics Conference 2020 (held virtually in 2021). This work was supported by the Sino-Danish Center for Education and Research.

APPENDIX

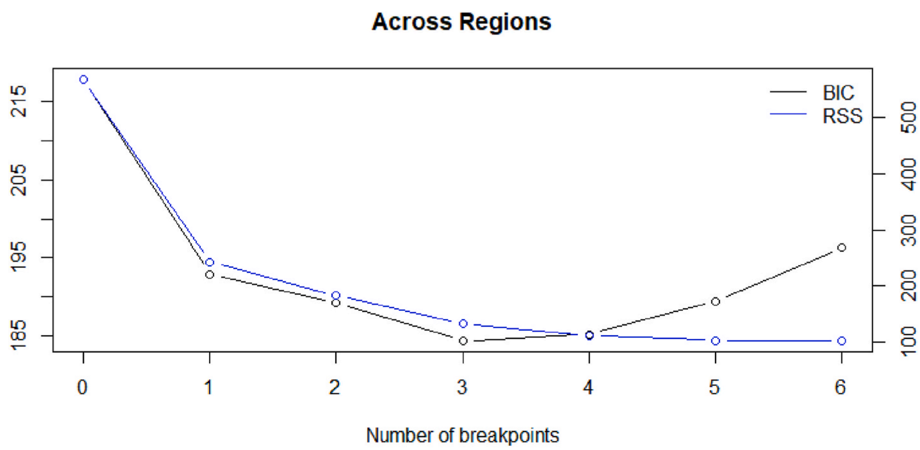

Fig. A1. BIC and RSS for our Across Region model with m breakpoint

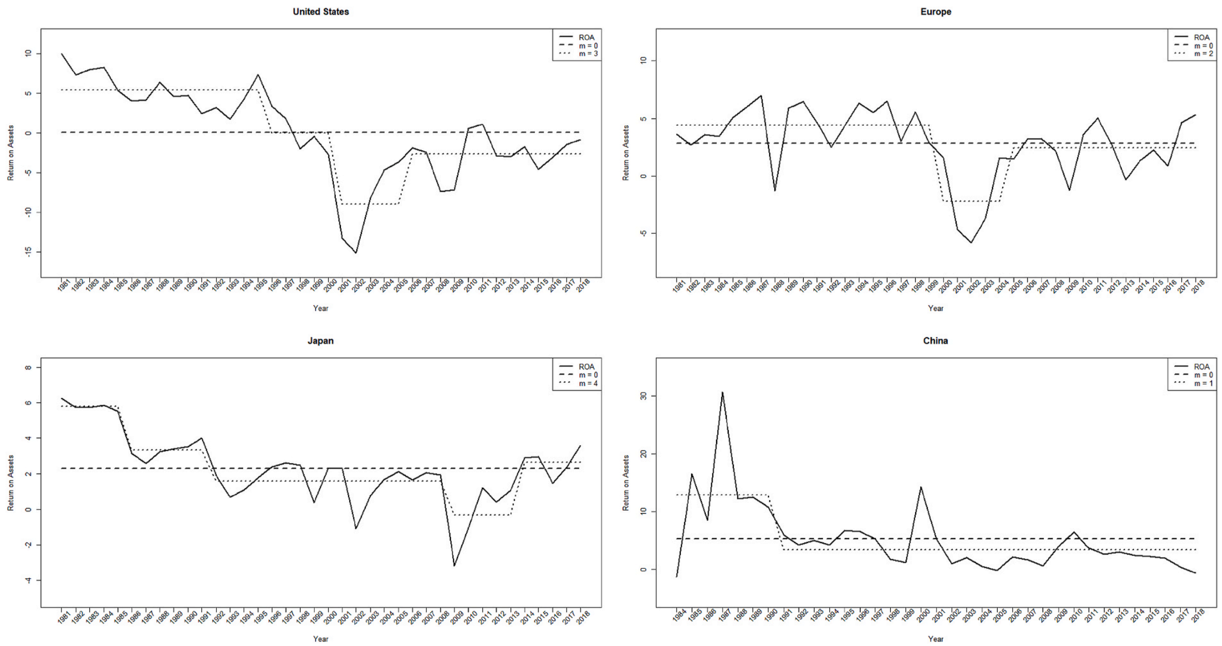

Fig. A2. Fitted models for the US, Europe, Japan and China

Table A1
Autoregressive models for each of the regions

	Control models				Interaction models			
	United States	Europe	Japan	China	United States	Europe	Japan	China
Constant	−3.0344***	−3.4021***	−1.8362***	2.8827*	−3.0503***	−3.3549***	−1.7914***	2.8741*
	(0.6953)	(0.9925)	(0.4327)	(1.3953)	(0.6951)	(0.9899)	(0.4297)	(1.4041)
Prior performance	0.5378***	0.5387***	0.5280***	0.4367***	0.5377***	0.5388***	0.5278***	0.4362***
(ROA_{it-1})	(0.0180)	(0.0323)	(0.0456)	(0.3928)	(0.0180)	(0.0322)	(0.0456)	(0.0393)
Year counter ($YEAR_t$)	−0.0817***	0.0458	0.0088	−0.0545	−0.0821***	0.0465	0.0082	−0.0566***
	(0.0194)	(0.0303)	(0.0117)	(0.0400)	(0.0195)	(0.0304)	(0.0116)	(0.0406)
World GDP growth	1.2200***	0.9686***	0.7685***	−0.1198	1.2213***	0.9602***	0.7686***	−0.1191
rate (GDP_G_t)	(0.1592)	(0.1902)	(0.1116)	(0.1879)	(0.1592)	(0.1899)	(0.1115)	(0.1880)
Interaction term					−0.0003	−0.0008	−0.0007•	0.0007
(ROA_{it-1} *$YEAR_t$)					(0.0004)	(0.0005)	(0.0004)	(0.0006)
F	1271.97***	380.173***	467.066***	256.569***	954.114***	285.675***	350.994***	192.991***
R^2	0.3032	0.3012	0.2740	0.1977	0.3032	0.3017	0.2744	0.1982
N	8774	2650	3717	3128	8774	2650	3717	3128

Significance levels: ***p < 0.001; **p < 0.01; *p < 0.05; •p < 0.1.
[a] Standard error terms appear in parentheses.

Table A2
Autoregressive models for the US and Europe (Estimations with Structural Breaks)

	United States				Europe			
	Control models		Interaction models		Control models		Interaction models	
	Model 1 1981–2000	Model 2 2001-18	Model 1 1981–2000	Model 2 2001-18	Model 1 (1981–2000)	Model 2 (2001-18)	Model 1 (1981–2000)	Model 2 (2001-18)
Constant	3.4451***	−17.3801***	3.4562**	−17.450***	5.0273*	−9.4550***	5.0307*	−9.4951***
	(0.9795)	(1.7420)	(0.9817)	(1.7383)	(1.9577)	(1.9091)	(1.9510)	(1.9212)
Prior performance	0.5003***	0.5270***	0.4990***	0.5269***	0.4643***	0.5413***	0.4634***	0.5403***
(ROA_{it-1})	(0.0260)	(0.0212)	(0.0262)	(0.0212)	(0.0837)	(0.0352)	(0.0835)	(0.0358)
Year counter ($YEAR_t$)	−0.2467***	0.3666***	−0.2458***	0.3667***	−0.1153	0.2214***	−0.1216	0.2221***
	(0.0450)	(0.0523)	(0.0450)	(0.0522)	(0.0854)	(0.0578)	(0.0847)	(0.0581)
World GDP growth	0.3420	1.4561***	0.3470	1.4529***	−0.4542	1.1525***	−0.4527	1.1525***
rate (GDP_G_t)	(0.2550)	(0.1819)	(0.2549)	(0.1823)	(0.5841)	(0.1927)	(0.5860)	(0.1927)
Interaction term			−0.0015•	−0.0006			0.0012	0.0004
(ROA_{it-1} *$YEAR_t$)			(0.0008)	(0.0004)			(0.0019)	(0.0007)
F	367.474***	840.044***	276.113***	632.825***	47.9136***	327.186***	35.9754***	245.453***
R^2	0.2678	0.3046	0.2682	0.3050	0.2075	0.3192	0.2080	0.3194
N	3018	5756	3018	5756	553	2097	553	2097

Significance levels: ***$p < 0.001$; **$p < 0.01$; *$p < 0.05$; •$p < 0.1$.
[a] Standard error terms appear in parentheses.

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