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COMPLEMENTARITY-BASED HYPERCOMPETITION IN THE SOFTWARE INDUSTRY: THEORY AND EMPIRICAL TEST, 1990–2002

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This study examines the hypercompetition phenomenon within the prepackaged software industry. It theoretically develops and empirically validates the idea that dynamically changing complementarity relationships among software product markets increase industry hypercompetition. The study also explains how dynamic capabilities for the management of complementary product markets can enable an independent software vendor (ISV) to create and renew temporary advantages. Specifically, an ISV can maintain or increase its performance rank in its product markets in three ways: (1) by competing with a portfolio of strongly complementary products; (2) by forming a product market portfolio that has strong complementarity relationships with other product markets in the industry; and (3) by dynamically and purposefully responding to the changing product market complementarities: (a) reconfiguring resource allocations of its products to strengthen the complementarities of its product portfolio and (b) undertaking entry and exit moves that reposition the portfolio in a stronger complementarity position. These dynamic capabilities enable the ISV to coevolve with the changing complementarities, change and improve its performance rank, and trigger new competitive moves by rivals; and accordingly, contribute to the escalation of rivalry in the industry. The study finds support for these ideas in a study of 1,200 ISVs from 1990 to 2002.

INTRODUCTION

A hypercompetitive industry is ‘characterized by intense and rapid competitive moves, in which competitors must move quickly to build advantage and erode the advantage of their rivals’ (D’Aveni and Gunther, 1994: 217–218). Frequent, bold, and aggressive competitive moves of rivals create a condition of constant disequilibrium and change (D’Aveni and Gunther, 1994). In *the battle for king of the hill*, challengers quickly climb performance peaks to dethrone the leaders (Ferrier, Smith, and Grimm, 1999; Smith, Ferrier, and Grimm, 2001), only to find out in a few years that *they* are dethroned by new challengers. Performance rank

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orders of firms change frequently (McAfee and Brynjolfsson, 2008).

Proponents argue that a wide range of industries has exhibited hypercompetition in recent decades (Thomas, 1996; Wiggins and Ruefli, 2005). Skeptics argue that 'hypercompetition is a self-inflicted wound, not the inevitable outcome of a changing paradigm of competition' (Porter, 1996: 61). Some studies do not find empirical evidence supporting broad-based, long-term increases in hypercompetition (Castrogiovanni, 2002; McNamara, Vaaler, and Devers, 2003). They argue that hypercompetition may be limited to a subset of high-technology industries. As this debate illustrates, the main focus of the literature has been on understanding the presence or absence of hypercompetition (Wiggins and Ruefli, 2005). We know significantly less about the factors that drive hypercompetition and how firms gain and renew temporary advantages in hypercompetitive industries. In this study, we begin addressing these questions in the context of the prepackaged software industry.

The software industry is often cited as the epitome of high-technology industries in which hypercompetition may be the most pronounced. It is characterized by high-velocity innovation (Brown and Eisenhardt, 1997), technological change (Schmalensee, 2000), and turbulence in revenues, market shares, and profits of firms (Baldwin and Clark, 2000; Schmalensee, 2000; Shapiro and Varian, 1999). However, there is lack of large sample empirical evidence concerning the presence and nature of hypercompetition in the software industry. Thus, one objective of this study is to contribute to the empirical base of the hypercompetition literature by conducting a large sample test of the presence of hypercompetition phenomenon in the software industry. Theoretical explanations about the causes of hypercompetition are also rare. The prevailing explanation is Schumpeter's notion of *gale of creative destruction*, which posits that innovation-based competition for markets will create a state of constant disequilibrium (Schumpeter, 1950). Thus, a second objective of this study is to contribute to the theoretical base of hypercompetition by explaining how and why a complex web of dynamically changing complementarity relationships among software product markets increases hypercompetition in the software industry. Finally, researchers speculate that the pursuit of sustained advantage could be a deadly distraction and that firms may be better off pursuing a continuous stream of temporary advantages when the competitive environment is relentlessly shifting (Brown and Eisenhardt, 1997; D'Aveni and Gunther, 1994; Wiggins and Ruefli, 2005). Thus, the third objective of the study is to explain how software firms or independent software vendors (ISVs) gain and renew temporary advantages in the hypercompetitive software industry.

SYSTEM-BASED COMPETITION IN THE SOFTWARE INDUSTRY

In the prepackaged software industry, products are highly complementary. Two software products are defined to be complementary when changes in activity levels of one of the products (e.g., sales, functionality, and ease of use) affect marginal returns to changes in the activity levels of the other software product as well (Milgrom and Roberts, 1990; Topkis, 1998). Complementary products mutually depend on each other and reinforce each other's performance outcomes. Customers prefer to purchase software products as a system of complements (e.g., office productivity suite as a whole) rather than as stand-alone products (e.g., word processor alone, spreadsheet alone, and presentation package alone) because software must interoperate. The value of the system is greater than the sum of values of the individual products (Tanriverdi and Lee, 2008). Customer demand for a system of complementary software products motivates ISVs to become *single-stop* shops from which customers can purchase all their complementary product needs. Thus, many ISVs enter multiple software product markets and compete on systems of complementary software products rather than stand-alone products, a phenomenon also known as system-based competition (Katz and Shapiro, 1994).

THE ECONOMIC THEORY OF COMPLEMENTARITY

The economic theory of complementarities (TOC) and the strategy research on complementarities address the nomological relationships between complementarities and firm profitability (Milgrom and Roberts, 1990, 1995; Porter and Siggelkow, 2008; Rothaermel, 2001b; Rothaermel and Hill, 2005; Tanriverdi and Venkatraman, 2005; Teece, 1986; Tripsas, 1997).

The TOC shows that the mathematical relationship between a system of complementary variables and the returns of the system is supermodular (Milgrom and Roberts, 1990; Topkis, 1995). Supermodularity means super-additive value synergies (Tanriverdi and Venkatraman, 2005). For a set of complementary software products, A and B, and starting from initial investment levels of (a, b), simultaneous, coordinated investments in both software products (a′, b′) would yield higher returns than uncoordinated investments, (a′, b) or (a, b′), into the same products. More formally, $\text{Return}(a', b') - \text{Return}(a', b) \geq \text{Return}(a, b') - \text{Return}(a, b)$. The TOC also shows that the mathematical relationship between a system of complementary variables and the costs of the system is submodular (Milgrom and Roberts, 1990). Submodularity means sub-additive cost synergies (Tanriverdi and Venkatraman, 2005). Simultaneous, coordinated investments in complementary software products A and B would yield lower costs than the sum of costs of independent, uncoordinated investments into the products: i.e., $\text{Cost}(a', b') - \text{Cost}(a', b) \leq \text{Cost}(a, b') - \text{Cost}(a, b)$. The TOC implies that an ISV, which competes on a system of complementary software products, could potentially improve its profitability through supermodular return and submodular cost advantages.

The strategy research posits that a firm can gain competitive advantages by choosing an industry position that is characterized by a complementary set of value chain activities that positively reinforce each other (Porter and Siggelkow, 2008; Porter, 1996). The resource-based view recognizes that a firm's system of complementary assets is much more valuable, rare, difficult to imitate, and difficult to substitute than the firm's stand-alone assets (Barney, 1991). Thus, a firm's system of complementary assets is viewed as an important source of competitive advantage. The strategy research also posits that the system of complementary assets required for the commercialization of an innovation raises barriers to imitation and enables the appropriation of profits from the innovation (Teece, 1986). These arguments assume that the complementarity relationships remain relatively stable over time. Thus, firms, which gain competitive advantages through complementary assets, are expected to sustain the advantages over long periods of time. However, more recent studies distinguish between industry-level and firm-level complementarities and posit that changes in industry-level complementarities could enable or inhibit performance advantages of firm-level complementarities depending on how the incumbent firm responds to the changes in the industry (Rothaermel and Hill, 2005).

In this study, we argue that rapidly changing complementarity relationships among software product markets, an industry-level phenomenon, could limit the sustainability of the advantages provided by firm-level complementarities of an ISV. Due to mutual dependencies among complementary software product markets, changes originating in one software product market can rapidly propagate to the others as well and start a domino effect in the entire industry: '...an upward or downward movement of a whole system of complementary variables [e.g., product markets], once begun tends to continue. This applies equally to the emergence and growth and to the decline and collapse of systems of complements' (Milgrom and Roberts 1995: 187). When the industry-level complementarity relationships shift significantly, e.g., due to radical technological change, they can potentially disrupt and erode the performance advantages of an ISV's system of complementary products. However, some established firms are able to survive and prosper in the face of such change (Tripsas, 1997). For example, innovative biotech firms have threatened to erode the performance advantages of established pharmaceutical firms by introducing radical technological change. However, some incumbents have responded successfully by: (1) gaining access to the new assets of the biotech firms through alliances or acquisitions (Rothaermel, 2001a), (2) reconfiguring their systems of complementary assets through the absorption of the newly acquired assets, and (3) repositioning their product portfolios through the development of new products with the reconfigured asset base (Rothaermel and Hill, 2005). Thus, we argue that an ISV's ability to gain and renew temporary advantages in the hypercompetitive software industry depends on how well it can dynamically reconfigure and reposition its firm-level complementarities in response to the changing complementarity relationships in the industry.

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HYPOTHESES

Complementarity of software product markets and hypercompetitiveness of the software industry

To assess the presence of hypercompetition in an industry, researchers examine if aggressive challengers erode market shares of market leaders and dethrone them (Ferrier *et al*., 1999; Young, Smith, and Grimm, 1996); how firm performance, firm mortality, industry dynamism, and munificence rates change over time (McNamara *et al*., 2003); if superior firm performance exists and persists over long periods of time (Wiggins and Ruefli, 2002); and how the length of time of sustained superior performance and the probability of loss of superior performance positions change over time (Wiggins and Ruefli, 2005). We build on these studies and define hypercompetitiveness of the software industry as the changes in performance rank orders of independent software vendors in their respective product markets.

Although neoclassical economics assumes relatively flat, static *performance landscapes* under conditions of perfect competition, the hypercompetition phenomenon implies rugged performance landscapes containing steep peaks and deep valleys. Thus, we build on the literature on performance and *fitness* landscapes (Wright, 1931) to explain why the performance landscape of the software industry has become more rugged over time and increased hypercompetition.

The literature on performance landscapes uses the NK model to explain how performance landscapes become more rugged as a function of choice variables (N) and the interdependencies (K) among them (Kauffman, 1993; Levinthal, 1997; Porter and Siggelkow, 2008; Rivkin, 2000). In this study, the choice variables of interest are software product markets and the interdependencies among them are the complementarity relationships. Each software product market is represented as a node, n_j, in the software industry. A product market (or node) denotes the aggregate demand for one type of product in the industry (Gimeno and Woo, 1999). For example, database management software is one type of product. There are multiple ISVs (e.g., Oracle, Sybase, and IBM) offering database management software. The aggregate demand for these database products makes up the *database product market*. We consider the ISVs offering database software as being positioned in and competing within the database product market. Similarly, ISVs offering inventory management software are positioned in and compete in the *inventory product market*. ISVs offering data mining software compete in the *data mining product market*. The complementarity relationship between a pair of software product markets, n_j and $n_{j'}(j \neq j')$, is represented with an arc[1], $k_{jj'}$. Across all product market pairs, there can exist $N^2 - N$ arcs among the nodes.

The ruggedness of the industry's performance landscape is a function of the complementarity relationships among the product markets. If there were no complementarity relationships among the software product markets, i.e., $k_{jj'} = 0$ for all pairs $(j,\ j')$, the performance landscape of the software industry would be relatively smooth and it would contain one global peak (Gavetti and Levinthal, 2000). However, as noted above, there are strong complementarity relationships among software product markets. The values of $k_{jj'}$ are usually greater than zero. As the strengths of the complementarities, i.e., the values of $k_{jj'}$, become higher, and they do so for more pairs of $(j,\ j')$, multiple local performance peaks emerge in addition to the global performance peak. Hence, the performance landscape of the industry becomes more rugged (Gavetti and Levinthal, 2000; Porter and Siggelkow, 2008).

When changes are introduced into one product market, due to mutual dependencies, they also propagate to the others through the complementarity arcs, $k_{jj'}$ and $k_{j'j}$ (Baldwin and Clark, 2000). The trigger for change could be sudden and unpredictable *gales of creative destruction* in a software product and innovation-based rivalry for the product market (Schumpeter, 1950), technological standards wars (Shapiro and Varian, 1999), shifts in customer preferences, government regulations, and so forth. Because of the changes, a performance peak representing a highly profitable product market at one point in time can swiftly turn into a performance valley representing a less profitable product market and vice versa. In addition, the growth or decline of a product market also affects the growth or decline of the complementary product markets. Thus, a change originating

[1] We use the term *arc* instead of *link* because a link is symmetric ($k_{ii'} = k_{i'i}$) whereas an arc can be symmetric or asymmetric.

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in one product market has the potential to disrupt the competitive equilibrium and change the performance rank orders of ISVs in the complementary product markets as well. Over time, as the new software product markets wax or the old ones wane, the overall number of nodes, N, in the industry changes. The changes in N, in turn, change the number and strengths of the complementarity arcs, K, among the nodes. The nodes representing performance peaks or valleys in the performance landscape dynamically shift and cause disruptions and turbulence in the performance rank orders of ISVs. Thus:

Hypothesis 1 (H_1): The software industry has exhibited greater hypercompetition over time. Performance rank orders of independent software vendors have changed significantly from one year to the next over time.

Complementarity of an ISV's product portfolio and performance rank of the ISV

In this section, we focus on firm-level complementarities and argue that, all else being equal, an ISV, which competes on a system of complementary products, can increase its performance rank in the hypercompetitive software industry.

First, competing on a portfolio of complementary products provides synergy benefits in production and consumption (Tanriverdi and Lee, 2008). Integration of a complementary set of software products requires the use of common development resources and standards to ensure compatibility, interoperability, and ease of use of the products. The use of common development resources such as application programming interface (API) sets, operating system services, design skills, experience, and know-how, creates synergies in production and reduces the overall production costs of the portfolio (Tanriverdi and Lee, 2008). An integrated portfolio of complementary products enables the ISV to serve multiple software needs of the same customer. Commonality of the customer allows the ISV to exploit the same customer knowledge and the same marketing, advertising, and sales resources across multiple products and reduce the overall marketing costs of the portfolio (Tanriverdi and Lee, 2008).

Second, competing on a system of complementary products enforces norms of mutual forbearance and enables the ISV to enjoy profitable positions for relatively longer periods of time (Young *et al*., 2000). In system-based competition, an ISV seeks to match each product in a rival's portfolio. In industries where products are interconnected, 'a product is not just a product, but is also an entry point to a broader set of products and benefits' (Korn and Rock, 2001; 64). Thus, system-based competition increases multimarket contact among ISVs. However, after a certain level, multimarket contact creates mutual forbearance effects (Baum and Korn, 1996). Rivals tacitly collude with each other, respect each others' spheres of influence in their respective product markets, avoid price wars, charge higher prices to customers, and hence, enjoy higher profits. Defections from this state of equilibrium could trigger price wars and erode profits. An ISV, which has strong complementarities in its portfolio, can credibly threaten potential defectors with retaliatory action not just in the market in which the defection occurs, but also in all complementary product markets (Greve and Baum, 2001). By enforcing norms of forbearance, it can enjoy profitability for relatively longer periods of time.

Finally, competing on a system of complementary products can raise barriers to imitation and enable the firm to appropriate profits. In addition to making the imitation of innovative aspects of the software products more difficult by increasing product co-specialization (Teece, 1986), complementarities can raise financial costs of the imitation effort. A rival has to incur significant costs to imitate the complementary products within the focal firm's portfolio. In addition, it has to switch existing customers of the focal firm to its system of complementary products. Customers will have to de-integrate their business processes from the focal firm's system of complementary software, integrate them into the rival's system, unlearn the old system, and learn the new system of complements. The network externalities created by the focal firm's system of complements raise switching costs of the customers (Farrell and Saloner, 1986). The rival has to cover all switching costs to make switching economically attractive for customers (Shapiro and Varian, 1999). Thus:

Hypothesis 2a (H_{2a}): The extent of complementarity within an ISV's existing product portfolio at time (t) increases the firm's performance rank at time (t+1).

Industry position of an ISV's product portfolio and performance rank of the ISV

The industry position of a firm is also an important determinant of the firm's performance (Porter, 1985). Thus, in theorizing about the performance rank of an ISV, we also consider how the firm's product portfolio is positioned within the overall web of complementary software product markets in the industry.

Within a complex and evolving system, such as the web of complementary product markets in the software industry, a firm's ability to benefit economically depends less on *extensive control* of all elements of the system, but on *intensive control* of the critical nodes (Baldwin and Clark, 2000). The nodes, which have higher levels of dependencies with the other nodes, are strategically and economically more important (Baldwin and Clark, 2000). Thus, we conceptualize the industry position of an ISV's product portfolio in terms of the complementarity relationships of the products inside the ISV's portfolio with all other product markets in the industry. As the ISV's products develop stronger complementarity relationships with the other product markets in the industry, the firm's product portfolio occupies a more central complementarity position in the industry. It starts creating more network externalities (Tanriverdi and Lee, 2008) and accounting for bigger shares of the overall value created in the industry. In the distribution of profits, ISVs occupying more central industry positions receive bigger shares (Teece, 1986). Thus, an ISV whose product portfolio has a strong complementarity position in the industry at time (t) is likely to increase its performance rank at time ($t + 1$).

Hypothesis 2b (H_{2b}): The extent of complementarity between an ISV's product portfolio and all other product markets within the software industry at time (t) increases performance rank of the ISV at time (t+1).

ISV's dynamic capabilities for managing complementary product markets

In the high-velocity, rapidly changing competitive environment of the software industry (Brown and Eisenhardt, 1997), industry-level complementarity relationships among software product markets do not remain static. As empirically shown in the methods section, pairwise complementarities among the software product markets change statistically significantly every year. Some product markets become more strongly complementary while others, which used to be strongly complementary, turn into weak complements. These changes affect the extent of complementarity within an ISV's product portfolio and the strength of the portfolio's complementarity position in the industry. Thus, they can potentially disrupt and erode the advantages provided by the ISV's firm-level complementarities. To maintain or improve its performance rank on an ongoing basis, the ISV needs to dynamically and purposefully respond to these changes. We build on the dynamic capabilities literature to conceptualize what types of dynamic capabilities an ISV needs to do so.

Helfat and colleagues review the literature and synthesize the various definitions of the concept of dynamic capability as follows: 'the capacity of an organization to purposefully create, extend, and modify its resource base' (Helfat *et al*., 2007; 4). Since there are many different types of dynamic capabilities, they also recommend that researchers specify which dynamic capabilities they investigate. In this study, we investigate dynamic capabilities for managing complementarity relationships among product markets. We assess the extent to which an ISV can purposefully: (1) reconfigure the resource base of its product portfolio and (2) reposition the portfolio in the industry in response to the changing complementarity relationships among software product markets. The purpose of such dynamic capabilities is to enable the ISV to continuously maintain a strongly complementary product portfolio, which occupies a central complementarity position in the industry.

ISV's ability to reconfigure resources within its product portfolio in response to changing product market complementarities in the industry

As industry-level complementarities shift, a purposeful response an ISV can develop within its product portfolio is to increase the resource allocations of products that become strongly complementary and reduce the resource allocations of products that become weakly complementary. These are two coherent resource reconfiguration moves that could enable the firm to maintain a strongly complementary product portfolio in

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the face of the shifts in industry-level complementarities. Products whose complementarity relationships become stronger need more resources because, due to stronger mutual dependencies, they require more integration, compatibility, and interoperability. The ISV also needs to coordinate its development, versioning, and customer support (Rindova and Kotha, 2001). In comparison, products whose complementarities become weaker require less integration and coordination. Thus, in reconfiguring resource allocations in the product portfolio, it is in the interest of the ISV to de-emphasize resource allocations of such products.

Intel's management of the complementarities between dynamic random access memory (DRAM) and microprocessor products provides an example of purposeful resource reconfiguration in the face of changing complementarity relationships. Intel started as a DRAM company. Later, it also introduced the microprocessor and managed the two products as a system of complements. When the two products competed for resources such as production capacity, Intel purposefully gave priority to the product that made greater contributions to the profits. Initially, DRAM was the stronger product in the system of complements. Due to its higher contributions to the profits, DRAM received more production capacity. Over time, however, as the strength of complementarity changed in favor of the microprocessor, Intel's resource allocation policy purposefully decreased production capacity allocation to DRAM and increased it for the microprocessor (Burgelman, 2002).

However, due to the challenges entailed in sensing how the industry-level complementarities are changing or in responding to the changes, some firms may develop incoherent responses such as not allocating sufficient resources to strong complements or wasting resources on weak complements. Thus, ISVs are likely to exhibit heterogeneity in their response to the changing product market complementarities in the industry. An ISV, which is able to reconfigure resource allocations to strengthen the complementarities of the portfolio, is likely to benefit from the complementarities and increase its performance rank. An ISV, which makes incoherent resource allocations, is likely to reduce the complementarities of the portfolio and, hence, decline in performance rank.

Hypothesis 3 (H_3): *Performance rank of an ISV is affected by the firm's ability to purposefully reconfigure resource allocations inside its product portfolio in response to changing product market complementarities in the industry. An ISV, which is able to increase (decrease) its emphasis on product markets that become more (less) complementary at time (t) increases its performance rank at time (t + 1).*

ISV's ability to change industry position of its product portfolio in response to changing product market complementarities in the industry

Emergence of new technological platforms such as mobile computing, video gaming, service-oriented architectures (SOA), and software as a service (SaaS) platforms create entirely new product markets and new systems of complementary software products. In system-based competition, such changes can potentially destroy the value of an existing system of complementary products and replace it with new systems (Tripsas, 1997). In the face of such change, reconfiguring resource allocations within a product portfolio may not be sufficient for an ISV to maintain or improve its performance rank. The ISV may also need to change the industry positioning of its portfolio by entering into new product markets and/or exiting from some of the existing product markets (Shapiro and Varian, 1999). The Internet, for example, was a Schumpeterian innovation (Afuah and Tucci, 2003) that engendered ISVs to reposition their product portfolios.

When new product markets emerge, it is not clear whether they will complement or substitute the products inside the existing portfolio of an ISV. Their position within the web of software product markets may not be clear either. Nevertheless, ISVs need to make these assessments and decide whether they should enter (or not) even before the emerging product markets become established and legitimated (Lee and Paruchuri, 2008).

An ISV, which has strong dynamic capabilities in managing complementary product markets, is likely to make coherent, purposeful portfolio repositioning moves and improve its performance rank. The capability enables the ISV to continuously enter new product markets that exhibit strong

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complementarities with each other and with the established product markets in the industry. Thus, the ISV can maintain strong complementarities within its product portfolio and hold a strong complementarity position in the industry. As a result, it can enjoy the advantages discussed earlier, such as synergies in production and consumption, network externalities, and mutual forbearance. It can also raise temporary barriers to the imitation of those advantages. Thus, it is likely to improve its performance rank.

Hypothesis 4 (H_4): Performance rank of an ISV is affected by the firm's ability to purposefully change the industry positioning of its product portfolio in response to changing product market complementarities in the industry.

Hypothesis 4a (H_{4a}): An ISV, which enters into product markets that exhibit high degrees of complementarity with each other at time (t), increases its performance rank at time (t+1).

Hypothesis 4b (H_{4b}): An ISV, which enters into product markets that exhibit high degrees of complementarity with all other product markets within the industry at time (t), increases its performance rank at time (t+1).

In contrast, an ISV, whose dynamic capabilities in managing complementary product markets are weak or absent, is likely to make incoherent portfolio repositioning moves and decline in performance rank. An example of an incoherent portfolio repositioning move is to exit *established* product markets, which exhibit strong complementarities with each other and with other product markets in the industry. While the term *established* may imply stability, product markets are rarely stable. Their definitions and boundaries evolve constantly as ISVs and customers try to make sense of the perpetually changing variety of software products by summarizing, classifying, and labeling their functions, attributes, uses, and benefits (Rosa, Judson, and Porac, 2005). Product markets are engendered or recalibrated by market events, environmental changes, and accompanying shifts in customer preferences (Rosa and Porac, 2002). Managers often misperceive complements as substitutes and vice versa (Siggelkow, 2002). In environments in which product markets morph continuously, understanding whether products are developing complementarity or substitution relationships becomes challenging. For an ISV, which has weak dynamic capabilities for the management of complementary product markets, these challenges are greater. The firm's probability of making mistakes goes up in classifying its existing products into product markets, distinguishing boundaries of the product markets, and identifying which ones become more or less complementary. If the firm mistakenly exits product markets, which have strong complementarities within the portfolio and with other product markets in the industry, the firm will decline in performance rank.

Hypothesis 4c (H_{4c}): An ISV, which exits from product markets that exhibit strong complementarities with each other at time (t), will decrease its performance rank at time (t+1).

Hypothesis 4 (H_{4d}): An ISV, which exits from product markets that exhibit strong complementarities with all other product markets in the industry at time (t), will decrease its performance rank at time (t+1).

METHODS

Data and sample

We test our hypotheses with a longitudinal sample of about 1,200 distinct ISVs (e.g., IBM, Microsoft, Oracle, SAP) in the prepackaged software industry (SIC 7372) from 1990 to 2002. Our primary data source is the International Data Corporation's (IDC) revenue database.[2] IDC databases are considered to be the most comprehensive sources on the computer software and hardware industries. They have been used in prior studies (Brynjolfsson and Kemerer, 1996; Cottrell and Nault, 2004; Tanriverdi and Lee, 2008).

The IDC database contains annual revenues data of public and private ISVs in each of their product markets. Revenues are further broken down by about 10 OS platforms (e.g., Windows, Unix, and Linux) on which an ISV's software products

[2] The database contains both *pure* software firms (e.g., Adobe) and multibusiness (e.g., hardware and software) firms (e.g., IBM). For multibusiness firms, the database lists revenues only for the prepackaged software segment.

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run. The database contains about 90 orthogonal product markets, which cover consumer software (e.g., productivity or Corel's WordPerfect Office Suite™); professional software (e.g., enterprise inventory management or Geac's Smartstream Inventory Management™); and developer software (e.g., unified development environments or Computer Associates' Ingress II™). Overall, the database contains approximately 700 distinct product market-OS platform pairs. This granular data enables us to examine the hypercompetition phenomenon at the product market level, the competitive locus in the software industry. The sample contains about 55,000 unique ISV-year-product market-revenue observations over the 13-year period.

We supplement the IDC database with Mergent Online, CompuStat, and Securities Data Company (SDC). We use Mergent Online to determine ISV characteristics (such as age) and compute some of the control covariates. We corroborate the IDC revenue data—after appropriate aggregation—with the Compustat segment databases for publicly traded ISVs. Finally, we use the SDC database to compute controls for ISVs' mergers and acquisitions.

Research design

This study uses a longitudinal research design in which three contiguous years of data are needed for temporally lagged measurements: $(t-1)$, (t), and $(t+1)$. We start by measuring how complementarities among software product markets change from year $(t-1)$ to year (t). Then, in year (t), we measure how an ISV responds to these changes. We examine how the ISV changes resource reconfigurations within its product portfolio and how it repositions the portfolio in the industry. We infer whether the ISV has good dynamic resource reconfiguration capabilities or not by examining the extent to which it develops coherent responses to changes in the industry level. For example, if the firm decreases (increases) its resource allocations to product markets that have become strongly (weakly) complementary, it is an incoherent (bad) resource reconfiguration response. Hence, we infer that the firm has low levels of dynamic resource reconfiguration capability. In contrast, if the firm develops a coherent (good) response by increasing (decreasing) resource allocations to product markets that have become strongly (weakly) complementary, we infer that the firm has high levels of dynamic capability. This approach avoids the fallacy of inferring dynamic capabilities from performance outcomes (Arend and Bromiley, 2009). In addition, we measure performance rank of the firm in year $(t+1)$ to test if the dynamic capabilities of the firm in year (t) subsequently affect performance rank of the firm in year $(t+1)$.

We compute some of our control variables and take benchmark measurements of the complementarity relationships among product markets of the industry in year $(t-1)$. In year (t), we compute how these industry-level complementarities have changed since $(t-1)$. We also measure the extent to which an ISV exhibits dynamic capabilities in responding to the changes. To establish the purposefulness of the firm's dynamic capabilities (Arend and Bromiley, 2009; Helfat *et al.*, 2007; Helfat and Peteraf, 2009), we measure if the firm's response seeks to maintain a strongly complementary product portfolio, which occupies a strong complementarity position in the industry. First, we measure the extent to which the ISV reconfigures resource allocations in its portfolio to emphasize (deemphasize) products that have become more strongly (weakly) complementary. Second, we measure the extent to which the ISV undertakes entry and exit moves in (t) to reposition its portfolio to a stronger complementarity position in the industry. In $(t+1)$, we measure the performance rank of the ISV. We repeat these computations over the 13-year study time frame.

Operationalization

Notation

Let $N_{i,t}$ denote ISV i's product markets at time t. The set $N_{i,t}$ *contains* all of the ISV's distinct j product markets. We subdivide ISV i's time t product markets into three non-overlapping subsets: (1) $N_{i,t}^{entry}$, (2) $N_{i,t}^{exit}$, and (3) $N_{i,t}^{existing}$. The set $N_{i,t}^{entry}$ contains ISV i's time t product market entries. If a product market j does not exist in the firm's portfolio at time $(t-1)$ but it exists at time (t), then the ISV entered j $(N_{i,t} \backslash N_{i,t-1})$. Similarly, the set $N_{i,t}^{exit}$ contains product markets exited by the ISV at time t. If a product market j is found in the ISV's time t portfolio but not in the time $t+1$ portfolio, then the ISV exited j $(N_{i,t} \backslash N_{i,t+1})$. The set $N_{i,t}^{existing}$ contains the ISV's time t product markets that are *neither* entries *nor* exits.

Dependent variable

Performance rank group of $ISV_{i,t+1}$

We measure hypercompetitiveness of the software industry with annual changes in the performance rank orders of ISVs.

We use ISVs' market shares to operationalize *performance*. Since the IDC data set lacks profitability data, we are not able to use profitability measures for all ISVs in the sample. But, as reported in the Appendix, we conduct robustness tests with a subsample of 153 ISVs for which both market share and profitability (ROA) data are available. We find that the results are qualitatively the same with the two measures. This finding confirms prior arguments that the economics of software goods make market share a very strong predictor of profitability (Shapiro and Varian, 1999). Since the market share measure is available for the full sample, we report our main results with market share.

Many ISVs operate in multiple product markets. Thus, we compute an ISV's market share by taking a weighted sum of the ISV's market shares in all software product markets in which it operates. Focusing on the ISV's product markets rather than all product markets in the industry provides a finer-grained measure of the ISV's performance. In these computations, the weights are the percentages of the ISV's total revenues coming from the different product markets. More formally, an ISV i's weighted market share score at time $t+1$ is: $\sum_j p_{ij,t+1}\left(x_{ij,t+1}/Product\ market\ size_{j,t+1}\right)$, where $p_{ij,t+1}$ is the proportion of ISV i's total revenues coming from product market j at time $t+1$, $x_{ij,t+1}$ is ISV i's revenues from product market j at time $t+1$, and *Product market size*$_{j,t+1}$ is the total revenues of product market j. The summation is over all j product markets in which the ISV operates at time $t+1$.

We operationalize *performance rank* by ordering all ISVs' time $t+1$ weighted market share scores (ROA scores in the Appendix) from highest to lowest. Using this ordering, we classify the ISVs into five performance groups: (1) lowest 20 percent; (2) low-mid 20 percent; (3) mid 20 percent; (4) mid-high 20 percent; and (5) highest 20 percent. Each performance group is numbered from 1 to 5, with 5 denoting the highest 20 percent. The results are robust to the use of more than five rank groups. We repeat these computations and rank classifications for all years.

Computation of independent variables

Pairwise complementarity of product markets$_{jj',t}$

In preparation for computing the complementarity constructs of this study, we first compute pairwise complementarity scores for all product market pairs j and j' ($j \neq j'$) in the industry at time t. Pairwise product market complementarities can be inferred from the extent to which customers purchase and use the products of the two markets together (Lemelin, 1982). One approach for assessing the extent to which customers purchase a pair of markets together is to compute the similarity of the sales patterns of the two markets (Brooks, 1995; Burt and Carlton, 1989). We use a cosine similarity metric developed by Sohn (2001) since it is commonly used in assessing interdependence between two product markets (Li and Greenwood, 2004; Tanriverdi and Lee, 2008).

We compute the complementarity of a pair of product markets using sales data of *all* ISVs that offer products in those markets at time t because a single ISV cannot offer all the products required by customers (Garud and Kumaraswamy, 1995) and sales patterns of a single ISV cannot unilaterally determine the evolution of pairwise relationships in a complex system (Baldwin, 2007). Using the entire IDC database, we compute the complementarity, $k_{jj',t}$, of a pair of product markets j and j' ($j \neq j'$) at time t, as follows: $k_{jj',t} = \dfrac{\sum_i x_{ij,t}\, min(x_{ij,t}, x_{ij',t})}{\sum_i x_{ij,t}^2}$. The sum is over all i ISVs in the industry in time t. We repeat this computation for *all* product market pairs in *all* years in our sample. The computation takes into account potential asymmetries in complementarity relationships. It recognizes that $k_{jj',t} \neq k_{j'j,t}$ because product market j may depend on product market j' more than j' depends on j or vice versa. The values of the cosine measure range from 0.0, denoting independent product markets, to 1.0, denoting highly complementary product markets. We find that 45.7 percent of the product markets in the sample are complementary, $k_{jj',t} > 0.0$, with other product markets, confirming the presence of complementarities among software product markets. Furthermore, the computation over all product market pairs captures, for a given product market j, its complementarity with all other j product markets in time t.

Complementarity within an ISV's product portfolio

We compute the extent of complementarities within an ISV i's existing product portfolio at time t, $N_{i,t}^{existing}$, by taking a weighted sum of all pairwise complementarity scores in the portfolio, or *Complementarity of* $N_{i,t}^{existing} = \sum_j \sum_{j'} p_{ij,t} k_{jj',t}$. The double sum captures the asymmetric complementarity relationships between all product market pairs. Larger values of this computation denote higher levels of complementarity within the product portfolio. We use the same approach in computing complementarities within the ISV's portfolios of newly entered (*Complementarity of* $N_{i,t}^{entry}$) and exited product markets (*Complementarity of* $N_{i,t}^{exit}$) at time t. Higher levels of *Complementarity of* $N_{i,t}^{entry}$ are observable manifestations of the firm's ability to enter strongly complementary product markets in the constantly shifting web of complementarity relationships among product markets in the industry. In contrast, higher levels of *Complementarity of* $N_{i,t}^{exit}$ indicate that the firm is not able to recognize some of the strongly complementary product markets in the industry and, hence, it exits them and forgoes their potential performance advantages.

Resource reconfiguration within ISV's product portfolio

We measure an ISV i's dynamic resource reconfiguration capability by computing the extent to which it is able make resource reallocations inside its product portfolio at time (t) in response to the changing complementarity relationships among product markets in the industry from ($t - 1$) to (t). If a firm increases (decreases) its time (t) resource allocations to product markets whose complementarities have strengthened (weakened) from ($t - 1$) to (t), we consider it a coherent response. If a firm decreases (increases) resource allocations to product markets that have become strongly (weakly) complementary, we consider it an incoherent response. First, we measure the direction of change in the strengths of complementarity of each pair of product markets in the portfolio from time $t - 1$ to t, or *Complementarity change*$_{jj',t} = \ln\left(k_{jj',t}/k_{jj',t-1}\right)$. The log of the ratio of the two values is an established computation for determining change directionality (Carroll and Hannan, 2000). If the strength of complementarities is increasing from $t - 1$ to t, the result is positive; otherwise, it is negative. Second, we measure the direction of change in the firm's resource allocation between the product markets by assessing if the sales between the pair increased or decreased. If it increased, we infer that the firm allocated relatively more resources (e.g., development and marketing resources). Formally, we compute the change in emphasis or *Emphasis change*$_{ijj',t} = \ln[\left(p_{ij,t}/p_{ij',t}\right)$. Third, we multiply *Complementarity change*$_{jj',t}$ and *Emphasis change*$_{ijj',t}$ to capture an ISV's coherent (incoherent) resource reconfiguration for a product market pair. We sum this multiplication for all product market pairs j and j' in the ISV's portfolio $N_{i,t}^{existing}$: *Resource reconfiguration in* $N_{i,t}^{existing} = \sum_j \sum_j$ *Emphasis change*$_{ijj',t}$ *Complementarity change*$_{jj't}$. A net positive sum indicates that the firm is making coherent resource reconfigurations, whereas a negative sum indicates that the firm is not making coherent reconfigurations to its portfolio in response to the changing product market complementarities in the industry.

Industry position of an ISV's product portfolio

As discussed in the theory section, we conceptualize the industry position of an ISV's product portfolio in terms of the strength of complementarity relationships between the portfolio and all other product markets in the industry. Let $N_{i,t}^{inside}$ capture the set of product markets j in the portfolio of ISV i at time t, and $N_{i,t}^{outside}$ capture all other product markets j' in the industry at time t, in which the ISV does not participate. We compute the complementarity position of the ISV i's product portfolio in the industry as the revenue weighted sum over all of the ISV i's j product markets in $N_{i,t}^{inside}$ with all other j' product markets in $N_{i,t}^{outside}$ or $\sum_j \sum_{j'} p_{ij,t} k_{jj',t}$. We use the same approach in computing complementarity positions of the ISV's portfolios of existing (*Industry position of* $N_{i,t}^{existing}$ *), entered* (*Industry position of* $N_{i,t}^{entry}$), and exited (*Industry position of* $N_{i,t}^{exit}$) product markets. Large values of these measures are observable manifestations of the firm's ability to reposition its portfolio to a more central, complementarity position in the industry in response to

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the shifting web of complementarity relationships among product markets in the industry.

Control variables

To rule out alternative explanations and minimize endogeneity concerns, we control for factors that are likely to have a bearing on our dependent variable and are likely to influence both independent and dependent variables.

Size of ISV$_{i,t}$

Size can influence firm performance. Large firms offer more extensive product lines, have more synergy exploitation opportunities, and suffer more from managerial diseconomies. We control for an ISV i's size at time t, $ln(Size_{i,t})$, by taking the log of its total revenues.

Age of ISV$_{i,t}$

Firm age could be associated with firm performance. We compute an ISV i's *age* at time t, $ln(Age_{i,t})$, as the log of the difference between time t and the ISV's founding.

Count of an ISV's mergers and acquisitions$_{i,t}$

Acquisitions at time t could affect an ISV's performance rank at time $t + 1$. Thus, we control for the total number of acquisitions, $M\&A\ count_{i,t}$, completed by an ISV at time t.

Growth level of an ISV's product portfolio$_{i,t}$

The growth level of the product markets in which the ISV operates could affect performance rank of the ISV and some of the independents (e.g., $Emphasis\ change_{ijj',t}$). Thus, we control for growth level of an ISV's product portfolio. First, we compute the growth level for each product market j in the industry at time t or $Product\ market\ growth_{j,t} = ln\left(\frac{Product\ market\ size_{j,t}}{Product\ market\ size_{j,t-1}}\right)$ (Carroll and Hannan, 2000). Second, we compute the growth level of an ISV's product portfolio by taking a revenue weighted sum of the growth levels of all product markets j in the ISV i's product portfolio: $Growth_{i,t} = \sum_j p_{ij,t}\ Product\ market\ growth_{j,t}$.

Density level of an ISV's product portfolio$_{i,t}$

Product market density is an industry structure variable that can impact firm performance (Carroll and Hannan, 2000). We control for the density level of an ISV's product portfolio. First, we compute a count of the firms found in each product market j in time t: $Product\ market\ ISV\ count_{j,t}$. Second, we compute the density level of an ISV's product portfolio by taking the revenue weighted sum of the densities of the ISV's product markets j or $Density_{i,t} = \sum_j p_{ij,t}\ Product\ market\ ISV\ count_{j,t}$. A large value denotes a highly dense product portfolio.

Concentration level of an ISV's product portfolio$_{i,t}$

Industry and product market concentration are structural covariates that can impact a firm's performance (Wiggins and Ruefli, 2005). Thus, we control for concentration level of an ISV's product portfolio. First, we compute the top four concentration ratio for each product market in the industry at time t or $Product\ market\ concentration_{j,t} = Revenues\ of\ Top\ 4\ ISVs_{j,t}\ (Product\ market\ size_{j,t})^{-1}$. Second, we compute the concentration level of an ISV's product portfolio by taking a revenue weighted sum of concentration levels of all product markets j in the ISV i's product portfolio: $Concentration_{i,t} = \sum_j p_{ij,t}\ Product\ market\ concentration_{j,t}$. A large value denotes a highly concentrated product portfolio.

Diversification level of an ISV's product portfolio

Diversification level of a firm's product portfolio can affect the firm's performance rank by creating scope economies. We control for the total diversification level of an ISV's product portfolio by computing the entropy measure of total diversification (Palepu, 1985) for all product markets j in the portfolio: $\sum_j p_{ij,t} ln(p_{ij,t}^{-1})$. We control for diversification levels of $N_{i,t}^{existing}$ or *Diversification* ($N_{i,t}^{existing}$), $N_{i,t}^{entry}$ or *Diversification* ($N_{i,t}^{entry}$), and $N_{i,t}^{exit}$ or *Diversification* ($N_{i,t}^{exit}$).

Network effects of an ISV's product portfolio

Network effects of the product markets in which the ISV operates could potentially improve the

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performance rank of the firm by increasing customers' switching costs, locking out rivals from competition (Katz and Shapiro, 1994; Parker and Van Alstyne, 2005), and enabling the firm to charge higher prices (Brynjolfsson and Kemerer, 1996). Different network effects among different product markets could also affect independent covariates (e.g., *Emphasis change*$_{ijj',t}$). Thus, we control for network effects of product markets in the firm's portfolio. Building on prior research, we use market share as a measure for network effects (Brynjolfsson and Kemerer, 1996). First, we compute market share of each product market in the prepackaged software industry at time t, *Product market share*$_{j,t}$ = *Product market size*$_{j,t}$(*Industry size*$_t$)$^{-1}$. Then, we compute network effects of an ISV's portfolio by taking a revenue weighted sum of network effects of all product markets in the firm's portfolio, $\sum_j p_{ij,t}$ *Product market share*$_{j,t}$. We use the same approach in computing controls for *Network effects of* $N_{i,t}^{existing}$, *Network effects of* $N_{i,t}^{entry}$, and *Network effects of* $N_{i,t}^{exit}$. Large values denote large network effects.

Count of product markets in an ISV's product portfolio

The extent of complementarity within a product portfolio could be sensitive to the number of product markets. Thus, we control for the number of product markets in the firm's existing (*Count of* $N_{i,t}^{existing}$), entered (*Count of* $N_{i,t}^{entry}$), and exited (*Count of* $N_{i,t}^{exit}$) product portfolios at time t.

Prior performance rank group of ISV$_{i,t}$

Controlling for firm's prior year performance is common in tests of hypercompetition (McNamara *et al.*, 2003). Thus, we control for an ISV's performance rank group in the previous year.

Year dummies$_t$

Finally, we include year dummies for all years in our study period. They control for industry-level effects that are not captured by the controls described above, such as technological innovations in the software industry over time.

Table 1 presents descriptive statistics and zero-order correlations of the study variables.

Model specification

We use a pooled longitudinal ordered logistic regression design. It estimates the time $t + 1$ probability of an ISV being in one of the five performance rank groups as a function of the ISV's time t response to the changing product market complementarities in the industry, and the firm's characteristics at t.

$$Pr(y_{i,t+1} = m|x_{i,t}, \beta, \tau) = F(\tau_m - x_{i,t}\beta) - F(\tau_{m-1} - x_{i,t}\beta)$$

The dependent variable, ISV i's time $t + 1$ performance rank, is an ordinal, ordered variable numbered m = 1, . . ., 5 for each of the five rank groups (lowest 20% to highest 20%); τ is the cutoff vector for the five rank groups; $x_{i,t}$ is the variables vector capturing strategic responses and characteristics of the ISV i at time t; β is the coefficient vector; and F is the logistic function. Ordered logistic regression is a generalization (Greene, 2003; Long, 1997) of the traditional logistic regression used in prior studies (e.g., Wiggins and Ruefli, 2005). The five states of an ISV's time $t + 1$ performance rank are estimated simultaneously. Because the ordered logistic regression fits a log distribution, it models the distribution tails (i.e., highest and lowest performers which are of key interest in this study) better than ordinary least squares regression. Estimating ISV's performance rank ordinally rather than cardinally (i.e., market share) leads to some information loss, but it reduces reliance on the Gaussian assumption and, thus, increases accuracy (Wiggins and Ruefli, 2005).

RESULTS

Before presenting the formal statistical results, we present some descriptive statistics to assess the face validity of our arguments about the extent of complementarity relationships in the software industry and their impacts on the competitive dynamics of the industry.

Descriptive results

The number of distinct ISVs in the industry increased 14-fold during our study time period (1990 to 2002). The number of distinct product markets (nodes N) in the industry increased more than seven-fold. The complementarity arcs

Table 1. Means, standard deviation, and zero-order correlations

	1	2	3	4	5	6	7	8	9	10	11	12
1. ln ($Size_{i,t}$)	1.00											
2. ln ($Age_{i,t}$)	0.52	1.00										
3. M&A $count_{i,t}$	0.36	0.15	1.00									
4. $Growth_{i,t}$	0.00	−0.14	0.02	1.00								
5. $Density_{i,t}/10$	−0.14	−0.13	−0.04	−0.19	1.00							
6. $Concentration_{i,t} \times 100$	0.22	0.17	0.09	0.17	−0.47	1.00						
7. Diversification level of $N_{i,t}^{entry}$	0.08	0.05	0.04	0.06	−0.08	0.07	1.00					
8. Diversification level of $N_{i,t}^{existing}$	0.53	0.49	0.20	−0.12	−0.07	0.12	0.01	1.00				
9. Diversification level of $N_{i,t}^{exit}$	0.16	0.05	0.05	0.22	−0.11	0.13	0.11	−0.03	1.00			
10. Network effects of $N_{i,t}^{entry} \times 10$	0.20	0.23	0.01	−0.01	0.11	−0.03	0.08	0.14	0.11	1.00		
11. Network effects of $N_{i,t}^{exit} \times 10$	0.15	0.09	0.05	−0.11	0.41	−0.14	−0.10	0.07	−0.11	0.42	1.00	
12. Network effects of $N_{i,t}^{existing} \times 10$	0.05	−0.02	0.00	0.09	0.02	0.03	0.05	−0.08	0.39	0.14	−0.04	1.00
13. Count of $N_{i,t}^{entry}$	0.39	0.29	0.16	0.09	−0.10	0.15	0.08	0.28	0.53	0.22	0.01	0.17
14. Count of $N_{i,t}^{exit}$	0.31	0.24	0.12	0.01	−0.10	0.13	0.45	0.26	0.11	0.16	−0.01	0.03
15. Count of $N_{i,t}^{exiting}/100$	0.51	0.44	0.23	−0.07	−0.09	0.16	0.03	0.48	0.02	0.17	0.08	−0.03
16. Prior performance rank $group_{i,t}$	0.00	−0.25	0.04	0.29	0.00	−0.04	0.01	−0.15	0.13	−0.11	−0.12	0.10
17. Complementarity within $N_{i,t}^{existing}$	0.18	0.20	0.10	−0.14	0.05	0.01	−0.16	0.31	−0.23	0.06	0.17	−0.16
18. Industry position of $N_{i,t}^{existing}$	0.10	0.11	−0.02	0.00	−0.18	0.27	0.08	0.14	0.11	0.26	0.31	0.08
19. Resource reconfiguration in $N_{i,t}^{existing}/100$	−0.24	−0.18	−0.12	−0.01	0.05	−0.09	−0.03	−0.27	−0.05	−0.10	−0.03	0.01
20. Complementarity within $N_{i,t}^{entry}$	−0.04	−0.07	−0.01	0.07	−0.03	0.02	0.48	−0.15	0.03	0.04	−0.13	0.00
21. Industry position of $N_{i,t}^{entry}$	−0.07	0.06	−0.07	0.14	−0.37	0.19	0.08	0.01	0.08	0.33	−0.28	0.00
22. Complementarity within $N_{i,t}^{exit}$	0.00	−0.06	−0.01	0.27	−0.09	0.09	0.05	−0.18	0.43	0.01	−0.15	0.41
23. Industry position of $N_{i,t}^{exit}$	−0.13	−0.15	0.00	−0.02	0.24	−0.34	−0.07	−0.16	−0.10	−0.31	−0.40	−0.09
Mean	3.20	1.60	0.32	0.24	0.48	65.82	0.06	0.79	0.11	0.01	0.48	0.03
S.D.	1.79	0.81	1.13	0.39	0.50	13.57	0.18	0.68	0.26	0.01	0.66	0.16

Table 1. (*Continued*)

	13	14	15	16	17	18	19	20	21	22	23
13. Count of $N_{i,t}^{entry}$	1.00										
14. Count of $N_{i,t}^{exit}$	0.37	1.00									
15. Count of $N_{i,t}^{existing}$/100	0.45	0.44	1.00								
16. Prior performance rank group$_{i,t}$	0.05	−0.02	−0.09	1.00							
17. Complementarity within $N_{i,t}^{existing}$	0.18	0.19	0.44	−0.10	1.00						
18. Industry position of $N_{i,t}^{existing}$	0.09	0.07	0.06	−0.08	0.02	1.00					
19. Resource reconfiguration in $N_{i,t}^{existing}$/100	−0.40	−0.31	−0.36	−0.04	−0.41	−0.02	1.00				
20. Complementarity within $N_{i,t}^{entry}$	−0.01	0.20	−0.06	0.03	−0.23	0.05	0.01	1.00			
21. Industry position of $N_{i,t}^{entry}$	0.08	0.06	0.02	−0.03	0.00	0.10	−0.03	0.08	1.00		
22. Complementarity within $N_{i,t}^{exit}$	0.29	0.01	−0.06	0.21	−0.30	0.05	−0.02	0.05	0.05	1.00	
23. Industry position of $N_{i,t}^{exit}$	−0.11	−0.08	−0.11	0.12	−0.05	−0.47	0.04	−0.03	−0.13	−0.07	1.00
Mean	1.26	0.69	0.06	3.00	0.80	0.11	−0.01	0.04	0.08	0.07	0.40
S.D.	3.80	2.52	0.13	1.41	0.55	0.07	0.06	0.15	0.07	0.20	0.13

N = 4, 513 with 1,005 firms; absolute correlation $\geq$ 0.03 significant at $p < 0.05$ or greater due to large sample size.

among the nodes, K, increased more than four-fold, indicating that an average product market started interacting about four times more strongly with the other product markets. Thus, building on the predictions of the NK models, we can conclude that the performance landscape of this industry has become more rugged over the years. As noted above, 45.7 percent, i.e., almost one-half of all pairwise complementarity scores among the product markets, are greater than zero. This means that the web of software product markets is approaching a *mesh* network in which each product market is connected to every other product market through a complementarity relationship. We also assess whether these complementarity relationships have changed significantly year over year, as claimed. First, we use the pairwise complementarity scores of each possible product market pair in the industry in each year to create a distribution of pairwise complementarities for year t. Then, we repeat this computation to generate complementarity distributions for all years in the sample. For each year, we nonparametrically test the significance of the changes between the complementarity distributions in years t and $t + 1$. As Table 2 shows, the changes in pairwise complementarity relationships in the industry are statistically significantly for every year. These findings provide face validity to our argument that the web of complementarity relationships among product markets is changing significantly from year to year and that it is potentially a source of disruption and turbulence in performance rank orders of ISVs.

Table 2. Statistical test of annual changes in pairwise complementarity relationships between product markets

Start year	End year	Kolmogorov Smirnov
1991	1992	0.15†
1992	1993	0.14**
1993	1994	0.18***
1994	1995	0.10**
1995	1996	0.17***
1996	1997	0.06*
1997	1998	0.11***
1998	1999	0.05*
1999	2000	0.05*
2000	2001	0.07***

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

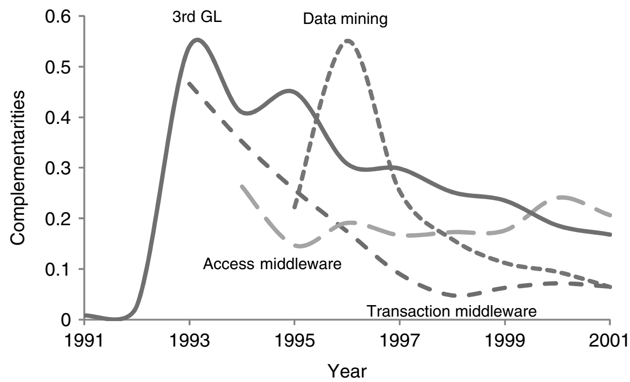

Figure 1. Changes in the importance of industry positions of four product markets (complementarities with all other product markets in the industry)

As the web of complementarity relationships changes significantly from year to year, the industry positions and attractiveness of individual product markets also change. As noted above, we measure industry position of a product market by examining its pairwise complementarity relationships with all other product markets in the industry. Figure 1 illustrates how the industry positions of four product markets, i.e., 3rd GL, data mining, access middleware, and transaction middleware, shifted over time. For example, the 3rd GL product market increased its importance in the industry by developing stronger complementarities with other product markets within about a year, from 1992 to 1993. In a few years however, its complementarities with other product markets weakened significantly. Similarly, the data mining product market rapidly increased its centrality within about a year (1995 to 1996), but it also rapidly lost it in the subsequent time period.

Statistical results

As presented in Table 3, we use hierarchically nested models to test our hypotheses. Model 1 is the base model containing the study's control covariates. Model 2 adds prior performance rank group of an ISV. Models 3 through 5 add the ISV's existing, entered, and exited product portfolios covariates, respectively. Models 6 and 7 present further details on the incremental predictive power of some of the study's covariates. All models are estimated with the sandwich variance estimator (White, 1982) to correct for possible correlations between the multitime observations of the same ISV. Post-estimation marginal effects and discrete change analyses (Long, 1997), required with nonlinear estimation methods such as ordered logit, confirm the direction and significance of the reported coefficients.

All models are statistically significant. Adding covariates of interest significantly add to the explanatory power of the model at levels better than $p < 0.05$ (i.e., Models 2–5). Adding the covariates for existing product portfolio (i.e., Model 3) increases model fit (29.86, $p < 0.001$) above that of the control model (i.e., Model 2). Adding the covariates for entered product markets (i.e., Model 6) and exited product markets (Model 7) also improves the model fit above the baseline (11.69, $p < 0.01$ and 36.79, $p < 0.001$). The control covariates are significant even in the presence of theoretical variables of interest, suggesting that we included relevant and important control variables. Finally, the Brant test for proportionality assumption violations is not significant ($p > 0.10$) in all seven models (Brant, 1990).

Test of Hypothesis 1 (H_1)

H_1 states that the software industry has exhibited greater hypercompetition over time and that the performance rank orders of ISVs have changed significantly from one year to the next. We test H_1 by using Model 1. All year dummies in this model are significant, indicating that the performance rank orders of the ISVs have indeed changed statistically significantly every year. To better understand the specific nature of the changes, we depict the results pictorially in Figure 2. We set the covariates in the model to their yearly means and use the coefficients of the year dummies to plot the time

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Table 3. Ordered logistic regression results (dependent variable = performance rank group of $ISV_{i,t+1}$)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
ln ($Size_{i,t}$)	0.06*	0.03	0.10***	0.02	0.11***	0.02	0.10***	0.02	0.10***	0.02	0.09***	0.02	0.10***	0.02
ln ($Age_{i,t}$)	−0.42***	0.06	−0.31***	0.05	−0.31***	0.05	−0.31***	0.05	−0.31***	0.05	−0.31***	0.05	−0.31***	0.05
$M\&Acount_{i,t}$	0.08**	0.03	0.07**	0.02	0.06*	0.03	0.06*	0.03	0.06*	0.03	0.06**	0.03	0.07**	0.02
$Growth_{i,t}$	0.86***	0.11	0.46***	0.09	0.43***	0.09	0.44***	0.10	0.44***	0.10	0.47***	0.09	0.46***	0.09
$Density_{i,t}/10$	0.01*	0.01	0.01†	0.01	0.01†	0.01	0.01†	0.01	0.01†	0.01	0.01†	0.01	0.01†	0.01
$Concentration_{i,t} \times 100$	0.06†	0.04	0.07*	0.04	0.09*	0.04	0.08*	0.04	0.08*	0.04	0.07†	0.04	0.07†	0.04
Diversification level of $N_{i,t}^{entry}$	0.23	0.15	0.17	0.16	0.09	0.16	0.17	0.17	0.15	0.18	0.25	0.16	0.11	0.18
Diversification level of $N_{i,t}^{existing}$	−0.11	0.07	−0.06	0.06	−0.07	0.06	−0.05	0.06	−0.04	0.06	−0.03	0.06	−0.04	0.06
Diversification level of $N_{i,t}^{exit}$	2.26***	0.29	2.36***	0.29	2.33***	0.29	1.43***	0.32	1.56***	0.33	1.43***	0.33	2.47***	0.29
Network effects of $N_{i,t}^{entry} \times 10$	3.10***	0.67	3.21***	0.63	3.13***	0.62	2.80***	0.63	3.29***	0.63	2.86***	0.64	3.73***	0.63
Network effects of $N_{i,t}^{exit} \times 10$	−0.01	0.16	−0.16	0.16	−0.18	0.16	−0.11	0.15	−0.12	0.15	−0.09	0.15	−0.16	0.16
Network effects $N_{i,t}^{existing} \times 10$	0.05	0.06	0.03	0.05	0.01	0.06	0.00	0.05	0.00	0.05	0.04	0.05	0.03	0.05
Count of $N_{i,t}^{entry}$	0.02†	0.01	0.01	0.01	0.02*	0.01	0.02*	0.01	0.02*	0.01	0.02†	0.01	0.01	0.01
Count of $N_{i,t}^{existing}/100$	0.80*	0.32	0.81**	0.27	0.33	0.54	0.26	0.55	0.10	0.54	0.65*	0.27	0.68*	0.28
Count of $N_{i,t}^{exit}$	−0.02	0.01	−0.02	0.01	−0.02	0.01	−0.01	0.01	0.01	0.01	−0.01	0.01	0.01	0.01
Prior performance rank $group_{i,t}$			0.08***	0.02	0.08***	0.02	0.08***	0.02	0.08***	0.02	0.08***	0.02	0.08***	0.02

Table 3. (*Continued*)

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Year 1992	−0.32†	0.18	−0.28†	0.17	−0.24	0.30	−0.24	0.30	−0.25	0.30	−0.25	0.30	−0.27	0.30
Year 1992	−0.32†	0.18	−0.28†	0.17	−0.24	0.30	−0.24	0.30	−0.25	0.30	−0.25	0.30	−0.27	0.30
Year 1993	−1.01***	0.23	−0.68**	0.22	−0.62**	0.22	−0.66**	0.23	−0.66**	0.23	−0.71**	0.23	−0.69**	0.22
Year 1994	−0.82***	0.23	−0.65**	0.23	−0.63**	0.22	−0.66**	0.22	−0.68**	0.23	−0.69**	0.23	−0.67**	0.23
Year 1995	−1.09***	0.24	−0.89**	0.24	−0.74**	0.24	−0.77**	0.24	−0.78**	0.24	−0.81**	0.24	−0.81**	0.24
Year 1996	−1.86***	0.24	−1.70**	0.22	−0.65**	0.22	−0.68**	0.22	−0.69**	0.22	−0.73**	0.22	−0.71**	0.22
Year 1997	−1.91***	0.23	−1.70**	0.22	−0.65**	0.22	−0.67**	0.22	−0.68**	0.22	−0.72**	0.22	−0.71**	0.22
Year 1998	−1.80***	0.22	−1.58**	0.21	−0.53*	0.21	−0.54**	0.21	−0.54**	0.21	−0.59**	0.21	−0.58**	0.21
Year 1999	−1.75**	0.22	−1.55**	0.21	−0.49*	0.21	−0.50*	0.21	−0.50*	0.21	−0.55**	0.21	−0.55***	0.21
Year 2000	−1.64**	0.22	−1.45*	0.21	−0.40†	0.21	−0.40†	0.21	−0.40†	0.21	−0.44***	0.21	−0.44**	0.21
Year 2001	−1.43*	0.21	−1.33†	0.20	−0.29	0.20	−0.29	0.20	−0.29	0.20	−0.32†	0.20	−0.33†	0.20
H2a. Complementarity within $N_{i,t}^{existing}$					0.09†	0.06	0.08	0.06	0.09†	0.05				
H2b. Industry position of $N_{i,t}^{existing}$					0.03*	0.01	0.03*	0.01	0.03*	0.01				
H3. Resource reconfiguration in $N_{i,t}^{existing}/100$					0.90*	0.35	0.86*	0.34	0.78*	0.30				
H4a. Complementarity within $N_{i,t}^{entry}$							0.26*	0.11	0.25*	0.11	0.28*	0.11		
H4b. Industry position of $N_{i,t}^{entry}$							0.41***	0.09	0.38***	0.09	0.41***	0.09		
H4c. Complementarity within $N_{i,t}^{exit}$									−2.10***	0.53			−2.50***	0.49
H4d. Industry position of $N_{i,t}^{exit}$									−0.01	0.04			−0.03	0.04
df	25		26		29		31		33		28		28	
Wald χ^2			(2)-(1)		(3)-(2)		(4)-(3)		(5)-(4)		(6)-(2)		(7)-(2)	
Models	454.51***		658.99***		688.85***		702.42***		710.31***		670.68***		695.78***	
$\Delta\chi^2$			204.48***		29.86***		13.57**		7.89*		11.69**		36.79***	

† $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; N = 4, 513 with 1,005 firms.

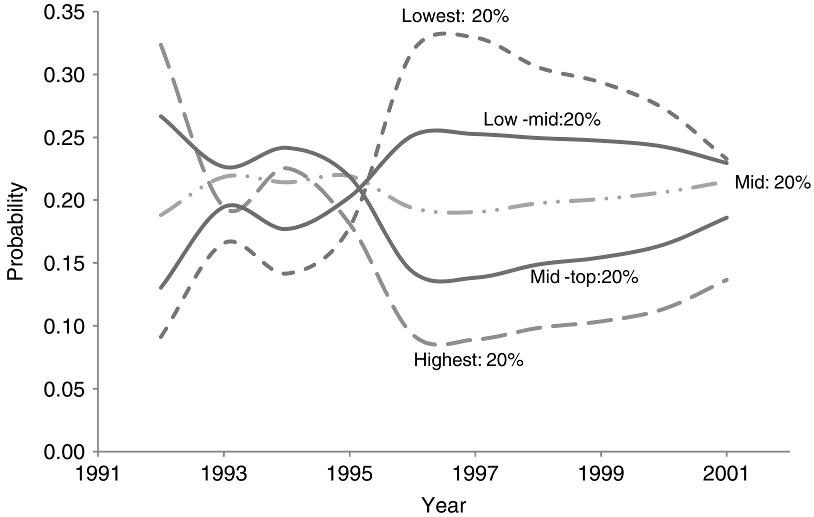

Figure 2. Changes in probabilities of an ISV being classified into one of the five performance rank groups at time $t + 1$, 1991–2001

($t + 1$) probability of an ISV being classified into one of the five performance rank groups (Long, 1997). We use year 1991 as the baseline.

As Figure 2 shows, the probability of an ISV being classified into one of the $t + 1$ performance rank groups does not remain static over time. If the software industry were *not* hypercompetitive, the probabilities for each of the five performance rank groups would have remained relatively stable, would not have had any inflexion points (i.e., peaks or valleys), or they would not have intersected with one another. However, Figure 2 illustrates that there *are* inflexion points and intersections. Consider the probability of an ISV of being in the highest 20th percentile at $t + 1$. Starting with the baseline value in 1991, the probability of being in the top 20 percent in year 1992 is 32 percent; it declines to 9 percent by 1996 and it slowly increases to 14 percent in 2001. These findings suggest that it has become more challenging for ISVs to be classified into the highest 20 percent performance rank group over time. In contrast, the probability of an ISV being classified into the lowest 20th percentile performance rank group increases from 9 percent in 1992 to 33 percent in 1996 and *settles* above the probability for modal performance rank in 2001 (i.e., 23%). The probability for being in the mid 20 percent performance rank group also shows a downward slope, suggesting that even maintaining modal performance becomes less likely for ISVs from 1992 to 2001. The overall patterns of the probabilities of the five rank groups suggest that the industry experienced significant turbulence in performance rank orders of firms in the mid-1990s. This is attributable to the advent of the Internet, which is considered to be a Schumpeterian innovation (Afuah and Tucci, 2003) that has fundamentally altered the competitive landscape and the web of complementarities in the software industry. Thus, H1 is supported.

We also retested H_1 using the autoregressive modeling approach of some prior studies (McNamara *et al.*, 2003). In Model 2, we replaced an ISV's time t and $t + 1$ *Performance rank group* with its time t and $t + 1$ *Market share*; and we used an *Industry clock*$_t$ instead of the year dummies. Then, we ran a fixed-effects panel regression to assess the decay rate of market share positions of ISVs as a function of the industry clock. The regression model is significant ($R^2 = 0.29$, $F = 42.70^{***}$). The interaction of *Industry clock*$_t$ and *Prior market share*$_{i,t}$ is negative and significant (−0.02, $p < 0.01$), suggesting significant decay of the ISVs' market share positions over time. This result affirms the support for H1.

Test of Hypothesis 2 (H_2)

H_2 argues that the extent of complementarities inside an ISV's product portfolio (H_{2a}) and the industry position of the portfolio (H_{2b}) at time

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t will improve performance rank of the ISV at time $t + 1$. In Model 5, the coefficient for the complementarities of an ISV's product portfolio is positive (0.09) and marginally significant ($p < 0.10$). H_{2a} receives weak support. The coefficient for the complementarities of the ISV's existing product portfolio with other product markets is positive (0.03) and significant ($p < 0.05$). H_{2b} is supported.

Test of Hypothesis 3 (H_3)

H_3 argues that an ISV that coherently reconfigures resource allocations within its portfolio in response to the changing complementarities is likely to improve its performance rank. The coefficient for ISV's resource reconfiguration in its existing product portfolio is positive (0.78) and significant ($p < 0.05$). H_3 is supported.

Test of Hypothesis 4 (H_4)

H_4 argues that the performance rank of an ISV will be affected by its ability to change the industry position of its product portfolio in response to the changing product market complementarities in the industry. The coefficient for entry complementarities is positive and significant (0.25, $p < 0.05$). Thus, H_{4a} is supported. The coefficient for entry into product markets that are highly complementary with other products in the industry is positive and significant (0.38, $p < 0.001$). Thus, H_{4b} is also supported. The coefficient for exit complementarities is negative and significant (-2.10, $p < 0.001$). H_{4c} is also supported. The coefficient for exit from product markets that are highly complementary with other product markets in the industry is negative but insignificant (-0.01, $p > 0.10$). H_{4d} is not supported.

DISCUSSION AND CONCLUSIONS

This study develops new theoretical explanations and presents new empirical evidence to advance our understanding about the presence, antecedents, and consequences of hypercompetition in the software industry. Theoretical explanations and empirical findings of the study make important contributions to strategic management research and practice. We discuss some limitations of the study before discussing the contributions.

Limitations

The context of inquiry is the software industry. The limitation of a single-industry study is that its empirical findings may not be generalizable to other industries. However, in-depth study of hypercompetition within industries is necessary for complementing studies using broad-based, multi-industry studies. While the multi-industry studies enable the detection of whether the hypercompetition phenomenon exists or not, they have limitations in understanding antecedents and consequences of hypercompetition and how strategic actions of firms affect their performance ranks. Broad-based, multi-industry studies also miss important subsample differences. In-depth studies of hypercompetition within industries are desirable for addressing some of these limitations. In addition, the theoretical explanations advanced in this study have potential applicability in industries in which product markets exhibit complementarities. The boundary condition of our theoretical explanations is the presence of complementarity relationships among product markets of an industry. Prior studies documented that this boundary condition is satisfied in high-technology or computer-based industries such as computers, networking, semiconductors, telecommunications, online video gaming, consumer electronics, and information services by showing that the product markets of these industries are characterized by strong complementarities and mutual dependencies (Baldwin and Clark, 2000; Bresnahan and Greenstein, 1999; Garud and Kumaraswamy, 1995; Katz and Shapiro, 1994; Shapiro and Varian, 1999). The complementarity and mutual dependency relationships exist in product markets of other, more traditional industries as well. For example, prior research found evidence of synergies arising from resource complementarities and resource-based dependencies among city-pair markets in the airline industry (Gimeno and Woo, 1999), loan markets in the commercial banking industry (Kim and Finkelstein, 2009), and insurance product lines (e.g., auto, home, life) in the insurance industry (Li and Greenwood, 2004). Complementarities are also detected among component product markets of very traditional industries such as metal stamping and powder metal industries (Parmigiani and Mitchell, 2009). Since the boundary condition of our theory is satisfied in these industries, our theoretical explanations

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have potential to explain the hypercompetition phenomenon in these industries as well.

Second, we measured dynamic capabilities by focusing on their observable manifestations and capturing the extent to which an ISV is able to reconfigure resource allocations of its products to strengthen the complementarities of its product portfolio and undertake entry and exit moves that reposition the portfolio in a stronger complementarity position in the industry. We did not measure how the ISV is able to do so. Our measurement approach is sufficient for testing if dynamic capabilities for the management of complementary product markets enable an ISV to improve its performance rank in the hypercompetitive software industry. Now that this nomological link is verified, further research is warranted to understand how an ISV builds and renews dynamic capabilities for the management of complementary product markets.

Theoretical contributions

Our first contribution is to the theoretical base of the hypercompetition literature. We explicate the distinction between complementarities at the industry level of analysis, i.e., product market complementarities within the software industry, and complementarities at the firm-level of analysis, i.e., complementarities within the product portfolio of an ISV and the complementarity position of that portfolio in the industry. We explain why the industry-level complementarities increase hypercompetition and lead to turbulence in performance rank orders of ISVs, and how the firm-level complementarities enable an ISV to achieve a higher performance rank in such an environment. We also explain how and why an ISV's dynamic capabilities for the management of product market complementarities increase the performance rank of the ISV.

The TOC and the strategy research on complementary assets posit that a firm can create and sustain competitive advantages with complementary assets (Barney, 1991; Milgrom and Roberts, 1990; Porter, 1996; Teece, 1986). An implicit assumption of this proposition is that the complementarities remain relatively stable over time. Our findings on H_2 show that firm-level complementarities improve the performance rank of an ISV, all other factors being equal. However, as Table 2 shows, the industry-level complementarities do not remain stable over time. They change statistically significantly every year throughout the study period. Due to mutual dependencies among industry-level and firm-level complementarities, the changes in the industry-level complementarities also lead to changes in the firm-level complementarities. Thus, the advantages provided by an ISV's firm-level complementarities are temporary. They need to be renewed on an ongoing basis as the industry-level complementarities shift.

Our study also contributes to the dynamic capabilities literature. We explain how and why dynamic capabilities for the management of product market complementarities enable an ISV to maintain or improve its performance rank in the hypercompetitive software industry. First, they enable the firm to continuously monitor the shifting web of complementary product markets and identify which product markets become strongly or weakly complementary over time. Second, they enable the firm to respond to the changes to create a more strongly complementary product portfolio, which occupies a stronger complementarity position in the industry. Specifically, the dynamic capabilities enable the firm to reconfigure resource allocations within its product portfolio to emphasize product markets that are emerging to be strongly complementary. They also enable the firm to enter new, strongly complementary product markets, which strengthen the overall complementarity position of the firm's portfolio in the industry. Overall, stronger dynamic sensing and responding capabilities enable the firm to better coevolve with changing product market complementarities within the industry, improve its performance rank relative to firms whose capabilities are weaker, change the performance ranking in the industry, and trigger further competitive responses by rivals. Accordingly, the dynamic sensing and responding capabilities may also lead to escalating rivalry in the industry.

Empirical contributions

This study also makes empirical contributions. Competition takes place primarily at the level of product markets within industries. However, most prior empirical studies examined the hypercompetition phenomenon at the industry level. The industry-level studies have addressed high-level questions such as: (1) is hypercompetition present or absent in industries? and (2) how does the level of hypercompetition change over time across different industries? Their lack of access to granular data at the level of product markets inhibited their ability to address questions about drivers of hypercompetition within industries and firm capabilities that impact a firm's performance rank in a hypercompetitive industry. This study makes an empirical contribution by beginning to address some of these questions. By using granular data at the level of software product markets, this study develops annual, time-varying measures of complementarities among product markets in the software industry, complementarities within product market portfolios of individual software firms, how firms reconfigure resource allocations within their product portfolios and how they reposition their product portfolios within the software industry. With these empirical advancements, the study is able to uncover that complementarities among software product markets change statistically significantly from year to year. Furthermore, complementarities among products increase over time, making product markets in this industry more interdependent. Changes or perturbations in one product market thus propagate to other product markets and, by implication, the entire industry. These changes, in turn, cause significant turbulence in performance rank orders of software firms and increase the level of hypercompetition in the industry. The study also shows that firms able to dynamically adapt to the changing complementarities in the industry are able to achieve higher performance ranks.

Contributions to practice

Our findings inform practitioners that a major driver of the hypercompetition phenomenon in the software industry is the web of complementary product markets, which changes statistically significantly every year. To gain and renew temporary advantages in this industry, an ISV needs dynamic capabilities that enable it to maintain a strongly complementary product portfolio, which holds a strong complementarity position in the industry. First, the ISV needs to sense how the strengths of complementarity relationships are changing among product markets of the industry. This enables the ISV to identify which product markets are emerging to be strongly (weakly) complementary and decide how to reconfigure resource allocations among its existing products, which new product markets to enter, and which existing product markets to exit. Second, the ISV needs to implement those decisions rapidly. As shown in Figure 1, a software product market can rapidly emerge as an important and profitable node in the software industry within a matter of a year. After sensing the emergence of such a product market and deciding to enter it, the ISV needs to rapidly launch products for the market. The ISV can do so by developing the new products in-house, gaining access to them through mergers and acquisitions, or forming strategic alliances with other firms and offering the products jointly. Third, the ISV also needs capabilities for exiting from some of its existing product markets. Exiting a product market may not be easy for firms competing on a portfolio of complementary products. Due to the mutual dependencies among the products, the disentanglement and disintegration of a divested product can negatively affect the other products and cause major disruptions in the portfolio. Developing a capability for controlled disentanglement and disintegration of divested products could help mitigate such risks.

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APPENDIX: ROBUSTNESS TEST WITH A PROFITABILITY MEASURE

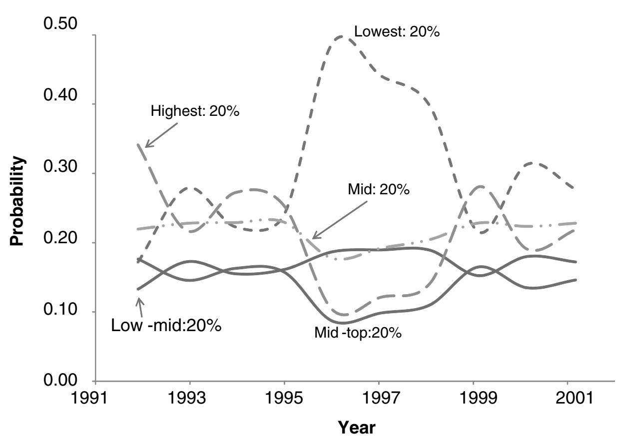
In the article, we use market share as a proxy to profitability in determining performance rank orders of ISVs, since the IDC data set lacks profitability data. In this Appendix, we conduct robustness tests with a subsample of publicly traded ISVs for which return of assets (ROA) data are available to allow the computation of a profitability measure.

In the IDC sample, 251 ISVs are publicly traded firms that also appear in the CompuStat database. Some of these firms operate in both hardware and software segments. But, since many of them do not report total assets by segment, it is not possible to compute ROA scores for their software segments. Thus, we focus on *pure* play ISVs that operate only in the prepackaged software segment (SIC 7372). We also lose some ISVs because they do not have data for at least three contiguous years ($t - 1$, t, and $t + 1$), as required by our research design. This procedure results in a subsample of 153 ISVs for which the ROA measure can be computed, an 81 percent reduction in the original market share sample.

We compute $ROA_{i,t}$ and $ROA_{i,t+1}$ for *all* SIC 7372 CompuStat ISVs at time t. Following the procedures described in the article, we form five ROA rank groups. Then, we classify each of the 153 public ISVs in time t into its corresponding ROA rank group while keeping all other predictors the same. Appendix Table 1 presents the results. We use Panel-I to retest H1 and Panel-II to retest H2, H3, and H4. In Panel-III, we reproduce the results obtained from the market share rank models for comparison with results from the ROA rank models.

In Panel-I, all year dummies are significant, indicating that the performance rank orders of the ISVs have changed statistically significantly every year. To understand the nature of the changes, we depict the results pictorially in Appendix Figure 1. As before, we set the covariates in Panel-I to their yearly means and use the coefficients of the year dummies to plot the time $(t + 1)$ probability of an ISV being classified into one of the five performance rank groups (Long, 1997). We use year 1991 as the baseline. The patterns observed in this figure are similar to those in Figure 2 of the article. The probability of an ISV being classified into one of the five ROA rank groups does not remain static over time. The figure suggests that the *fall from high performance group*, found around 1996 and 1999 for the original sample with market share ranks, is also found in the public ISV subsample analysis, with the ROA rank. Moreover, the probability for modal performance hovers near 20 percent for the public ISV subsample—which is consistent with the market share rank results. Thus, the support for H_1 is replicated with the ROA rank measure as well.

A comparison of Panel-II and Panel-III results indicates that the findings on H_2 through H_4 are highly consistent across the ROA and market share rank models. The only exception is the lack of support for H_{2b} in the ROA rank model. At face value, this discrepancy implies that the industry position of an ISV's product portfolio has a



Appendix Figure 1. Changes in the probabilities of an ISV being classified into one of the five ROA-based performance rank groups at time $t + 1$, 1991–2001

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Appendix Table 1. Robustness tests with $ROA_{i,t+1}$ and Market $Share_{i,t+1}$ rank measures

	$\mathbf{ROA_{i,t+1}}$				$\mathbf{MarketShare_{i,t+1}}$	
	Panel-I		Panel-II		Panel-III	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
ln ($Size_{i,t}$)	−0.12†	0.07	−0.36***	0.07	0.10***	0.02
ln ($Age_{i,t}$)	−0.43***	0.11	−0.34***	0.08	−0.31***	0.05
M&A $count_{i,t}$	−0.04*	0.02	−0.08†	0.05	0.06*	0.03
$Growth_{i,t}$	0.94**	0.28	0.05	0.20	0.44***	0.10
$Density_{i,t}/10$	0.01	0.03	0.01	0.02	0.01†	0.01
$Concentration_{i,t} \times 100$	0.21*	0.09	0.19*	0.09	0.08*	0.04
Diversification level of $N_{i,t}^{entry}$	−0.16	0.42	−0.57	0.47	0.15	0.18
Diversification level of $N_{i,t}^{existing}$	−0.01	0.17	−0.35†	0.19	−0.04	0.06
Diversification level of $N_{i,t}^{exit}$	2.37***	0.64	0.94	0.73	1.56***	0.33
Network effects of $N_{i,t}^{entry} \times 10$	1.21	1.16	0.93	0.85	3.29***	0.63
Network effects of $N_{i,t}^{exit} \times 10$	1.20	1.26	0.82	0.85	−0.12	0.15
Network effects of $N_{i,t}^{existing} \times 10$	0.15	0.22	0.11	0.27	0.00	0.05
Count of $N_{i,t}^{entry}$	0.02	0.02	0.05	0.03	0.02*	0.01
Count of $N_{i,t}^{existing}/100$	0.10	0.55	−0.63	0.79	0.10	0.54
Count of $N_{i,t}^{exit}$	−0.08**	0.03	−0.11**	0.04	0.01	0.01
Prior ROA performance rank $group_{i,t}$			0.18***	0.07		
Prior share performance rank $group_{i,t}$					0.08***	0.02
Year 1992	−0.30†	0.17	−0.13	0.33	−0.25	0.30
Year 1993	−0.92†	0.48	−0.25†	0.15	−0.66**	0.23
Year 1994	−0.62**	0.23	−0.25†	0.14	−0.68**	0.23
Year 1995	−0.72†	0.43	−0.29†	0.17	−0.78**	0.24
Year 1996	−1.81**	0.56	−0.37†	0.23	−0.69**	0.22
Year 1997	−1.62**	0.50	−0.27†	0.16	−0.68**	0.22
Year 1998	−1.45*	0.62	−0.18	0.31	−0.54**	0.21
Year 1999	−0.58†	0.32	−0.12	0.31	−0.50*	0.21
Year 2000	−1.08*	0.53	−0.48†	0.28	−0.40†	0.21
Year 2001	−0.91*	0.42	−0.55†	0.32	−0.29	0.20
$\mathbf{H_{2a}}$: Complementarity within $N_{i,t}^{existing}$			0.19†	0.10	0.09†	0.05
$\mathbf{H_{2b}}$: Industry position of $N_{i,t}^{existing}$			0.04	0.03	0.03*	0.01
$\mathbf{H_{3}}$: Resource reconfiguration in $N_{i,t}^{existing}/100$			1.27*	0.58	0.78*	0.30
$\mathbf{H_{4a}}$: Complementarity within $N_{i,t}^{entry}$			0.68†	0.37	0.25*	0.11
$\mathbf{H_{4b}}$: Industry position of $N_{i,t}^{entry}$			0.58*	0.26	0.38***	0.09
$\mathbf{H_{4c}}$: Complementarity within $N_{i,t}^{exit}$			−1.80†	0.98	−2.10***	0.53
$\mathbf{H_{4d}}$: Industry position of $N_{i,t}^{exit}$			−0.05	0.16	−0.01	0.04
Distinct ISVs	153		153		1005	
Sample N	852		852		4513	
df	25		33		33	
Wald χ^2	123.43**		208.69***		710.31***	

significant effect on the firm's market share rank, but not the ROA rank. However, given that we lose 81 percent of the original sample in generating the ROA sample, the lack of support for H_{2b} in the ROA sample could be due to the dramatic reduction in statistical power of the test. In addition, the software industry is a networked industry. Analyzing the dynamics of a networked industry with only 19 percent of the original sample could generate unstable results. Nevertheless, the robustness tests indicate that the results of the ROA and market share rank models are remarkably consistent. These findings reinforce the observations of technology researchers (Cusumano, 2004; Shapiro and Varian, 1999) that, in the software industry, an ISV's revenue weighted product market share is an appropriate proxy for financial performance of the firm.