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The Coevolution of Organizational Knowledge and Market Technology

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Abstract. A coevolutionary perspective on knowledge strategy is developed, where variant positions in knowledge space are predicted to result in differential advantages in product space. In particular, advantages to being both consistent and specialized in knowledge space are predicted to generate advantages in product space. Results in support of this prediction are found in an analysis of the history of the computer industry. The theory and findings have implications for both technology strategy and for researchers interested in introducing choice to evolutionary models of organizations. In particular, the findings imply that exploration in knowledge space inhibits exploration in product space.

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Keywords: organizational coevolution • organizational ecology • organizational knowledge • organizational learning • innovation • technological change • technology strategy • computers • microprocessors

Evolutionary thinking has progressed in the strategy field in recent years, with developments in a range of theoretical perspectives, including complexity theory (Siggelkow and Rivkin 2009) evolutionary economics (Knudsen et al. 2013), technology studies (Eggers 2014), and organizational ecology (Khessina and Carroll 2008). Meanwhile, the field of strategic management continues to emphasize the importance of decision making and leadership. A noteworthy feature of the strategy field is that it allows such incompatible bedfellows to lie together, if not in harmony, then at least in parallel. Paging through a journal in the field, one will read an evolutionary analysis describing processes of variation and selective retention akin to biology, and then move on to a study of behavioral decision making and its effects on firm strategies.

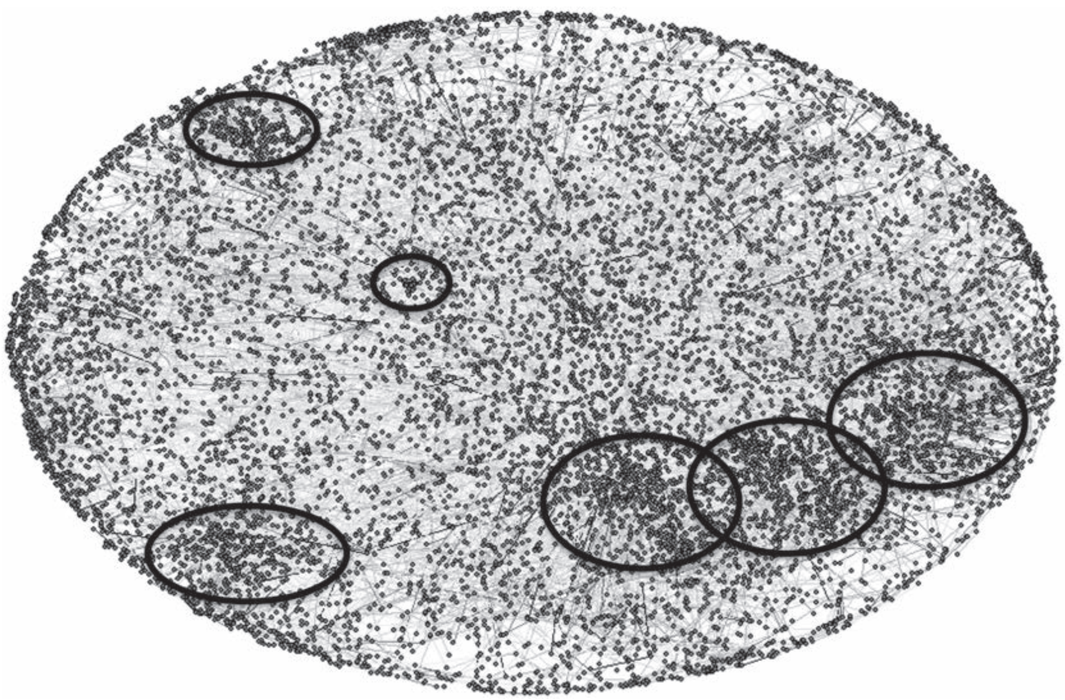
In this paper, we employ a coevolutionary analysis of strategy that emphasizes the importance of decision making. Our approach draws heavily on cultural anthropological theory, and in so doing, introduces choice to the coevolutionary model. We do this in a study of organizational strategies in two distinct but related areas: organizational knowledge and products. Describing variation and selection within each of these "spaces," we model the coevolution of the two using data from the history of the computer industry. Choice turns out to shape this coevolution in two ways. First, choices by organizations shape the variant positions that they take in knowledge space. Second, these knowledge positions, in turn, help to determine which organizations are advantaged in product space. Certain choices in knowledge space thus trigger and constrain the ability to make choices in product space, as organizations coevolve in both areas.

Knowledge Space and Market Space: Two Systems of Organizational Learning

Research highlights two domains where organizational learning takes place. One involves organizations interacting directly with the resource environment—for example, business firms interacting with their markets. In this setting, which we call "market space," organizations learn by doing, taking in new information from the environment and adjusting activities accordingly (Argote 1999, Greve 2003). Another domain that we call "knowledge space" encompasses the research and development (R&D) activities carried out by organizations. How organizations develop knowledge through R&D and its implications for an organization's innovative behavior is the central focus of this research tradition (Pisano 1990, Sørensen and Stuart 2000). Over time, organizations build up a base of knowledge from their R&D activities, enabling them to adopt new technologies embodied in new products or services (Pavitt 1998). Organizational learning occurs within each of two distinct but related domains: experientially through market interaction, and by knowledge development through R&D.

At any point in time, an organization can be located within each of these two domains. In market space, an organization's location is based on the products and services that it offers (Carroll and Hannan 2000). We place organizations in knowledge space according to the knowledge they have developed through

Figure 1. Knowledge Space for 1984

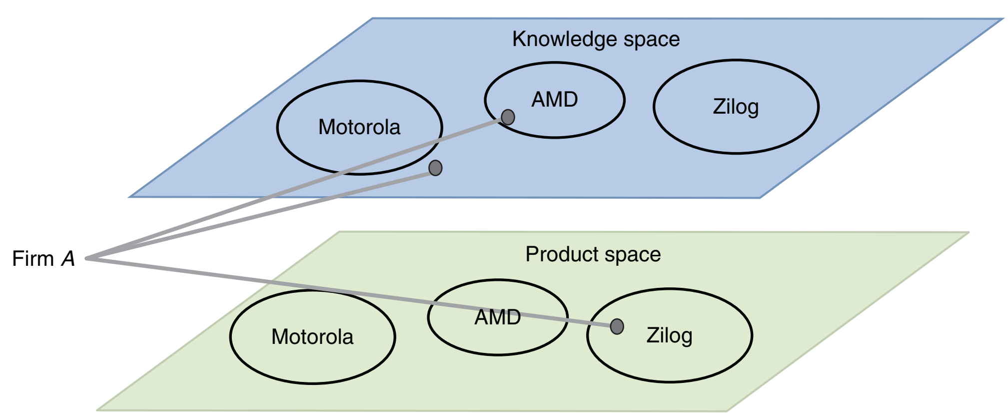


Notes. Similarity network based on co-citation patterns of patents for all 1984 patents in Electronics or Computers. Nodes are patents. Patents that are located closer to one another use a similar knowledge base. Clusters of nodes indicate that many patents use a particular knowledge base. Six areas of heavy patenting are highlighted.

R&D. Following Stuart and Podolny (1996), we locate organizations in an n-dimensional knowledge space based on whether their knowledge is similar, measuring similarity using citation patterns of their patents (Podolny et al. 1996, Fleming 2001). An example of knowledge space is illustrated in Figure 1, which shows the co-citation networks for all computer and electronics patents in the United States in 1984. Proximate patents share many citations, meaning that they draw on the same prior knowledge, while distant patents do not. Organizational locations in knowledge space are distinct from their locations in product space. For instance, an organization may research technologies that do not yet appear in its current products. An organization may research in several related areas, even if it has not attempted to translate these research programs into new products, as illustrated in Figure 2.

Some existing research investigates the relationship between an organization's position in knowledge space and its behavior in market space. Katila and Ahuja (2002) found that the depth and breadth of an organization's search in knowledge space affects the number of products it introduces to the market. This finding is consistent with previous studies showing that organizations with relevant knowledge are more able to understand and develop a given technology

Figure 2. (Color online) An Example Showing an Organization in Both Knowledge Space and Product Space



Note. In *product space* Firm *A* uses Zilog only, but in *knowledge space* Firm *A* is developing research similar to AMD and Motorola.

(Helfat 1997, Argote 1999, Jaffe et al. 2000). They also employ researchers who have relationships with others who share their view of the market (Powell et al. 1996). As a result, organizations that engage in similar research have similar options for future paths of change (Kogut 2008), which may involve direct or indirect applications of the organization's knowledge (Cohen and Levinthal 1990). These studies show how an organization's position in knowledge space constrains the positions it can take in market space. We think that there is much to be gained by looking into the interdependencies between these two systems of organizational learning. Specifically, we think that knowledge and products *coevolve*. By analyzing coevolution between knowledge space and market space, we can reveal interesting patterns of strategic choice.

Coevolution and Strategic Choice

The term "coevolution" has been used by researchers studying organizations for some time, generally taking on one of two meanings. In some cases, the term refers to recursive, cause-effect dynamics that cross levels of analysis (Levinthal and Myatt 1994, Lewin and Volberda 1999). For instance, organizational dynamics at the population level may affect variation and selection among organizational communities (Astley 1985, Barnett and Carroll 1987). Cross-level coevolution is found within organizations (Burgelman 2002). We see this, for example, in Ingram and Roberts' (1999) study of evolutionary change among pharmaceutical firms. A second use of the term refers to evolutionary interdependence between distinct systems, as with coevolution among populations of organizations (Aldrich and Ruef 2006). Similarly, institutional explanations of economic development, such as those of Murmann (2004) and Padgett and Powell (2012), highlight coevolution between industries and institutions. More generally, the second use has long been featured in biological ecology (Janzen 1980), and among anthropologists studying coevolutionary interdependence between cultural and biotic systems (Campbell 1965, Durham 1991, Richerson and Boyd 2005). Coevolution as interdependence between evolving systems, as elaborated in Durham's (1991) cultural theory of coevolution, has been particularly useful for our analysis.

We draw on Durham (1991) and build a theory of coevolution between knowledge space and market space. Organizational knowledge and the products organizations sell on the market can be considered coevolving systems, as defined by Durham. To be considered coevolutionary, two systems each need to be made up of "recognizable subunits" held by "carriers." In knowledge space, one can identify distinct units of knowledge—as is done when organizations (the "carriers") generate patents.[1] Similarly, the recognizable units making up product space are the product components brought to market by organizations. Durham stipulates that for two systems to coevolve, there must be sources of variation in the units within each system. As both units of knowledge and products exhibit variability, we are able to array units of each kind over a multidimensional space (see Figure 2). Finally, Durham's third criterion is "that there exist one or more mechanisms of transmission through which these units are conveyed among the individuals of the population" (Durham 1991, p. 421). Units of knowledge are transmitted among organizations when they build on each other's knowledge as revealed in patent citations. Additionally, transmission occurs in product space too, when organizations imitate or improve upon each other's products over time. In these ways, organizational knowledge and product technologies constitute distinct systems that coevolve.

Organizations, as carriers in this evolutionary analysis, are a key source of variation within each system. Theories of coevolution in culture and biology look at the different variant forms exhibited by the carriers in an evolving system, because they are what drive the observed patterns in the world around us. These variant forms are referred to as "alleles" in biological evolution, and as "allomemes" in cultural evolution (Durham 1991, p. 423). We can similarly characterize the carriers in our study (organizations) by the variant positions they assume within each system. Some organizations are knowledge generalists while others are knowledge specialists, and some are product generalists while others are product specialists.

Evolutionary analysis focuses on differential preference of variant forms—in our case why some positions in knowledge or product space prevail over others. Typically, organizational scholars study differential selection among alternatives in terms of differences in rates of organizational failure. But cultural anthropologists argue that coevolutionary processes involve other, potentially more important mechanisms. Specifically, human choice plays a prominent role. Durham concludes his monumental study by summarizing: "The single most important force in the differential transmission of allomemes is conscious, value-based decision making by culture carriers" (Durham 1991, p. 436). Campbell's (1965) seminal article foreshadowed this finding, observing learning and imitation shape variability in socio-cultural evolution. Richerson and Boyd (2005) note that the ability to choose gives flexibility and direction to cultural evolution. In short, as Durham (1991, p. 436) states, cultural systems are characterized by "self selection."

In the same way, choices made by organizations clearly shape the variant positions they take, and we think that these choices lead to coevolutionary interdependence between knowledge space and product space. We know that organizations vary in their innovativeness within knowledge space (Mowery et al. 1996, Ahuja 2000, Zollo and Winter 2002). We also know that an organization's knowledge shapes its ability to create and deploy new products (Cohen and Levinthal 1990, Katila and Ahuja 2002). If organizational positions in knowledge space map onto product space in a one-to-one correspondence, then choices made with regards to knowledge development lead to straightforward predictions about product development. This interdependence would be coevolutionary, but unsurprising. We would see differences in the rate of product adoptions in market space across firms (Chatterjee and Eliashberg 1990, Kogut and Zander 1992) that vary over time according to an "S-shaped" curve (Strang and Soule 1998, Rogers 2003). But a one-to-one mapping between knowledge and market space implies that organizations that develop the requisite knowledge are the ones differentially favored to introduce products based on that knowledge.

Of course, the relationship between organizational knowledge and product development is more complex than a one-to-one mapping. Organizations vary in their ability to translate knowledge into products (Zollo and Winter 2002). Some organizations may not choose to capitalize on knowledge due to other market-based factors, and often organizations must maintain a wider range of activities in knowledge space than they do in product space (Brusoni et al. 2001). Furthermore, knowledge coevolves with other activities an organization undertakes (Van den Bosch et al. 1999). We look at how variant positions in knowledge space lead organizations to be differentially favored for product introductions in market space. In this way, we examine coevolution where variants in knowledge space drive outcomes in product space.

Knowledge Consistency

The first variant we consider is whether an organization's knowledge has been rapidly acquired. An idea fundamental to studies of scientific development is that knowledge built gradually over time is more complete and more fully understood. Philosophers of science find that productive research programs build paradigmatic bodies of interrelated research, referred to as the requirement of consistency (Lakatos 1970). In the sociology of science, Merton (1973) observes that especially novel and influential innovations build heavily on prior knowledge and link well-established lines of research. For this reason, R&D departments in large firms historically have been important to technological change because they coordinate consistent and cumulative research over relatively long periods of time (Galbraith 1967). Other studies reaffirm this finding, showing that accretive knowledge development facilitates change (Dewar and Dutton 1986, Iansiti 2000, Katila and Ahuja 2002). Building knowledge over time in a consistent research program leads to a comprehensive knowledge base that cannot be easily replicated by a quick move into a particular research area.

Attempts to shortcut the accretion of knowledge often fall short. To be effective, processes in organizations need to unfold over time and cannot be compressed into a short and intense period of activity (Ancona et al. 2001). Coordination problems escalate when more people are devoted to research in an effort to produce results faster. This is behind the "mythical man month" problem identified in R&D, where having two people work on an initiative for one month is not equivalent to having one person work for two months (Brooks 1975). On top of coordination problems, organizations with rapid learning tend to lose background information from the past that makes knowledge more complete (Levinthal and March 1993). With rapid learning, organizations have difficulty distinguishing information from "noise" (Holland et al. 1989, March 1994). This implies that having the relevant knowledge is not enough. Also important is that an organization build its knowledge in a particular area consistently over time.

Knowledge Consistency Hypothesis. Organizations following a consistent strategy in knowledge space are differentially favored in the relevant area of product space.

Knowledge Specialism

The consistency hypothesis implies that by foreseeing where to research, organizations can prepare for changes in the market. But knowing in advance where to research is difficult. There is uncertainty over the technologies that will prevail (Anderson and Tushman 1990), especially in early stages of an industry when organizations experiment along different technological paths. After the fact, it may seem obvious that a particular technology would end up as the "dominant design" (Abernathy and Utterback 1978), but a priori many alternative technologies seem viable (Barnett 2008). In the microcomputer market, for instance, consensus emerged around the Intel chip design, but this convergence was far from obvious in early years. Dozens of possible designs were available to microcomputer manufacturers, some which seemed stronger than Intel's offerings.

In the face of uncertainty, decision makers can choose either to specialize knowledge development on what they believe is the most promising technology, or to hedge their bets as a generalist and research in various areas of knowledge space. Knowledge generalism has "option value" (Kogut 2008), giving managers the ability to place bets on various possible future time paths. Managers may hope that knowledge generalism will keep the organization able to adopt the most attractive technologies once that choice becomes clearer in the future. In this spirit, Leiponen and Helfat (2010) find that managers who report having a broader range of knowledge sources also are more likely to report that their organization is innovative. Knowledge generalism will have an innovation advantage as long as there is no downside to involvement in multiple areas. In the extreme, this implies that research in one area of knowledge space is independent of an organization's engagement in other areas. Under this assumption, knowledge generalism will increase the likelihood of innovation simply because the generalist is researching in a greater variety of areas.

We reach a different conclusion, however, if we relax the assumption that there is no downside to being involved across multiple areas of knowledge space. Rather than assuming independence across research areas, we allow that knowledge generalism can spread an organization's resources too thin. This problem is well researched with respect to material and human resources, and often operates to the disadvantage of generalists in product strategy (Hannan and Freeman 1989). This constraint should also apply to organizations that pursue a generalist position in their knowledge development. In addition to spreading material resources too thin, knowledge generalism can lead to increased disagreement regarding the right direction for an organization. Knowledge not only provides a technical basis for change, but also helps to build a social consensus about an organization's proper course of action (Barley 1986). As Stinchcombe (1990) argues, organizations innovate when there is a shared understanding of what is involved in the innovation including its technical requirements, personnel requirements, its likely costs and benefits, and implications for the distribution of benefits. These understandings form a social basis for change (March 1994). In this light, knowledge generalism reduces the chances that the organization will develop a consensus around the promise of any particular technology. The specialist to a given area of knowledge space devotes all its resources to innovating in that area, and is likely to benefit from a clear consensus among managers as to the appropriateness of innovation in that area. While a knowledge generalist may have an advantage when it comes to its overall rate of innovation, we think it will be less likely than a specialist to innovate in any given area.

Knowledge Specialism Hypothesis. A knowledge specialist is differentially favored in its relevant product space compared to a knowledge generalist.

Combined, our hypotheses describe a coevolutionary process favoring, in product space, firms that choose to focus in knowledge space. This pattern is especially interesting when seen in light of March's (1991) well-known distinction between exploration and exploitation, referring to searching broadly vs. searching within a more narrowly-defined and well-understood region. Following March, organization theory has for decades depicted organizations in terms of where they stand on the exploration-exploitation continuum. By contrast, our theory allows for the fact that organizations are simultaneously searching both in knowledge space and in product space, and that the two search domains are interdependent. Specifically, our theory predicts that exploration in knowledge space retards exploration in product space, a result consistent with other models allowing for multiple searches (Lounamaa and March 1987) or search in multiple spaces (Levinthal and Posen 2007). Furthermore, like March's (1991) original model, we describe a dynamic that inhibits exploration in product space—but in our theory, this results from attempts to explore in knowledge space.

Empirical Setting and Methods

We investigate these ideas over the evolution of the U.S. microcomputer industry, from the early growth of commercial microcomputers in 1980 through the onset of the Internet era in 1994. Microcomputers were initially developed by computer hobbyists in the 1970s and became a large and commercially viable product category in the early 1980s. Microcomputers were dramatically smaller and cheaper than earlier computers and made computing widely accessible. One of the most important elements of the microcomputer was the microprocessor, a small component once called a "computer on a chip," that contained all central processing unit (CPU) functions. A critical technical decision for microcomputer manufacturers concerned which CPU to use in their products. Initially, the functions and specifications of the CPU were not well-defined, and only with technical advances over time would they become clear. Consequently, during the early years of this industry, there was a great deal of uncertainty about which suppliers would consistently be able to offer a CPU with the best performance.[2]

Our interviews and articles from archives indicate that manufacturers actively managed their choice of CPU as a strategic decision. On the one hand, there were clear economies from specializing. *Electronic Data News* (*EDN*), a top industry publication on electronic design, stated in 1979, "Why choose a single family? The most compelling reason is the human-factors benefit of having to deal with only one instruction set, one hardware architecture, one bus structure and one development system," (*EDN*, October 20, 1979, p. 133). On the other hand, specializing increased the risks of tying one's fate too closely with one design. Should that design cease to be competitive, so would the microcomputer firm's products. Early on, there was considerable uncertainty around which microprocessor manufacturer would consistently develop the best CPU. For example, in the late 1970s, Texas Instruments seemed to be a front-runner, only to give way to Motorola, Intel, and others (*EDN*, various issues). Even as late as 1986, *EDN* predicted that despite the prominence of the Motorola 6,800 and Intel 8,086 families, there would be plenty of room for other designs. At the time, this source asserted that one microprocessor would not come to dominate the market, and instead suggested that standardization would occur only at the level of the operating system (*EDN*, November 27, 1986).

Consequently, microcomputer manufacturers often maintained the knowledge required to employ different CPUs, and valued being able to change CPUs. Managers weighed technical benefits, the risks of being too dependent on a particular design, and the costs of creating new knowledge when deciding whether or not to adopt a new CPU. If managers decided that the organization should offer a CPU of a different design, then the organization needed the particular knowledge about controls, instruction sets, architectures, and bus configurations that would work with the new chip. All aspects of product design were affected by such a decision. For these organizations, knowledge development was an important factor in their ability to adopt a new CPU.

The experts we interviewed emphasized that adopting a new CPU was a major technical change for microcomputer organizations, involving the architectural design of the computer and the creation of assembly language code to enable the CPU to work within this design. Functioning within a microcomputer, the CPU includes three general components (see Rafiquzzaman 2005). The "control section" of the CPU performs the basic operations of the computer, receiving instructions from memory, storing them, decoding them to be understandable by the computer's hardware, and then carrying them out. Second, the "arithmetic and logic unit" of the CPU deals with data manipulation, instructing at a fundamental level the registers, circuitry, memory, and input/output devices. Third, the "register section" of the CPU includes circuitry that temporarily stores data and program codes. Finally, these three components of the CPU are connected by the system bus, where the architecture of the computer is organized. All of these functions are controlled by "instruction sets," detailed assembly-language commands particular to each CPU design. Designing a microcomputer to work with a new CPU involved developing these instruction sets.

The adoption of a new CPU was further complicated by the fact that the specific instruction sets for each CPU depended on the other components of the microcomputer. Later in the history of the industry, the specifications of each CPU and its relationship to the architecture of the microcomputer were well understood.[3] But during the period we study, new CPU designs were introduced frequently, often expanding the range of functions carried out by the CPU to incorporate functionality that previously had been performed by other components within the microcomputer. Each new design brought improved performance, but required that the CPU interact in different ways with the rest of the microcomputer. Our interviews suggest that even adopting a new version from the same manufacturer was a difficult and involved process, requiring the redesign of the rest of the microcomputer and rewriting the CPU's instruction sets. Moving to a different CPU manufacturer was even more involved and amounted to a complete rethinking of the architecture of the computer.

Data

We used archival sources to track microcomputer organizations and the microprocessors used in their products between 1980 and 1994. These data were constructed from *Data Sources*, a publication that lists all computer manufacturers and the technical specifications of their products sold in each year. This project is a subset of a larger data collection effort that tracks all microcomputer organizations that ever existed in the United States using every known source that documents the computer industry. Of these, only *Data Sources* contains comprehensive information on the technologies within the products sold, and it includes information for 1,657 organizations over 4,798 organization-years, out of 1,922 total microcomputer organizations over 6,510 organization-years in the complete data. This sample is not size-biased, nor biased in any other known way, and is the most complete known census of U.S. microcomputer organizations and the technologies provided in their products for the years we cover.

We study technical change in terms of when a microcomputer company adopts a CPU from a new supplier. For each CPU in these data, we collected information on its manufacturer, technical details, and its first release year, from the annual microprocessor report provided in *Electronic Data News*. There are 115 distinct CPUs in these data produced by 23 different manufacturers. Table 1 shows descriptive statistics for the CPU manufacturers in these data.

Fifty-five percent of organizations use a supplier other than Intel, with AMD, Zilog, Motorola, and Cyrix also popular suppliers. At any given time, organizations tended to offer products using between one and three microprocessor suppliers, but which suppliers they used varied.

Organizations might be more likely to adopt a new CPU if its technologies are more compatible with those

Table 1. CPU Supplier Descriptive Statistics

	No. of organization-years	No. of organizations	First year in data
AMD	282	253	1975
AT&T	8	1	1985
Chips & Technologies	1	1	1991
Cyrix	124	97	1992
Data General	2	1	1981
DEC	18	7	1975
Fairchild	1	1	1979
Hewlett Packard	4	2	1986
Hitachi	9	4	1982
IBM	28	22	1990
Intel	4,124	1,463	1974
Intersil	19	9	1975
MIPS	19	9	1985
MOS	67	30	1975
Motorola	457	145	1974
National Semiconductor	16	9	1975
NEC	152	64	1987
RCA	10	2	1976
Sun Microsystems	44	19	1987
Texas Instruments	15	9	1975
Western Design Center	6	2	1984
Western Electric	9	5	1982
Zilog	625	227	1976

of their current suppliers. Computer technologies are affected by the diffusion of standards, which benefit technologies that become more widespread in their use (Katz and Shapiro 1985). These network effects have been shown to shape rates of technology adoption (Farrell and Saloner 1985). To take this into consideration, we construct the transition matrix shown in Table 2. This matrix identifies organizations that use CPUs from one supplier at time t_1 (listed in the rows) that adopt a CPU from a different supplier at time t_2 (listed in the columns). This matrix indicates that there is clustering, showing how patterns of technological compatibility shaped the diffusion of these technologies. We employ this transition matrix, broken out over time, in supplementary analyses to determine whether our findings are sensitive to compatibility among manufacturers.

To investigate our hypotheses, we measure each organization's position in knowledge space. We do this based on the patenting behavior of these organizations, as documented by the United States Patent Office. To obtain a U.S. patent, an organization must apply with a new, unique and nonobvious invention. Patents also must cite all "prior art" on which the new invention is based, which reveals the knowledge foundation for the patent. We construct our measure of knowledge space from patent and patent citation data from the National Bureau of Economic Research patent citations data file (Hall et al. 2001). In this file, patents have been categorized into six broad categories; we use all patents granted in the Computers and Communications or Electrical and Electronic categories, the two research areas that are relevant to computers. There are 440,530 patents in these categories granted between 1975 and 1994.

Measures

These data allow us to measure organizational positions in knowledge space, under the assumption that patent citations measure the technical foundation of

Table 2. Number of Transitions for Across-Supplier Change: Organizations That Offer a CPU by One Supplier, That Subsequently Adopt a CPU by Another Supplier, Over All Years

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
AMD	(1)	0	0	0	39	0	1	0	0	0	7	5	0	1	0	1	0	0	0	0	1	0	1	1
AT&T	(2)	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	0	1
Chips & Technologies	(3)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Cyrix	(4)	8	0	0	0	0	0	0	0	0	2	3	0	0	0	0	0	0	0	0	1	0	0	0
Data General	(5)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DEC	(6)	0	0	0	0	0	0	0	0	0	0	1	0	2	0	4	1	0	0	0	1	0	1	1
Fairchild	(7)	0	0	0	0	0	0	0	0	0	0	2	0	0	0	1	0	0	0	0	0	0	0	2
Hewlett Packard	(8)	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0
Hitachi	(9)	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	1
IBM	(10)	2	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Intel	(11)	159	1	1	71	1	3	0	2	0	14	0	4	9	2	48	2	35	0	14	10	1	2	22
Intersil	(12)	0	0	0	0	0	1	0	0	0	0	1	0	0	0	3	0	0	0	0	1	0	0	1
MIPS	(13)	1	0	0	1	0	2	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0
MOS	(14)	0	0	0	0	0	0	0	0	0	0	7	0	0	0	7	0	0	0	0	0	2	0	2
Motorola	(15)	3	0	0	0	1	2	0	2	0	3	40	6	12	6	0	3	4	0	4	7	2	0	17
National Semiconductor	(16)	0	0	0	0	0	1	0	0	0	0	4	0	0	0	1	0	0	0	0	0	0	0	1
NEC	(17)	6	0	0	3	0	0	0	0	0	0	3	0	1	1	2	0	0	0	2	0	0	1	1
RCA	(18)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sun Microsystems	(19)	4	0	0	4	0	0	0	1	0	1	3	0	0	0	3	0	0	0	0	1	0	0	0
Texas Instruments	(20)	1	0	0	0	0	0	0	0	0	1	1	1	0	0	2	0	1	0	0	0	0	0	0
Western Design Center	(21)	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Western Electric	(22)	0	1	0	0	0	0	0	0	0	0	3	0	0	0	1	0	1	0	0	1	0	0	2
Zilog	(23)	3	1	0	0	1	1	0	1	0	1	66	1	1	4	23	4	9	0	2	3	0	4	0

research. The citations included in a patent are identified by the inventor, professional consultants, patent attorneys and the patent examiner (Gittleman 2008, Alcácer and Gittleman 2006). For research on the knowledge of the specific inventor, this adds troublesome noise. However, here we use citation overlap to place organizations within knowledge space. We seek to determine if they are engaging in research very similar to or different from other organizations, not to approximate the direct knowledge of the inventor. For our purposes, citations added by attorneys, patent examiners, or others are helpful in refining the position of the organization in knowledge space.

We construct knowledge space at the level of the individual invention, using all 440,530 patents issued in the Electronics and Computers categories from 1975–1994. Note that knowledge space is based on *all* patents relevant to computers in the U.S. patent database, not just those issued to microcomputer organizations. Building on previous research, we use citation overlap to quantify how similar two patents are (Podolny et al. 1996, Fleming 2001, Stuart and Podolny 1996). Similarity between patents i and j is measured by dividing the number of shared citations between i and j by the total citations made by patent i:

$$\alpha_{ij} = s_{ij}/s_i. \tag{1}$$

We also account for second-degree similarity, so that if two patents are similar to a third, they can have nonzero similarity to each other. Similarity between any patent m and n is measured by multiplying their similarities to a third patent k. The third patent that yields the highest similarity is used:

$$\sigma_{mn} = \max_{\alpha_{mk}>0 \wedge \alpha_{nk}>0} (\alpha_{mk} \cdot \alpha_{nk}). \tag{2}$$

If patents m and n have nonzero first-degree similarity, then $\sigma_{mn} = \alpha_{mn}$. Figure 1 shows a network map of this knowledge space for 1984. The nodes in Figure 1 are patents from 1984 in the Electronics and Computers categories, and lines between nodes represent shared citations. Nodes that are close to one another build on a common knowledge foundation.

Next, we use a microcomputer organization's patents to locate it within knowledge space for each year it existed over the study period. We then can identify areas in knowledge space that are populated by microcomputer manufacturers that use a particular CPU. For example, Figure 3 identifies patents that belong to microcomputer organizations that used the Zilog Z80 in their products as well as microcomputer organizations that used any other CPU. This figure shows three areas of heavy patenting activity associated with the Zilog Z80: Z1, Z2, and Z3, and two areas of heavier patenting for non-Zilog Z80 CPUs: O1 and O2.

As Figure 3 shows, a CPU can be associated with more than one area of knowledge space. By defining knowledge space initially at the level of the patent, we can locate various areas of knowledge space associated with different CPUs. An organization whose patents are only in areas Z1, Z2, and Z3 is close in knowledge space to the Zilog Z80 CPU and is specialized in knowledge space. An organization whose patents are in these areas and also in areas O1 and O2 is close in knowledge space to the Zilog Z80, but is more of a generalist.

An organization's knowledge space proximity to other microcomputer organizations is calculated by observing every patent issued to organization A and measuring each patent's *maximum* similarity to all patents issued by organization B.[4] We take into account historical knowledge development by including similarity to B's historical patents, discounted for the passage of time. Summing over patent-level similarities yields the knowledge-space similarity between organization A's patents in the given year, and organization B:

$$kprox_{A,B,t_k} = \sum_{i \in A_{t_k}} \max_{j \in B} \left[\frac{\sigma_{ij}}{\sqrt{t_k - t_j + 1}} \right]. \tag{3}$$

To measure knowledge specialism, we calculate how close A is in knowledge space to areas associated with a "target" CPU. Knowledge generalism is measured based on the organization's proximity to areas associated with all other CPUs. We map areas of knowledge space to a particular CPU based on the patenting behavior of computer manufacturers that use the CPU. We sum A's knowledge space proximity to every organization B that uses a CPU, and divide by the total number of patents issued to A in the given year:

$$kprox_{A,\mathrm{CPU}_i,t_k} = \frac{\sum_{B \in \mathrm{CPU}_i} kprox_{A,B,t_k}}{N_A}. \tag{4}$$

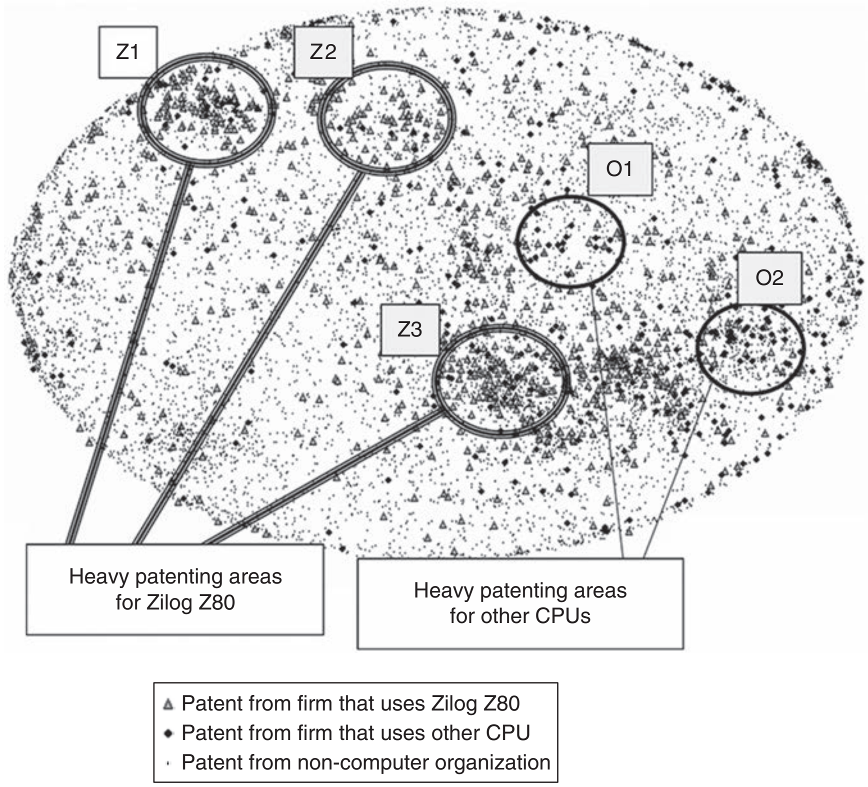
This measure provides A's proximity to the region of knowledge space relevant to a particular CPU based on A's patents in the current year. We take into account A's past similarity to this CPU by summing its past knowledge space proximities, discounting by the square root of time:[5]

$$kprox_{A,CPU_i,T} = \sum_{t=t_o}^{T} \frac{kprox_{A,CPU_i,t}}{\sqrt{T - t + 1}}. \tag{5}$$

To measure knowledge consistency, we proceed using the same logic for comparing two organizations, but instead compare an organization's patent portfolio in the current year to its portfolio in previous years:

$$consistency_{A,t_k} = \sum_{i \in A_{t_k}} \max_{j \in A_{t_n}} \left[\frac{\sigma_{ij}}{\sqrt{t_k - t_n + 1}} \right]. \tag{6}$$

Figure 3. Knowledge Space for 1984; Only Nodes Are Shown



Notes. Heavy patenting areas for firms that use the Zilog Z80 CPU in 1984 are highlighted. We also see some clustering from firms that use any other CPU, although this patenting tends to be more dispersed. Nodes are differentiated based on whether patents are issued to computer manufacturers that use the Zilog Z80 CPU or that use another CPU.

To take into account the consistency of organization A's patent portfolio in previous years, we sum past consistencies, discounting for time:

$$consistency_{A,T} = \sum_{t=t_o}^{T} \frac{consistency_{A,t}}{\sqrt{T-t+1}} \tag{7}$$

The knowledge consistency hypothesis is tested by interacting an organization's knowledge space proximity to a target CPU (5) with its knowledge consistency (7).

To test the knowledge specialism hypothesis, we construct a measure of knowledge generalism (versus specialism) by computing A's knowledge space proximity to every organization C that uses a CPU *other than the target CPU*:

$$kgen_{A,\mathrm{CPU}_i,t_k} = \frac{\sum_{C\in \mathrm{CPU}_{k\neq i}} kprox_{A,C,t_k}}{N_A}. \tag{8}$$

Again, A's past similarity to other CPUs are taken into account by summing past proximities and discounting by time:

$$kgen_{A,\mathrm{CPU}_i,T} = \sum_{t=t_o}^{T} \frac{kgen_{A,CPU_i,t}}{\sqrt{T-t+1}} \tag{9}$$

Model

To test our hypotheses, we estimate the likelihood of an organization adopting a CPU from a different supplier. Our interviews made clear that these changes were nontrivial both technically and strategically for computer manufacturers. Adopting a new CPU from an existing supplier typically meant staying within the same design family and so was often not as significant a change. We model the hazard rate of new-supplier technology adoptions, with changes taking place as a matching process for every potential organization-CPU dyad in our data. The risk set thus includes all dyads of each computer manufacturer matched with every CPU offered by a supplier that the manufacturer does not already use. Dyads enter the risk set when there is a new microcomputer manufacturer or new CPU, and an event occurs when the organization from the dyad adopts the CPU from the dyad. The hazard rate is estimated based on the time from dyad entry to the time when the organization adopts the target CPU. Using the dyad as the unit of analysis allows us to include variables at the organization-CPU level to test these hypotheses. We specify the model as a Cox (1972) proportional hazard rate, which does not make strong assumptions about the functional form of time dependence. This approach also allows us to remove possibly

Table 3. Descriptive Statistics[a]

	Mean	Standard deviation	Minimum	Maximum
Computer manufacturer adopts target CPU	0.0048	0.0693	0	1
(Knowledge proximity to target CPU) × (Knowledge consistency)	0.0044	0.0849	0	8.135
(Knowledge proximity to target CPU) × (Knowledge *in*consistency)	1.537	36.44	0	3,630
Knowledge proximity to target CPU	0.0048	0.0517	0	2.070
Knowledge generalism	0.1990	0.7009	0	7.074
Knowledge consistency	0.0961	0.7788	0	23.56
No. of patents issued to manufacturer	6.015	43.81	0	1265
No. of prior transitions from manuf's CPU suppliers to target CPU	2.435	6.332	0	111
CPU controls				
CPU is supplier's latest release	0.4223	0.4939	0	1
Time since CPU was released (latest releases only)	0.9505	1.869	0	10
No. of failures for manufs that did not use target CPU	129	71.96	23	273
No. of failures for manufs that used target CPU	0.2112	2.030	0	51
Organizational controls				
Manufacturer is medium sized	0.6109	0.4875	0	1
Manufacturer is large sized	0.1378	0.3447	0	1
Manufacturer is also in the midrange computer market	0.2156	0.4112	0	1
Manufacturer is also in the mainframe computer market	0.0324	0.1770	0	1
No. of years manuf has been in microcomputer market	4.177	2.806	0.5	20
No. of CPU suppliers used by manufacturer	1.310	0.6635	0	7
No. of CPUs offered in products sold by manufacturer	2.168	1.331	0	14
No. of alternative same-supplier CPUs	10.10	4.660	0	34
No. of alternative different supplier CPUs	33.84	6.688	12	59
Environmental controls				
No. of microcomputer manufacturers	357	96.07	177	478
No. of microcomputer manuf using target CPU				
No. of microcomputer manuf using another CPU				
No. of microcomputer manufs using a CPU from target supplier				
No. of microcomputer manufs using a CPU from another supplier				
Product shipments in the microcomputer market/1,000	7,338	3,408	1,157	15,691
GDP	4,544	424	3,760	5,135

[a]Data contain 58,992 organization-CPU pairings, including 618 adoptions over 128,011 organization-CPU years.

troublesome unobserved heterogeneity by specifying CPU-specific nuisances.

These data contain 58,992 potential organization-CPU pairings over 128,011 organization-CPU years. During the time period of analysis, there are 618 adoptions of a CPU from a different supplier. For the sake of comparison, the hazard rate of upgrading CPUs from a supplier that the computer manufacturer already uses is also estimated. For the same-supplier analysis, there are 12,242 potential organization-CPU pairings over 26,581 organization-CPU years, and 934 adoptions of same-supplier CPUs. Models are estimated as competing risks for adopting a new CPU from a different supplier or from a same supplier. Table 3 provides descriptive statistics.

Control Variables

We expect the hazard rate of CPU adoption to be a function of CPU-level, organization-level, and environmental variables.

Several CPU characteristics are likely to affect the hazard rate of adopting a particular CPU. We include whether the *CPU is the supplier's latest release*, to account for a propensity to adopt recent technologies. Because not all organizations had access to a new CPU immediately following its release, we also include *time since CPU release*. To measure perceived risks associated with a particular CPU, we include the *number of organizational failures for computer manufacturers that did not use the target CPU* and *number of organizational failures for computer manufacturers that used the target CPU*.

We also control for organization-level covariates: *size* (categorized into small, medium, and large with small as the reference category), whether the organization is also in the *midrange* or *mainframe* markets,[6] *number of years the manufacturer has been in the microcomputer market*, *number of CPU suppliers the manufacturer uses*, *number of CPUs the manufacturer offers in its products*, *number of alternative CPUs available from the manufacturer's suppliers*, and *the number of CPUs available from different suppliers*.

At the environmental level, these manufacturers are adopting technologies in the midst of a broader technology diffusion process, as discussed above. Although we explicitly model differences in propensities to adopt, we also include several variables to control for effects that change with the development of the microcomputer market and the diffusion of the different CPUs: the *number of microcomputer manufacturers*, specified as an overall count, and then broken out into the numbers adopting different CPUs. We also control for the mass of the population by including *microcomputer product shipments*. Broader economic trends are included in the form of the U.S. *gross domestic product*. All independent variables are measured as of the beginning of each time period.

Results

Table 4 presents our hypothesis tests. Model 1 contains controls only, and is a baseline for comparison. Models 2–5 include various specifications of knowledge position. Models 2 and 4 both include the main effect of knowledge space proximity to a CPU, which is positive but never significant. These results cast doubt on the idea of a one-to-one correspondence between knowledge space and product space. Models 3–5 include the interaction of knowledge consistency and proximity, which is positive and significant in every specification in support of the knowledge consistency hypothesis. Note that the main effect of knowledge consistency, when included in models 2 and 4, is not significant and its inclusion or omission has no bearing on the interaction term's effect. Finally, across model 2–5, knowledge generalism has a negative and significant effect on technology adoption. In support of the knowledge specialism hypothesis, an organization that focuses its R&D on a particular area is more likely than is a generalist to bring technologies to market based on that area.

In sum, we find that organizations must have consistently done relevant research in an area to change technologies based on that area, but neither knowledge relevance nor consistency alone have this effect. Furthermore, knowledge generalists, who spread their research across multiple areas, have a lower rate of technological change in any particular area. Consequently, only model 3, which includes the (consistency × proximity) interaction and generalism, improves over the baseline model 1 (based on a comparison of log pseudolikelihoods). Figure 4 illustrates the magnitude of these effects, for organizations at the median level of knowledge consistency. The solid line shows a dramatic increase in the propensity to adopt a particular CPU, peaking at a multiplier of about 1.3. This implies a technology adoption rate about 30% higher for organizations consistently doing research relevant to a CPU than for those low on proximity or consistency. Meanwhile, the dotted line shows how knowledge space relevance cuts the other way when organizations research in many different knowledge areas. As knowledge generalism increases, the technology adoption rate in any particular area falls to about half at the maximum observed value of generalism. Hedging by being proximate to many different technological areas diminishes the rate of technological change in any given area.

One question may be whether the generalist knowledge strategy increases the likelihood that the organization will adopt *at least one* CPU from a different supplier, even though there is a reduced risk of adopting any particular CPU. To test this, we run organization-level models on the likelihood an organization will adopt at least one CPU from a different supplier in a given year, reported in Table 5 model 7. We sum the organization's knowledge space proximity to all CPUs from different manufacturers in the given year. Results do not indicate that knowledge generalists are favored in different supplier CPU adoption.

Robustness Checks

We also explore the implications of results and test their robustness against alternative explanations. Results are reported in Tables 4 and 6.

General Patenting Activity. One alternative hypothesis is that general knowledge development drives technology adoption, regardless of knowledge proximity and consistency. We address this possibility by including in model 5 the number of patents issued to the organization in the previous year. This does not have a statistical effect on its likelihood to adopt a CPU from a different supplier, and the model does not improve over model 3, which omits this effect. Our results remain robust to the inclusion of this variable. There are also similar results when the total number of patents issued to an organization over time is included.

Upgrading same-supplier CPUs. We have investigated what leads organizations to adopt new technologies that require significant technical changes within an organization. Scholars distinguish between organizations making significant as opposed to incremental changes (March 1991, Tushman and Anderson 1986, Henderson and Clark 1990, Hannan and Freeman 1984, Barnett and Carroll 1995). In this vein, it is informative to compare hazards of adopting a CPU from a different manufacturer to adopting a CPU from a supplier that the organization already uses. Same-supplier upgrades are routine, and typically are organized by standard procedures within an organization (consistent with the reasoning in Henderson and Clark 1990). For change of this sort, organizations already possess the relevant knowledge and have built that into their routines, making R&D less relevant to the capability to change.

We investigate whether this is the case in model 6 in Table 4. Consistent with these ideas, results show that neither an organization's knowledge proximity to the CPU nor its knowledge consistency has a significant effect on its likelihood to upgrade a same-supplier CPU. However, the number of patents issued to the

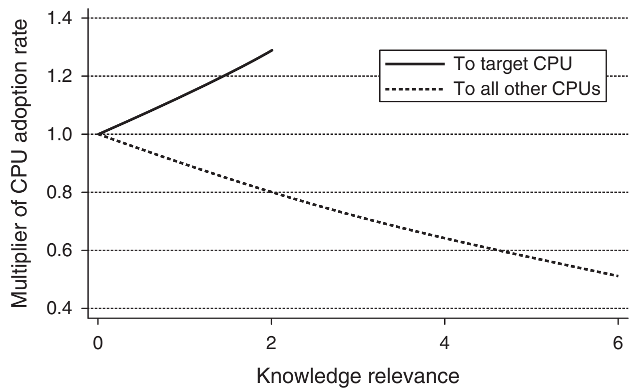
Table 4. Cox Proportional Hazard Rate Models for CPU Adoption[a]

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Adopting a new CPU from a new supplier					Adopting a new CPU from the same supplier
Knowledge proximity to target CPU		0.323		0.0305		−0.0617
		(0.472)		(0.524)		(0.294)
Knowledge generalism		−0.122**	−0.112**	−0.110*	−0.110*	−0.00423
		(0.0609)	(0.0567)	(0.0609)	(0.0583)	(0.0524)
Knowledge consistency		0.0150		−0.00686		−0.114
		(0.0294)		(0.0346)		(0.0761)
(Knowledge proximity to target CPU) × (Knowledge consistency)			0.316**	0.330*	0.325*	−0.00620
			(0.160)	(0.198)	(0.174)	(0.121)
No. of patents issued to manufacturer					−0.0000713	0.00371**
					(0.000583)	(0.00147)
CPU controls						
CPU is supplier's latest release	−2.732**	−2.731**	−2.719**	−2.720**	−2.720**	−2.317**
	(0.320)	(0.319)	(0.319)	(0.319)	(0.319)	(0.262)
Time since CPU was released (latest releases only)	1.031**	1.030**	1.032**	1.031**	1.032**	0.860**
	(0.0911)	(0.0912)	(0.0912)	(0.0912)	(0.0912)	(0.125)
No. of failures for manufs that did not use target CPU	0.0121**	0.0122**	0.0122**	0.0122**	0.0122**	−0.0123**
	(0.00171)	(0.00171)	(0.00171)	(0.00171)	(0.00171)	(0.00165)
No. of failures for manufs that used target CPU	−0.0315**	−0.0312**	−0.0309**	−0.0309**	−0.0309**	0.0338**
	(0.00789)	(0.00793)	(0.00790)	(0.00792)	(0.00790)	(0.0152)
Organization controls						
Manufacturer is medium sized	0.277**	0.285**	0.285**	0.284**	0.284**	0.703**
	(0.122)	(0.122)	(0.122)	(0.122)	(0.122)	(0.104)
Manufacturer is large sized	0.690**	0.715**	0.714**	0.712**	0.713**	1.335**
	(0.146)	(0.148)	(0.147)	(0.148)	(0.147)	(0.127)
Manufacturer is also in the midrange computer market	0.144	0.167	0.165	0.165	0.165	0.329**
	(0.112)	(0.112)	(0.112)	(0.112)	(0.112)	(0.0976)
Manufacturer is also in the mainframe computer market	0.406**	0.477**	0.454**	0.457**	0.455**	−0.181
	(0.179)	(0.184)	(0.184)	(0.185)	(0.184)	(0.170)
No. of years manuf has been in microcomputer market	0.0107	0.0195	0.0186	0.0189	0.0188	0.00958
	(0.0143)	(0.0152)	(0.0152)	(0.0152)	(0.0152)	(0.0133)
No. of CPU suppliers used by manufacturer	−0.221**	−0.195**	−0.198**	−0.199**	−0.199**	−0.0991
	(0.0967)	(0.0983)	(0.0980)	(0.0982)	(0.0983)	(0.0758)
No. of CPUs offered in products sold by manuf	−0.129**	−0.139**	−0.136**	−0.133**	−0.134**	−0.0345
	(0.0517)	(0.0533)	(0.0519)	(0.0533)	(0.0536)	(0.0401)
No. of alternative CPUs from the same supplier	0.129**	0.128**	0.127**	0.127**	0.127**	0.0206*
	(0.0124)	(0.0124)	(0.0124)	(0.0124)	(0.0124)	(0.0109)
No. of alternative CPUs from different suppliers	−0.0581**	−0.0587**	−0.0597**	−0.0597**	−0.0597**	−0.0162
	(0.0116)	(0.0117)	(0.0117)	(0.0117)	(0.0117)	(0.00993)
Environmental controls						
No. of microcomputer manufacturers	−0.00706**	−0.00709**	−0.00707**	−0.00707**	−0.00707**	−0.00727**
	(0.00128)	(0.00129)	(0.00128)	(0.00129)	(0.00128)	(0.00111)
Product shipments in the microcomputer market/1,000	−0.000369**	−0.000379**	−0.000379**	−0.000378**	−0.000379**	−0.0000973
	(0.0000846)	(0.0000849)	(0.0000847)	(0.0000848)	(0.0000848)	(0.0000717)
GDP	−0.0000518	−0.0000116	−0.0000200	−0.0000297	−0.0000254	0.00197**
	(0.000737)	(0.000739)	(0.000737)	(0.000739)	(0.000739)	(0.000613)
Log pseudolikelihood	−3,291.1	−3,288.9	−3,287.8	−3,287.8	−3,287.8	−4,847.1
Degrees of freedom	16	19	18	20	19	21

[a]All models include CPU-specific nuisances. New-supplier models are run on 58,992 organization-CPU pairings, including 618 adoptions over 128,011 organization-CPU years. Same-supplier models are run on 12,242 organization-CPU pairings, including 934 adoptions over 26,581 organization-CPU years.

$^{*}p < 0.10$, $^{**}p < 0.05$ (two-tailed tests).

Figure 4. Propensity to Adopt a Target CPU by Knowledge Proximity and Generalism



Note. This plot is illustrated for ranges observed in these data. The multiplier of the CPU adoption rate for target CPU is evaluated for organizations with knowledge consistency 0.4, the median value for a researching organization.

organization in the previous year has a positive and significant effect. This result may represent the consequences of internal investment in research speeding up the rate at which the organization can upgrade.

Historical research activity. We also address whether our results reflect simply the fact that some organizations have a long history of research activity—regardless of whether it is relevant and consistent. We investigate this alternative by checking to see whether previous knowledge development that was *inconsistent* yields the same results. The idea here is that if all knowledge development in the past increases the rate of technology adoption, then our measure of consistency might be tapping an overall development effect. So we need to be sure that our results are due to knowledge proximity and consistency. To test for this possibility, we create a *knowledge* in*consistency* variable, which is the organization's total knowledge development, represented by the total number of patents issued to it, minus its consistent development:

$$inconsistency_{A,T} = totalpatent_{A,T} - consistency_{A,T}. \quad (10)$$

Model 8 in Table 6 includes the interaction of knowledge proximity with knowledge *in*consistency. This interaction has a positive significant effect on CPU adoption, but its coefficient, 0.0007 (0.0003) is 400 times smaller than the effect of knowledge *consistency* from model 3: 0.316 (0.160). This indicates that there is a small effect of having consistently developed any knowledge, but it is dwarfed by the effect of having consistently developed relevant knowledge.

Technical Similarity and Standards. Next we investigate whether the results are sensitive to underlying technical similarities between CPUs. In this alternative, it is not the knowledge developed by an organization that leads to CPU adoption; rather, knowledge

Table 5. Cox Proportional Hazard Models on the of Adopting a CPU from a Different Supplier, Organization Level Effects[a]

	Model 7
Knowledge proximity to all CPUs from different suppliers	0.141 (0.176)
No. of patents issued to organization	0.0006 (0.0020)
Organization is medium sized	0.0828 (0.398)
Organization is large sized	0.329 (0.511)
Organization is also in the midrange computer market	0.879** (0.421)
Organization is also in the mainframe computer market	−1.604 (0.997)
No. of years the organization has been in the microcomputer market	1.642** (0.301)
No. of CPU *suppliers* used by organization	−0.470** (0.201)
No. of CPUs offered in products sold by organization	−0.207* (0.110)
No. of alternative CPUs from the same supplier	0.105** (0.0241)
No. of alternative CPUs from different suppliers	−0.138** (0.0261)
No. of microcomputer organizations	−0.0120** (0.0039)
No. of product shipments in the microcomputer market/1,000	−0.0009** (0.0003)
GDP	−0.0056** (0.0013)
Log pseudolikelihood	−206.6

[a]Models are run on 1,211 organizations at risk of adopting a CPU from a different supplier including 504 adoption events of one or more CPU over 3,281 organization-years.
$^{*}p < 0.10$ $^{**}p < 0.05$ (two-tailed tests).

space proximity to a CPU reflects underlying similarities between an organization's current CPU offerings and the target CPU. For instance, if particular CPUs are based on common standards, then their rates of adoption would be mutually reinforcing (Barnett 1990). To look at this, we revisit the transition matrix from Table 2, which counts the number of organizations that offer CPUs made by one supplier in time t_1 that adopt a CPU made by another supplier in t_2. If there is technical similarity between two CPU suppliers, we will see more computer manufacturers transitioning between CPUs made by these suppliers. We therefore include a count of the number of transitions from the organization's suppliers to the destination CPU up to a given point in time. Model 9 includes this variable, which is not significant. Meanwhile, our findings on knowledge generalism, proximity, and consistency remain with this variable included.

We further test against this alternative in model 10, which includes indicator variables for whether the

Table 6. Cox Proportional Hazard Rate Models, Adopting a New CPU from a New Supplier[a]

	Model 8	Model 9	Model 10	Model 11	Model 12
Knowledge generalism	−0.1100*	−0.1115**	−0.1317**	−0.107*	−0.115**
	(0.0567)	(0.0567)	(0.0641)	(0.0570)	(0.0569)
(Knowledge proximity to target CPU) × (Knowledge consistency)		0.3259**	0.3545**	0.281*	0.307*
		(0.1602)	(0.1617)	(0.166)	(0.164)
(Knowledge proximity to target CPU) × (Knowledge *in*consistency)	0.0007**				
	(0.0003)				
No. of prior transitions from manufacturer's CPU suppliers to target CPU		−0.004			
		(0.0061)			
Environmental controls					
No. of microcomputer manufacturers	−0.0071**	−0.0071**	−0.0053**		
	(0.0013)	(0.0013)	(0.0014)		
No. of microcomputer manufacturers using target CPU				0.00130	
				(0.00183)	
No. of microcomputer manufacturers using another CPU				−0.00831**	
				(0.00130)	
No. of microcomputer manufacturers using a CPU from target supplier					−0.00233
					(0.00157)
No. of microcomputer manufacturers using a CPU from another supplier					−0.00844**
					(0.00132)
Product shipments in the microcomputer market/1,000	−0.0004**	−0.0004**	−0.0004**	−0.000433**	−0.000399**
	(0.0001)	(0.0001)	(0.0001)	(0.0000851)	(0.0000845)
No. of alternative same-supplier CPUs	0.1271**	0.1269**	0.1504**	0.127**	0.117**
	(0.0124)	(0.0124)	(0.0130)	(0.0123)	(0.0125)
No. of alternative different-supplier CPUs	−0.0598**	−0.0601**	−0.0611**	−0.0570**	−0.0669**
	(0.0117)	(0.0117)	(0.0127)	(0.0116)	(0.0117)
GDP	0.0000	0.0000	0.0002	0.000362	−0.0000256
	(0.0007)	(0.0007)	(0.0008)	(0.000726)	(0.000727)
Supplier fixed effect	No	No	Yes	No	No
CPU controls					
CPU is supplier's latest release	−2.716**	−2.726**	−2.701**	−2.227**	−2.591**
	(0.3187)	(0.3189)	(0.3126)	(0.303)	(0.313)
Time since CPU was released (latest releases only)	1.031**	1.041**	1.064**	0.981**	0.993**
	(0.0912)	(0.0923)	(0.0922)	(0.0903)	(0.0905)
No. of failures for manufacturers that did not use target CPU	0.0122**	0.0121**	0.0100**	0.0133**	0.0128**
	(0.0017)	(0.0017)	(0.0018)	(0.00172)	(0.00171)
No. of failures for manufacturers that used target CPU	−0.0309**	−0.0309**	−0.0266**	−0.0537**	−0.0494**
	(0.0079)	(0.0079)	(0.0080)	(0.00891)	(0.00895)
Organizational controls					
Manufacturer is medium-sized	0.2848**	0.2850**	0.1384	0.272**	0.300**
	(0.1221)	(0.1221)	(0.1257)	(0.122)	(0.122)
Manufacturer is large	0.7149**	0.7120**	0.5705**	0.713**	0.734**
	(0.1470)	(0.1471)	(0.1502)	(0.147)	(0.147)
Manufacturer is also in the midrange computer market	0.1651	0.1669	0.2710**	0.161	0.150
	(0.1121)	(0.1122)	(0.1251)	(0.112)	(0.111)
Manufacturer is also in the mainframe computer market	0.4503**	0.4422**	0.3137	0.424**	0.428**
	(0.1847)	(0.1853)	(0.2127)	(0.184)	(0.184)
No. of years the manufacturer has been in the microcomputer market	0.0185	0.021	0.0142	0.0179	0.0159
	(0.0152)	(0.0156)	(0.0158)	(0.0152)	(0.0152)
No. of CPU suppliers used by manufacturer	−0.1993**	−0.1986**	−0.1653	−0.221**	−0.202**
	(0.0980)	(0.0981)	(0.1949)	(0.0978)	(0.0975)
No. of CPUs offered in products sold by manufacturer	−0.1351**	−0.1341**	0.0261	−0.114**	−0.117**
	(0.0519)	(0.0519)	(0.0557)	(0.0519)	(0.0519)
Log pseudolikelihood	−3,287.75	−3,287.59	−3,215.54	−3,268.9	−3,277.3
Degrees of freedom	18	19	41	19	19

[a]All models include CPU-specific nuisances. Models are run on 58,992 organization-CPU pairings, including 618 adoptions over 128,011 organization-CPU years.

*$p < 0.10$, **$p < 0.05$ (two-tailed tests).

organization in the dyad uses a CPU from each of the 23 CPU suppliers in the data. This captures whether there is an increased or decreased propensity for organizations using a particular supplier to transition to the destination CPU. Our findings are robust in this specification, indicating that technical similarities between CPUs are not driving the reported effects.

Finally, models 11 and 12 allow effects to vary based on the number of microcomputer manufacturers using the target CPU or the number using a CPU from the target supplier. Results are robust. Neither variable has a significant effect. The number of failures of manufacturers that used the target CPU, included as a control, has a negative and significant effect. This suggests that whether *successful* competitors use a CPU is more influential to adoption than the sheer numbers of other manufacturers that use a CPU.

Control Variables

We include a number of controls which affect the propensity of an organization to adopt a CPU from a different supplier. CPUs that are latest releases are less likely to be adopted initially, but are more likely to be adopted after they are out for some time, probably because microprocessor manufacturers would take time to ramp up their manufacturing capacities. The higher the failure rate of organizations that used the target CPU, the lower the likelihood of adoption; and the higher the failure rate of those who used a different CPU, the higher the likelihood of adoption. This pattern is consistent with organizations flocking into successful technologies and avoiding less successful ones—where perceived lack of success of a technology is strongly influenced by failures among those who use it (Pontikes and Barnett 2017).

Organizational characteristics also influence the propensity of an organization to adopt a CPU. Larger organizations and those that span multiple markets tend to adopt CPUs more frequently. Organizations that already use a wide range of suppliers and CPUs in their product offerings adopt CPUs less frequently, which we believe is the result of a limit to the number of alternative components an organization can support. We also include the number of alternative CPUs available, and whether the alternative CPU is from the same supplier or from different suppliers. The more alternatives available from the organization's suppliers, the more likely the organization is to adopt a CPU from a *different* supplier. This result might be picking up consequences of shared fates between organizations and their suppliers: when suppliers have the resources to release a number of new CPUs, the organizations that use their components are also doing well, and are expanding their offerings. The more alternatives available from different suppliers, the less likely the organization will adopt the target CPU. This result probably reflects a competitive effect.

Looking at the environmental controls, increases in microcomputer density and microcomputer shipments decrease the organization's likelihood to adopt a CPU. This changing pattern of adoption over the development of the industry is consistent with the received literature on technology diffusion (Rogers 2003). Adoption rates were highest early in the diffusion process, and then declined as the market matured.

Discussion and Conclusion

Taking a coevolutionary approach, we identify a role for choice within an evolutionary analysis of strategy. Choices made over time shape the variant positions organizations take in knowledge space. These choices, in turn, affect the ability of organizations to make choices to innovate in product space. Variant positions in knowledge space lead to differential advantages for organizations in product space—a coevolutionary effect. In particular, organizations that *consistently* engage in research relevant to an area are likely to adopt products that build on knowledge from that area. But simply having the relevant knowledge does not have a discernable effect on technological change. This means that organizations moving rapidly into new areas of knowledge space—"Johnny come lately" organizations—are not advantaged by that strategy. It follows that frequent changes to the research policies of organizations are not an advisable strategy for remaining on the cutting edge of technical knowhow. Rather, organizations need to consistently build knowledge in an R&D area for that knowledge to facilitate changes in the market.

Given technical and market uncertainty, organizations typically do not know well in advance where to invest in a long-term, consistent body of research. For this reason, some organizations choose to hedge their bets, researching generally. We argue that this strategy should be unlikely to pay off, since knowledge generalists will lose focus and suffer from spreading their material, human, and cognitive resources too thin. Consistent with this argument, we find that organizations are much less likely to adopt new technologies in any particular area if they spread their knowledge across multiple areas. And organizations that take the generalist strategy are not more likely to adopt any one different supplier CPU. The organizations most likely to adopt new technologies in our data are knowledge specialists that build a consistent base of relevant R&D.

It is noteworthy that our findings hinge on taking an ecological approach, including a consideration of the coevolution of knowledge and markets. Our identification of each organization's position—in both knowledge space and market space—is relative to other organizations. By comparison, many existing studies of technology look at patenting and patent citation patterns in absolute terms, measuring whether an organization searches close or far by comparison to itself. In contrast, our approach locates organizations in an ecology of organizations, each positioned relative to the others. Furthermore, we map the coevolution of both knowledge space and market space, allowing us to identify not only whether research is consistent, but also whether it is relevant to the firm's product changes. By making these distinctions, we are able to identify an underlying relationship between relevant knowledge development and knowledge consistency in fostering technological change.

These findings have implications for organizations that encourage university-like environments in their research labs, where many different areas of knowledge are simultaneously explored. Organizations that research in many different areas of knowledge space may hedge their bets technically, but they put themselves in a position where it is difficult to develop consensus to move in any one direction. Although it may seem that this strategy will keep an organization's options open, it reduces its ability to "close" on any one.

Similarly, these results suggest limits to whether organizations can effectively combat technological inertia. They may explain why old and large organizations are often eclipsed by younger competitors (Tushman and Anderson 1986). Cultivating agile or broad research strategies in an attempt to overcome inertia may make matters worse, as these approaches reduce the likelihood that an organization will come to consensus about a new technology. Managers may want to take a measured approach, balancing forays into new and different knowledge areas with a careful analysis of the organization's historical research strengths. Further, choosing to focus on a few important knowledge areas is likely to be more fruitful than dabbling in a wide range of research.

This pattern of findings highlights a limitation to our study, and suggests a direction for future research. In our data, we were able to identify organizations that moved recently into any particular knowledge area, but we did not know how they did so. In particular, many organizations attempt to change their strategies by merging with or acquiring other companies. Our data did not investigate the effects of mergers and acquisitions on knowledge development, but clearly these events could significantly alter the knowledge position of an organization. If mergers and acquisitions give rise to the "Johnny come lately" firms in different parts of knowledge space, and if these firms then underperform in terms of technical change, then our results will follow. We cannot tell if this mechanism plays a role in the pattern of results that we found, but future research can look into this possibility.

Organizations benefit from stability, but they also need to change to keep up with the times. This tension is an ongoing topic for research on strategy and organizations. Organizational learning theory highlights both the need to change and the ways that rapid change backfires (March 1994). Organizational ecology reveals the problematic side of change, with the benefits of adaptation available only after a period of disruptive adjustment (Barnett and Carroll 1995). Evolutionary economics theorizes that routines are stable repositories of knowledge as well as the adaptive units behind economic change (Nelson and Winter 1982, Becker 2004). Strategy research observes that organizations differ in terms of their dynamic capabilities, which facilitate the ability to change (Teece et al. 1997). Azoulay and Lerner (2013) highlight these differences, suggesting that organizations must balance retaining proven practices with generating uncertain improvements to effectively innovate. Complexity theory also addresses this problem and finds organizational adaptation leads to instability that makes population-level selection less effective (Levinthal and Posen 2007). Across this broad base of research, there is consensus that organizations face a fundamental tension between the benefits of stability and the need to change.

We think there is an underlying process that helps resolve the tension between organizational stability and change. Identifying this process requires that we distinguish between an organization changing its knowledge and changing its products. Often researchers study organizational change by observing alterations in products, technologies, or services. But organizations also build a body of knowledge that is distinct from its market offerings. Changes in products or services offered may or may not be coupled with changes in knowledge development. Sometimes organizations build knowledge consistently in a particular area, as when a pharmaceutical firm continues to do R&D in a particular area of immunology, or when a consulting firm continues to train its associates in a certain business technique. In other cases, an organization may shift the direction of knowledge development, choosing to move into new areas. This type of change is different from changes to an organization's market offerings.

Our research has implications for whether organizations can adapt to rapidly changing environments. It is well known that significant organizational change is difficult and hazardous (Carroll and Hannan 2000), and often such changes are technological in nature (Christensen 1997). If organizations can redirect their R&D so that they have the knowledge relevant to a new product, and if there is a one-to-one mapping between the two spaces, they should be able to adapt well as markets change. This idea appears frequently in the strategy field, where it is often proposed that more adaptive organizations have "dynamic capabilities"—an ability to change (Teece et al. 1997). Many organizations will have trouble adapting to technological change, but those that keep their R&D efforts relevant to the cutting edge of new market developments will be uniquely capable of adaptation (Helfat 1997). If market requirements change dramatically, organizations can rapidly adapt by changing R&D efforts (Ahuja and Lampert 2001). But the findings here suggest that persistence over time is required if knowledge is to lead to differential advantage in product markets.

In this paper, we argue that building a stable base of knowledge has important implications for an organization's ability to change the products it takes to market. We demonstrate that an organization can more easily draw from a knowledge base that is built consistently over time. In developing this argument, we draw from research on innovation among scientists. A scientist will typically come up with a number of new research projects, each different in some ways from the ones before—but normally, all will build on the scientist's underlying area of expertise. If the scientist changes areas of expertise frequently, she is less capable of innovation in any one area (Lakatos 1970). We apply this thinking to the organizational context and conclude that knowledge consistency facilitates an organization's ability to change the technologies in its products. Stability and change enhance one another within organizations, with knowledge stability and product change going hand-in-hand.

We think our theory and findings cast new light on how exploration takes place in the evolution of industries. In the years since March (1991) introduced the contrast of exploration and exploitation, it has been widely used to juxtapose alternative strategies for search and learning; organizations that focus on an area they know well are exploiters, while those who probe more broadly are explorers. Our findings demonstrate the utility of distinguishing between two different forms of exploration, according to whether such search occurs in knowledge space or product space. By making this distinction, we are able to identify an important interdependence. Organizations that explore in knowledge space end up less consistently focused in any one area, which in turn makes them less able to explore into new areas of product space. In this way, we demonstrate that a coevolutionary perspective illuminates patterns of change and adaptation that would escape notice if we looked only at exploration along a single dimension.

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Endnotes

[1] While of course not all units of knowledge are embodied in patents—or even codified for that matter—we study a context where much of the recognizable knowledge is in fact embodied in patents. Durham's analysis of cultural evolution features "memes" as the recognizable units, drawing on the term originally coined by Dawkins (1976). Interestingly, our units of knowledge come very close to Durham's (1991, p. 422) definition of memes: "configurations of information that show both variation and transmission."

[2] We conducted interviews with a number of experts who worked during the study period on the design of microcomputers, CPUs, and instruction sets.

[3] By 2005, when Rafiquzzaman published his massive text containing detailed schematics and instruction sets, the technical knowledge involved in changing CPUs was well known (if still complicated).

[4] By using maximum similarity at the patent level, we allow for two organizations that patent heavily in two distinct areas of knowledge space to measure as very similar. Consider an organization A that patents in two distinct areas of knowledge space, K1 and K2; and organization B also patents in these two areas. By taking the maximum similarity, A's patents in K1 will have high similarity to B's patents in K1, and A's patents in K2 will have high similarity to B's patents in K2. In the sum as defined in (1), A and B will correctly measure as highly proximate in knowledge space. If, for each of A's patents, we measured the average similarity to all of B's patents, each of A's patents in K1 and K2 would measure as somewhat similar to the average of B's patents in K1 and K2; and A and B would incorrectly be measured as moderately proximate in knowledge space.

[5] Results are not sensitive to the functional form of the temporal discount.

[6] Historically, the computer industry included two other markets aside from the microcomputer market. Mainframe computers, large machines operated centrally by an organization's information technology experts, were the first electronic digital computers. Midrange computers included minicomputers, servers, and workstations networked to servers. These systems ushered in the era of distributed computing that preceded the microcomputer, and the market for servers remains vital today because of their role in modern computing networks.

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