Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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MANAGEMENT SCIENCE
Vol. 58, No. 5, May 2012, pp. 843–859
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.1110.1446

The Extroverted Firm: How External Information Practices Affect Innovation and Productivity

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We gather detailed data on organizational practices and information technology (IT) use at 253 firms to examine the hypothesis that external focus—the ability of a firm to detect and therefore respond to changes in its external operating environment—increases returns to IT, especially when combined with decentralized decision making. First, using survey-based measures, we find that external focus is correlated with both organizational decentralization, and IT investment. Second, we find that a cluster of practices including external focus, decentralization, and IT is associated with improved product innovation capabilities. Third, we develop and test a three-way complementarities model that indicates that the combination of external focus, decentralization, and IT is associated with significantly higher productivity in our sample. We also introduce a new set of instrumental variables representing barriers to IT-related organizational change and find that our results are robust when we account for the potential endogeneity of organizational investments. Our results may help explain why firms that operate in information-rich environments such as high-technology clusters or areas with high worker mobility have experienced especially high returns to IT investment and suggest a set of practices that some managers may be able to use to increase their returns from IT investments.

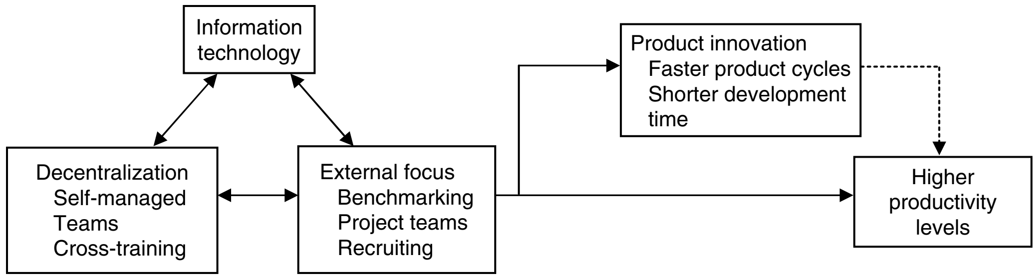
Key words: information technology; productivity; organizational practices; external focus; complementarities; high-performance work practices; product development; high-tech clusters
History: Received September 2, 2009; accepted February 12, 2011, by Sandra Slaughter, information systems. Published online in *Articles in Advance* January 13, 2012, and updated February 10, 2012.

1. Introduction

Falling internal communication costs and new internal information practices enable information-age firms to quickly respond to changes in consumer preferences, technology, and competition. However, improvements in the accuracy and timeliness of information are valuable only when combined with appropriate changes in decision rights and organizational practices (Brynjolfsson and Mendelson 1993, Mendelson and Pillai 1999). This suggests that the adoption of practices used to detect and respond to changes in the external operating environment should become increasingly common. Internet companies are an extreme example: firms like Amazon and Google record each customer's keystrokes and analyze the data to continuously optimize their products, processes, and marketing. Offline companies are also using customer data extensively. For example, Harrah's invested heavily in capturing data on consumer gaming patterns, which they used to design compelling packages to attract high-value customers and outperform competitors (Loveman 2003). Similarly, firms like Cisco, Capital One, UPS, and Walmart have been described as gaining competitive advantage by adopting an aggressive approach to learning about their customers and competitors (Davenport and Harris 2007).

A growing research literature on the behavior of modern organizations has linked firm performance to the ability to identify and respond to changes in a firm's competitive environment (Saxenian 1996, Dyer and Singh 1998, Dyer and Nobeoka 2000, Powell et al. 1996, Bradley and Nolan 1998, von Hippel 1988). Researchers have also emphasized the role of information technology (IT) in the development of information gathering and processing capabilities that facilitate external orientation (Mendelson and Pillai 1999, Malhotra et al. 2005, Pavlou and El Sawy 2006, Rai et al. 2006, Bharadwaj et al. 2007). However, the growing emphasis on external orientation has not

Figure 1 **Complementarities Model**



been integrated into the IT productivity literature, which has primarily emphasized the importance of adopting organizational changes like decentralization in conjunction with IT investments (Bresnahan et al. 2002, Brynjolfsson et al. 2002).

In this study, we argue that information technologies are most productive when they allow firms to quickly respond to external information. The central argument of this paper is that the combination of *external focus*, *changes in decision rights*, and *IT investments* forms a three-way system of complements resulting in higher productivity levels (Figure 1). For example, Harrah's, in addition to adopting new information technologies to monitor consumer gaming patterns, simultaneously made extensive changes to internal practices, such as implementing the appropriate incentives for customer service personnel to keep high-value customers happy. These changes were required to successfully handle the massive amounts of customer intelligence being generated.

The implication is that organizations that do not have the appropriate receptors in place through which to sense environmental change will not experience the same returns to IT investments, even if they have reorganized decision making. In keeping with earlier research (Mendelson and Pillai 1999), we define "external focus" as a set of practices that firms use to detect changes in their external operating environment. In information-rich environments, firms should engage in practices that make up-to-date, accurate information available to decision makers. The literature has emphasized several mechanisms through which firms can capture external information, such as customer interaction, benchmarking, and using interorganizational project teams. We argue that returns to IT and decentralization are higher in firms that have adopted these practices.

Conceptually, complementarities between external information awareness and internal information practices are grounded in the literature on information-processing organizations (Radner 1992, Cyert and March 1963). Because "boundedly rational" organizations are limited in the amount of information they can effectively process, improvements in internal information-processing capabilities, such as those offered by information technologies, increase the firm's capacity to process information for decision making and to therefore respond to external information. Thus, the largest productivity benefits from improving a firm's internal information-processing infrastructure should be observed in dynamic environments where the firm continuously captures and responds to external signals. Beyond broad performance benefits, this literature places special emphasis on product development as a mechanism through which IT-led improvements in information processing lead to higher productivity (Mendelson 2000, Pavlou and El Sawy 2006, Bartel et al. 2007). Firms that effectively sense and process external information should have market-based advantages when introducing new products (Kohli and Jaworski 1990, Mendelson and Pillai 1999).

Our study is based on a 2001 survey of organizational practices in 253 moderate-size and large firms, matched to data on IT investment and firm performance from private and public sources. In addition to including measures of internal organization used in prior work, we included constructs to capture external focus and product innovation, motivated specifically by the work done by Mendelson and Pillai (1999) on external practices in the computer manufacturing industry. But we adapted this to a more heterogeneous set of firms, and broadened it to include other sources of external information such as tacit knowledge obtained from the strategic recruitment of new employees.

We find that external focus, decentralized organization, and IT investment are correlated. Second, we find that these practices lead to higher product innovation rates. Third, we estimate a three-way complementarities model (IT, external focus, decentralization) and demonstrate that firms that combine all three practices derive substantially greater benefits from their IT investments. Our econometric identification strategy includes the assumption that organizational practices are quasi fixed in the short run. However, we also introduce an innovative set of instrumental variables based on inhibitors of organizational change to demonstrate that our results are not sensitive to this assumption. In our preferred specifications, the output elasticity of IT investment is about seven percentage points higher in firms that are one standard deviation above the mean on both our external focus and organizational decentralization measures than the average firm in our sample.

These findings suggest that firms can more successfully leverage IT investments if they effectively capture external information through networks of customers, suppliers, partners, and new employees. Mounting a more effective response to external information requires that firms have the mechanisms in place through which to absorb this information, as well as the mechanisms to allow effective local information processing. Internal workplace organization, external information practices, and information technologies appear to be part of a mutually reinforcing cluster associated with faster product development cycles and higher productivity.

Our paper contributes to a literature on IT value, supporting the argument that organizational complements lead to higher IT returns (Brynjolfsson and Hitt 1995, 2000; Dedrick et al. 2003; Melville et al. 2004). We build on prior work that addresses complementarities between IT and internal practices such as decentralized decision making (Bresnahan et al. 2002, Caroli and Van Reenen 2002) but add the external orientation dimension, which has been shown to be important in technology-intensive firms (Mendelson and Pillai 1999, Pavlou and El Sawy 2006). Identifying organizational complements is useful for managers who are restructuring their organizations to take advantage of improvements in computing. In addition, our results improve our understanding of why firms in information-rich environments such as Silicon Valley (Saxenian 1996) appear to receive greater benefits from technology investments and why IT returns may be influenced by geographic position (Dewan and Kraemer 2000, Bloom et al. 2012).

2. Data and Measures

Our organizational practice measures are generated from a survey that was administered to 253 senior human resource managers in 2001. The survey was conducted by telephone on a sample of 1,309 large and upper middle-market firms[1] that appear in a database of IT spending compiled by Harte Hanks (see further detail below) and that also have the requisite financial data in Compustat. The survey yielded a response rate of 19.3%, which was typical for large-scale corporate surveys at the time. The sample of responding firms has a slightly higher proportion of manufacturing firms relative to the sample population (62% versus 54%), and the firms tend to be slightly smaller when measured in sales, assets, employees, and market value. However, after conditioning on industry, the size differences between responding and nonresponding firms are not statistically significant. Furthermore, there is no significant difference between responding and nonresponding firms on performance measures such as return on assets or sales per employee.

Table 1 Organizational Practice and Human Capital Survey Variables

	Range	*N*	Mean	Std. dev.
External focus				
Regularly use competitive benchmarks	1–5	233	3.58	1.06
Project teams include suppliers, partners, customers	1–5	227	2.21	1.10
Adopt new technologies	1–5	225	3.10	1.09
Executives spend significant time recruiting	1–5	247	2.15	0.82
Successful in attracting new employees	1–5	239	2.92	0.92
Decentralization				
Self-managing teams	1–5	249	2.39	1.15
Cross-training	1–5	250	3.29	0.98
Team-building activities	1–5	249	2.70	1.04
Quality circles	1–5	243	2.51	1.17
Promotion based on teamwork	1–5	245	2.38	1.14
Who decides pace of work (5 = employees)	1–5	252	2.48	0.75
Who decides method of work (5 = employees)	1–5	251	2.78	0.83
Product cycles and new technology adoption				
Typically first to introduce new products	1–5	218	3.22	1.08
Leading edge adopter of new technologies	1–5	225	3.10	1.09
Weed out marginal product lines	1–5	208	3.34	0.99
Human capital variables				
% *College*	0–90	206	20.2	20.0
% *Professional*	0–79	227	22.6	18.6
% *Skilled*	0–88	227	23.6	20.5

The questions for this survey were drawn from a previous wave of surveys on IT usage and workplace organization administered in 1995–1996 and incorporated additional questions on external and internal information practices motivated by research on IT and organizational design (Mendelson and Pillai 1999). Our survey also includes questions related to firms' human capital mix, including occupational and educational distributions (see Table 1 for a summary of variables and their descriptive statistics).

2.1. External Focus

Our measure of external focus is based on an industry-specific "external information" construct utilized by Mendelson and Pillai (1999), which is in turn closely related to the customer-specific concept

[1] The target sample contains 806 Fortune 1000 firms as well as 503 firms that are present in Compustat but not Fortune 1000 that are routinely sampled by Harte-Hanks over our time period.

Table 2 External Focus Measure

	Kohli et al. (1993)	Mendelson and Pillai (1999)	Tambe et al. (2012)
Measure	Intelligence generation[a]	External information[b]	External focus
Definition	The collection and assessment of both customer needs preferences and the forces (i.e., task and macro environments) that influence the development and refinement of those needs	Whether the organization has receptors to sense changes in the external environment and provide it with quick and accurate feedback	External information practices used to detect environmental changes
Information scope	Customer preferences	Technology, product markets, customers, and competitors	Technology, product markets, customers, and competitors
Industry scope	All sectors	IT hardware manufacturing	All sectors
Scale items used	1. In this business unit, we meet with customers at least once a year to find out what products and services they will need in the future. 2. In this business unit, we do a lot of in-house market research. 3. We are slow to detect changes in customers' product preferences. 4. We poll end users at least once a year to assess the quality of our products and services. 5. We are slow to detect fundamental shifts in our industry (e.g., competition, technology, regulation). 6. We periodically review the likely effect of changes in our business environment (e.g., regulation) on customers.	1. How important are direct discussions with customers and input from marketing personnel as sources of ideas for product development? 2. How important are customer preferences in defining your cost reduction targets? 3. On what basis do you set order throughput time targets?	1. Project teams often include employees from customers, suppliers, or business partners. 2. Competitive benchmarks are regularly used in corporate strategic planning. 3. We are usually the leading edge adopter of new technologies in our industry. 4. Executives devote a significant part of their time to recruiting. 5. We are successful in attracting new employees because we pay better than industry average.

[a]Intelligence generation is one element of "market orientation" along with intelligence dissemination and responsiveness.
[b]Awareness of external Information is one element of the "information age organization," along with decentralization, incentives, internal knowledge dissemination, learning by doing, internal focus, and interorganizational networks.

of "market orientation" defined by Narver and Slater (1990) and Jaworski and Kohli (1993) and operationalized by Kohli et al. (1993). We broaden our measure to be applicable beyond customer information (like Mendelson and Pillai 1999) and to multiple industries. In Table 2, we present the components of our external focus measure alongside the components used in related work. Both Kohli et al. (1993) and Mendelson and Pillai (1999) include constructs for direct customer interaction (see Table 2, Kohli et al. (1993) scale items 1–3, Mendelson and Pillai (1999) scale items 1–2), which we capture in a question related to customer participation on project teams, but we also include partners and suppliers (variable *PROJTEAM*). Our second question focuses on the use of competitive benchmarking (*BNCHMRK*), which relates to a firm's awareness of the industry and broader business environment in Kohli et al. (1993) (scale items 5, 6) and the industry-specific measure of order throughput benchmarking used in Mendelson and Pillai (1999) (scale item 3).

To these measures, we add additional constructs for incorporating new technology (scale item 3, variable *NEWTECH*), as well as measures that examine how the firm might capture external information through employee mobility—the involvement of executives in recruiting (*EXECRCT*) and the use of higher pay to attract new employees (*NEWEMP*). The inclusion of employee mobility was motivated by work in strategic management that emphasizes this particular pathway as a means of gathering tacit knowledge related to the competitive or technological environment (Argote and Ingram 2000, Song et al. 2003). Executive involvement in recruiting and pay for performance were specifically identified as key components of digital strategy in a case study of Cisco Systems (Woerner 2001). Pay for performance has also been central to numerous other studies, including recent work by Aral et al. (2012). In summary, we cover many of the same constructs as prior work but adapt them to apply to a broader set of industries than the industry-specific measures in Mendelson and

Table 3 Correlations for Variables Used in External Focus Measure

	BENCHMARK	*PROJTEAM*	*EXECRCRT*	*NEWEMP*	*NEWTECH*
BENCHMARK	1.0				
PROJTEAM	0.22	1.0			
EXECRCRT	0.13	0.13	1.0		
NEWEMP	0.17	0.23	0.25	1.0	
NEWTECH	0.27	0.07	0.10	0.28	1.0

Note. $N = 201$.

Pillai (1999), and we place greater emphasis on noncustomer information (in contrast to Kohli et al. 1993) to reflect an operations rather than marketing focus that may better fit a heterogeneous cross-section of firms.

Correlations between the individual constructs are shown in Table 3. The measures are positively correlated, but not very highly correlated, and Cronbach's alpha for a five-item scale constructed from the individual variables is 0.521. The relatively lower alpha value is because these external measures are multidimensional in the sense that just because firms do one of these activities, they do not necessarily also have to do the others. This implies that firms in different industries may access environmental information in many ways, all of which may have similar economic impact. Indeed, in our main analysis, we could not reject the hypothesis that the standardized values of the five components of external focus have the same coefficients when entered into the regression individually. Consequently, we combined these measures in a similar manner to our workplace organization variables, where each factor is first standardized (STD) by removing the mean and then scaled by its standard deviation, yielding an external focus measure with a mean of zero and a standard deviation of one. The full form of our aggregate external focus variable is shown below.

$$\begin{aligned} EXT = STD\big(&STD(BNCHMRK) + STD(NEWTECH) \\ &+ STD(PROJTEAM) + STD(EXECRCRT) \\ &+ STD(NEWEMP)\big). \end{aligned}$$

Higher values on this scale represent more channels of external information acquisition, but firms that use none of these practices can still be externally focused (Type II error), although it is likely that firms that have implemented unmeasured external information practices will also rate high on our external focus scale. It is somewhat less likely that a firm that rates high on our external focus scale will know little about the external environment (Type I error). Regardless, to the extent that our construct mismeasures the true underlying external focus of some firms, measurement error is likely to bias *downward* the estimates on our external focus variables (Griliches and Hausman 1986). Results from productivity regressions using a variety of alternative external focus measure constructions, including one that omits the two variables associated with the employee mobility (and thus are more directly comparable to Mendelson and Pillai 1999 and Kohli et al. 1993), show similar results (available from authors on request).

2.2. Workplace Organization

To capture internal organizational processes that are complementary to external focus, we rely on a scale focused on decentralized and team-oriented work practices used in prior work (Bresnahan et al. 2002, Brynjolfsson et al. 2002), which was originally motivated by the extensive literature on "high performance work systems" (Ichniowski et al. 1996). The measure contains four constructs of group-based decentralized decision making [the use of self-managed teams in production (*SMTEAM*), the use of team-building activities (*TEAMBLD*), the use of teamwork as a promotion criterion (*PROMTEAM*), the use of quality circles or employee involvement groups (*QUALCIR*)], and two measures capturing individual decision rights [the extent to which individual workers decide the pace of work (*PACE*) and the extent to which individual workers decide methods of work (*METHOD*)]. The Cronbach's alpha for the four team-based measures is 0.732, and the alpha for all six measures is 0.671. Similar to external focus, we construct a scale (WO) from these measures using the standardized sum of the standardized values of each component. We utilized this scale because it shows significant variation across firms, it has been previously shown to be a useful summary metric of IT-related work practices (Hitt and Brynjolfsson 1997), and it has a clear economic interpretation as decentralized, team-based decision making, which is relatively narrow and specific, making our model and econometrics more precise and interpretable.

2.3. Organizational Inhibitors

Some of our analyses are based on the assumption that the organizational measures described above are quasi fixed over short time periods, which is theoretically justified by a large literature on organizational adjustment costs (Applegate et al. 1988, Attewell and Rule 1984, David 1990, Milgrom and Roberts 1990, Murnane et al. 1999, Zuboff 1988, Bresnahan and Greenstein 1996). However, in addition to organizational practice variables, our survey data include questions on individual inhibitors of organizational change. These were designed to allow us to create direct measures of organizational adjustment costs, which we can use as instrumental variables for our organizational asset measures. These survey questions ask respondents to describe the degree to which the following factors facilitate or inhibit the ability to make organizational changes: skill mix of existing staff, employment contracts, work rules, organizational culture, customer relationships, technological infrastructure, and senior management support. These responses are used as instruments in our product development and productivity regressions, as well as to create an aggregate adjustment cost measure, which was computed as the standardized sum of the standardized values of the individual inhibitors. Cronbach's alpha for the seven individual inhibitors is 0.725.

These organizational inhibitors are suitable as instrumental variables because they reflect the costs firms face in adopting new organizational practices. Firms that face constraints in terms of culture, work rules, or staff mix may find it more difficult or costly to reengineer existing practices or to adopt practices complementary to new IT investments. Therefore, these organizational inhibitors are a source of exogenous variation in the degree to which we are likely to observe the adoption of organizational practices when firms adopt IT. These inhibitors, however, are less likely to be correlated with firm performance directly.

2.4. Innovation, Product Cycles, and Technological Change

Three of the variables from our survey data reflect a firm's innovation and product development capabilities with respect to its competitors. Our goal in choosing these measures is not to fully characterize a firm's product development processes—the literature on product development is very large and includes a variety of perspectives on effective product development (Ulrich and Krishnan 2001). Instead, our variables were chosen to reflect different aspects of the innovation and product development process for which access to information might prove beneficial. We measure (1) whether a firm is normally the first to introduce a new product in its industry (*FIRST*), (2) the speed of internal product development once a new product has been approved (*SPEED*), and (3) whether a firm regularly weeds out marginal products (*PLMGMT*), which is a measure of the effectiveness of a firm's product line management. Access to different product development variables is useful because introduction of new products is related to innovation and the firm's ability to collect and process external information, but product development speed should be more closely associated with the ability to process information within the organization. Our innovation and product development measures are standardized to have a zero mean and standard deviation of one.

Table 4 **Comparison of Occupational Distribution in Sample of Domestic IT Workers with 2006 Occupational Employment Survey (OES)**

Occupation	IT worker sample	OES
Computer and IS managers	0.18	0.10
Computer support specialists	0.26	0.20
Systems analysts and programming	0.37	0.50
Network and data communications	0.19	0.20

2.5. Information Technology

We use two types of measures of computerization, one from our survey and one constructed from a separate data set on IT employment. Managers responding to our survey were asked both the percentage of workers in the organization that used personal computers (%*PC*) and the percentage of workers in the organization that used email (%*EMAIL*). However, these internal measures are only available in the survey base year. To construct our data set for the longitudinal productivity analysis, we include panel IT measures based on an external data set describing firm-level IT employment from 1987 to 2006 (Tambe and Hitt 2012), which we use as a proxy for firms' aggregate IT expenditures.

IT employment in this data set is estimated using the employment history data from a very large sample of U.S.-based IT workers. Table 4 shows the occupational composition of these IT workers. These data include fewer programmers and more support personnel. For our purposes, this employment-based data set compares favorably to alternative archival data sets, such as the Harte-Hanks Computer Intelligence Technology Database (CITDB) capital stock data, in several ways. Although much recent research on IT productivity has relied on the CITDB, complete panel data are generally only available for Fortune 1000 firms, the definitions of variables changed significantly after 1994, and—most importantly—the CITDB no longer includes direct measures of IT capital stock. Consequently, even using methods to infer capital stock from available data only yields self-consistent capital stock measures through about 2000.[2] Our employment-based data, by contrast, are available on a consistent basis through 2006 and include matches for nearly all the firms we surveyed. We have benchmarked these data against a number of other sources of IT data from *ComputerWorld*, Computer Intelligence, and *InformationWeek* and generally

[2] Chwelos et al. (2010) provide a method for extending CITDB 1994 valuation data through 1998 by imputing the values of equipment in the earlier part of the data set and adjusting for aggregate price changes. However, this differs from the method employed by Computer Intelligence, which determines equipment market values by looking at actual prices in the new, rental, and resale computer markets.

Table 5 Means, Standard Deviations, and Correlations for IT Measures

	Variable	N	Mean	Std. dev.	Min	Max	1	2	3
1. % IT employees	*%IT EMP*	177	2.3	2.2	0.1	16.2	1.0		
2. % use PC[a]	*%PC*	171	63.7	29.9	0	100	0.23	1.0	
3. % use email[a]	*%EMAIL*	171	61.3	30.4	0	100	0.21	0.85	1.0

[a]Survey variables.

find high correlations between these different sources in both cross-section and time series.

Descriptive statistics and correlations for the IT employment measures and the survey-based IT measures are shown in Table 5. The mean usage of both PCs and email for firms in our sample is about 60%. By comparison, similar measures from a survey conducted in 1995 indicated that in the average firm, about 50% of workers used computers, and only about 30% of workers used email, implying significant growth in IT intensity in the six-year interim period. The average firm in our sample had about 470 IT workers in 2001, comprising about 2.3% of total employment, compared to 2.2% of total employment accounted for by workers in Computer and Mathematical Occupations in the Bureau of Labor Statistics 2001 Occupational Employment Survey.[3] The large variation across firms for our measures of the fraction of IT workers, email use, and computer use suggests that some firms, such as those in IT-producing industries, have much greater IT usage than others. Therefore, we log-transform our IT measures to facilitate direct comparisons with our organizational factor data. Where we require normalized measures for size, we compute IT workers as a proportion of total workers.

2.6. Value Added and Non-IT Production Inputs

We obtained longitudinal data on capital, labor, research and development expense, and value added for the firms in our sample by using the Compustat database. We used standard methods from the microproductivity literature to create our variables of interest from the underlying data. Price deflators for inputs and outputs were taken from the Bureau of Labor Statistics and Bureau of Economic Analysis websites. Eight industry dummies were created using one-digit North American Industry Classification System (NAICS) headers. Table 6 shows statistics for the 2001 cross section of the Compustat variables included in our analysis. In 2001, the average firm in our sample had about $3.8 billion in sales and 15,200 employees.

[3] Available at http://www.bls.gov/oes/.

Table 6 Production Function Variables

	Variable	Mean	Std. dev.
2001 cross section			
Log(sales)	*LSALES*	6.80	1.77
Log(value added)	*LVA*	5.73	1.80
Log(employment)	*LEMPLOY*	8.44	1.66
Log(IT employment)	*LITEMPLOY*	4.61	1.68
Log(capital)	*LCAP*	6.01	2.02

Note. $N = 181$.

3. Methods

Providing direct evidence of complementarities is challenging because of the endogeneity of organizational practices in observational data (Athey and Stern 1998, Brynjolfsson and Milgrom 2009, Cassiman and Veugelers 2006, Novak and Stern 2009). Moreover, lack of information about the costs and value of specific organizational practices limits the ability to implement structural models of organizational investment. The existing empirical literature on organizational complements has therefore focused instead on providing evidence of the economic *implications* of complementarities between organizational practices (Arora and Gambardella 1990, Bresnahan et al. 2002). The empirical strategy followed in these studies is to marshal a number of different types of evidence consistent with the complementarities hypothesis, which, when considered in whole, strongly suggest complementarities between organizational practices.

In particular, complementarities imply that we should observe (1) the clustering of practices across firms and (2) that the simultaneous presence of these complements impacts performance more than the sum of the individual effects. To the extent managers understand and embrace complementarities, they would be expected to adopt them jointly, which should lead to significant correlations but lower power for the performance tests. In contrast, to the extent that the practices vary because of random shocks, the performance tests can be expected to have more power (Brynjolfsson and Milgrom 2009). We measure clustering as correlation within a survey base year as well as changes in correlations over time, and performance by regression models with interactions as well as newer tests proposed by Brynjolfsson and

Milgrom (2009) that contrast performance for different combinations of complementary practices. We also include two useful measurement innovations. First, unobserved human capital among firms is likely to be a significant omitted variable in prior work on organizational practices. Using our survey data, we are able to include human capital controls at the firm level. Second, we are able to consider the potential endogeneity of work practices by instrumenting these measures with our data on inhibitors to organizational innovation, which indirectly capture the cost variation of organizational investments across firms. Thus, we substantially increase the number of factors that we are able to directly measure, reducing the role that unobserved heterogeneity and endogeneity play in the analysis relative to earlier studies on organizational complementarities.

3.1. Correlation Tests

The first test we conduct is based on correlations among these organizational practices. First, using our cross-sectional data, we examine how the use of IT and the proposed complementary practices co-vary in the survey base year. If these practices are complements, price declines in IT should be accompanied by greater use of both complementary organizational practices. Second, we can examine time trends in correlations. If IT is complementary to the proposed organizational practices, we should see rising correlations over time as managers adjust IT levels to match levels of other complementary inputs.

3.2. Innovation and Product Development Regressions

We can also use our data to develop some insight into *how* these inputs affect the productivity of firms. We test how our organizational and IT variables are associated with various stages of the product development process by estimating the following model:

$$PROD_i = \beta_{EXT}EXT_i + \beta_{WO}WO_i + \beta_{IT}IT_i + \beta_{RD}RD_i + controls.$$

PROD represents one of our three possible product development outcomes (*FIRST, SPEED,* and *PLMGMT*), *EXT* is our external focus variable (*EXT*), *WO* measures workplace decentralization, *IT* is a measure of IT use within the firm, *RD* measures R&D intensity computed as the R&D expense per employee, and *i* indexes firms. For our *IT* usage variable, we use the percentage of workers who use email. As control variables, we include dummy variables for industry and the percentage of a firm's workers who are college educated.

One concern with these regression estimates is that organizational practice variables and product development measures may be simultaneously determined. Therefore, we use instrumental variables to conduct regressions in which the organizational measures (*WO* and) are treated as endogenous. As instruments, we use our individual inhibitors of organizational transformation, which reflect the ease or difficulty through which firms can develop these organizational assets, as well as the state in which a firm's corporate headquarters are located, which may affect a firm's cost for external information gathering.

3.3. Productivity Tests

We test complementarities in production by embedding our measures within a production function. The productivity framework has been widely used in IT productivity research (Brynjolfsson and Yang 1996 and Stiroh 2005 review much of this literature). IT productivity scholars embed measures of IT, along with levels of other production inputs, into an econometric model of how firms convert these inputs to outputs. Economic theory places some constraints on the functional form used to relate these inputs to outputs, but a number of different functional forms are widely used, depending on the firm's economic circumstances.

We use the Cobb-Douglas specification, which, aside from being among the simplest functional forms, has the advantage that it has been the most commonly used model in research relating inputs such as IT to output growth (e.g., Brynjolfsson and Hitt 1995, 1996; Dewan and Min 1997) and has been used extensively in research testing for complementarities between IT and organization (Bresnahan et al. 2002, Brynjolfsson et al. 2002). Our primary regression model can be written as

$$\begin{aligned} va = {} & \beta_k k + \beta_{nite} nite + \beta_{it} it + \beta_{WO} WO + \beta_{EXT} EXT \\ & + \beta_{WO\times EXT}(WO \times EXT) + \beta_{WO\times it}(WO \times it) \\ & + \beta_{EXT\times it}(EXT \times it) + \beta_{WO\times EXT\times it}(WO \times EXT \times it) + u, \end{aligned}$$

where *va* is the log of value added, *k* is the log of capital, *it* is the log of IT employees, *nite* is the log of non-IT employees, and *WO* and *EXT* are our organizational variables. Dummy variables are included for industry and year. In some specifications, we also control for the firm's human capital to rule out some alternative explanations for our principal results.

In the productivity regression, the organizational variables are entered in levels as well as in interactions with each other and with the technology variables. A positive coefficient on the three-way term in this model is not sufficient to indicate complementarities, because a high value of this variable when using standardized organizational measures can correspond to a number of different combinations of practices (e.g., high-high-high or any of the three high-low-low combinations). Therefore, interpreting what the estimated coefficients indicate for how different combinations of practices affect productivity requires evaluating the terms and cross-terms over the sample range for each factor. A derivation of what the estimates from our full-sample productivity regression model imply for how different combinations of practices affect the elasticity of other factors is provided in an online supplement to this paper (Tambe et al. 2012, Appendix A). In general, we find that complementarities are present for the movements of factors considered individually or with two factors moving simultaneously when other factors are above the mean.

Although our data on IT and other production inputs are longitudinal, our organizational factors data are based on a single survey conducted in 2001. We construct a seven-year panel (1999–2006) by making the assumption that organizational factors are quasi fixed in the short run. Our survey was administered in 2001, toward the middle of our panel. Similar assumptions regarding the quasi-fixed nature of organizational assets have been used in prior research on organizational factors (Bresnahan et al. 2002), and the assumption that organizational factors are associated with substantial adjustment costs and take considerable time to change is supported by substantial case and econometric evidence cited earlier. Furthermore, in our analysis, we use adjustment cost data as instrumental variables to directly test this assumption.

An additional potentially important source of endogeneity is our IT measures. Unobserved productivity shocks tend to exert an upward bias on the IT estimates as firms adjust IT to accommodate higher production levels. However, the endogeneity of IT investment may not exert too large an influence on our key estimates for two reasons. First, in other work we show that using generalized method of moments–based estimators that account for the endogeneity of IT investment lowers our IT estimates by no more than 10% (Tambe and Hitt 2012). Second, our key estimates, based on the three-way complementarity among IT, external focus, and decentralization, are less subject to bias than our main effect estimates because any biases that affect the complementarity term must be present only at the confluence of all three of these factors, but not when factors are present individually or in pairs.[4] For example, unobservable factors like "good management" might explain why some firms are simultaneously productive and extroverted. However, such an unobservable would *not* explain why *EXT* is productive in the presence of IT and WO but not in its absence. That would require a much more unusual sort of unobservable factor, which increased productivity only when the other inputs were present as a group, but not individually. Thus, although we cannot completely eliminate all sources of bias, the effects of unobservables on our key estimates should be limited.

[4] We thank an anonymous editor for making this observation.

4. Results

4.1. Correlation Tests

Table 7 shows partial correlations between our IT measures and our organizational practice variables. All correlations include controls for firm size. We also control for one-digit NAICS industry, as well as the percent of skilled blue-collar workers and the percent of professional workers, to account for the nature of the firm's production process. Although these correlations by themselves are neither necessary nor sufficient evidence of complementarities (Athey and Stern 1998, Brynjolfsson and Milgrom 2009), they provide preliminary evidence as to whether managers perceive these practices as mutually beneficial.

Our external focus measure is correlated with our IT measure and is highly correlated with the decentralization measure. Workplace organization is also positively associated with our IT measures. The correlation between workplace organization and external focus is 0.45 ($p < 0.01$), indicating that external information practices are significantly more likely to be found in firms with decentralized decision architectures. These correlations among external focus, workplace organization, and IT support the argument that external focus, workplace organization, and IT usage are complements in the production process. Furthermore, our aggregated adjustment cost variable, which we use as an instrument in both our product development and productivity regressions, is negatively and significantly associated with both organizational measures, indicating that firms that have higher adjustment costs are less likely to have implemented either of these systems of work practices, as theory would predict.

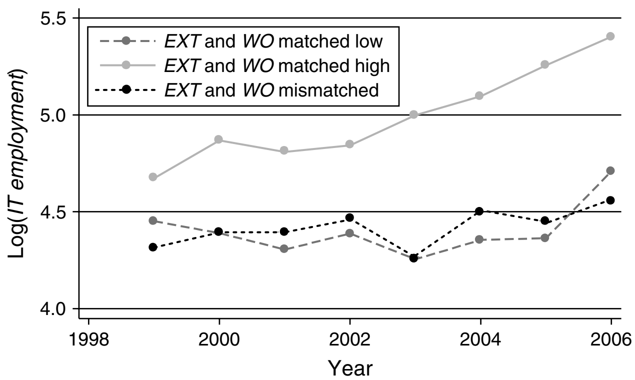
Table 7 Correlations Between Organizational Practices, IT Measures, and Organizational Inhibitors

	External focus (*EXT*)	Decentralization (*WO*)
Log(%*EMAIL*)	0.24***	0.25***
Log(%*PC*)	0.18**	0.16**
Log(%*IT EMP*)	0.21*	0.17**
WO	0.45***	
ADJ	−0.24***	−0.28***

Notes. Partial correlations controlling for industry, the percentage of professional workers, and the percentage of skilled workers. $N = 160$–210, because of nonresponse. Test is against the null hypothesis that the correlation is zero. ADJ is the aggregate measure of inhibitors of organizational transformation.

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Figure 2 Adjusting IT Levels over Time



We can also examine how managers adjust IT levels over time to match organizational practices. Figure 2 compares changes in aggregate IT employment levels over time, where firms are separated according to whether they are above or below the median in terms of adoption of *EXT* and *WO*. The trend lines suggest that IT demand in firms with high levels of both *EXT* and *WO* has been increasing faster than in firms that have not adopted these practices or firms that are mismatched on these practices.

4.2. Innovation and Product Cycle Regressions

Table 8 shows associations between our innovation and product development measures and our technology and organizational variables. In columns (1)–(3), we report ordinary least squares (OLS) regressions of how the different organizational practice and IT measures are related to product development. In (1), the dependent variable is how likely a firm is to be the first in its industry to introduce a new product. The point estimate on external focus is positive and significant ($t = 3.44$), suggesting that extroverted firms also tend to exhibit product leadership. The dependent variable in (2) is related to internal product development speed, which captures how quickly a firm can introduce a new product or service *after* it has been approved. Thus, this measure captures speed of execution, rather than of innovation per se. The estimates in (2) indicate that in addition to R&D intensity, technology usage, rather than organizational variables, is more closely associated with faster internal product development ($t = 2.12$). The dependent variable in (3) is effective management of the product line, and the coefficient estimates indicate that external focus ($t = 3.16$) and—to a lesser degree—decentralization ($t = 1.69$) are closely related to how well a firm manages its product line.

In columns (4)–(6), we report estimates from two-stage least-squares (2SLS) regressions, where our organizational measures are treated as endogenous, and individual inhibitors of organizational transformation and location variables are used as instruments. As in our OLS regressions, the estimates from this set of regressions indicate that external focus is positively and significantly associated with new product introduction ($t = 3.26$) and that IT investment is most closely associated with product development speed

Table 8 Regressions of IT and Organizational Practices on Product Development Measures

	(1) *FIRST* OLS	(2) *SPEED* OLS	(3) *PLMGMT* OLS	(4) *FIRST* 2SLS	(5) *SPEED* 2SLS	(6) *PLMGMT* 2SLS
External focus (*EXT*)	0.310***	−0.076	0.294***	0.437***	−0.045	0.079
	(0.090)	(0.097)	(0.094)	(0.134)	(0.144)	(0.142)
Decentralization (*WO*)	0.040	0.125	0.152*	−0.149	0.007	0.335**
	(0.086)	(0.093)	(0.090)	(0.146)	(0.157)	(0.154)
Log(%*EMAIL*)	0.051	0.267**	−0.170	0.085	0.281**	−0.154
	(0.117)	(0.127)	(0.123)	(0.119)	(0.128)	(0.126)
Log(*R&D intensity*)	0.045	0.200**	0.018	−0.008	0.175**	0.045
	(0.072)	(0.078)	(0.076)	(0.073)	(0.079)	(0.077)
Controls	Industry %college	Industry %college	Industry %college	Industry %college	Industry %college	Industry %college
Hausman test				$p = 0.143$	$p = 0.563$	$p = 0.124$
Observations	135	135	135	128	128	128
R^2	0.23	0.17	0.24	0.21	0.15	0.20

Notes. Huber–White robust standard errors are in parentheses. All regressions on 2001 cross-sectional survey data. *FIRST* is a measure of the extent to which firms are the first to introduce new products in an industry. *SPEED* is a measure of how long it takes to design and introduce a new product after approval. *PLMGMT* is a measure of internal product line management, and it indicates whether firms regularly weed out marginal products from their product line. Instrumental variables used in 2SLS regressions include individual inhibitors of organizational adjustment as well as state dummies. All first-stage regressions in columns (4)–(6) have an R^2 of at least 42. The Hausman test is a test of the null hypothesis that OLS is consistent.

*Significant at 10%; **significant at 5%; ***significant at 1%.

Table 9 Regressions of IT and Organizational Practices on Productivity Measures (1999–2006)

Dependent variable: Log(*value added*)	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) OLS	(6) OLS	(7) 2SLS
Log(*capital*)	0.325***	0.306***	0.319***	0.324***	0.319***	0.131***	0.337***
	(0.032)	(0.030)	(0.030)	(0.030)	(0.034)	(0.042)	(0.046)
Log(*non-IT emp*)	0.564***	0.576***	0.563***	0.588***	0.622***	0.889***	0.617***
	(0.055)	(0.052)	(0.054)	(0.046)	(0.051)	(0.054)	(0.066)
Log(*IT emp*)	0.084**	0.079**	0.077**	0.035	0.006	−0.048	−0.020
	(0.037)	(0.037)	(0.037)	(0.036)	(0.038)	(0.029)	(0.050)
WO		0.104***		0.081**	0.072**	0.040	0.115
		(0.032)		(0.035)	(0.034)	(0.040)	(0.095)
WO × *IT*		0.019		0.013	0.023	0.003	0.015
		(0.030)		(0.027)	(0.025)	(0.020)	(0.082)
EXT			0.075**	0.011	0.017	0.010	−0.070
			(0.036)	(0.039)	(0.038)	(0.038)	(0.112)
EXT × *IT*			−0.002	−0.021	−0.034	0.005	0.092
			(0.036)	(0.034)	(0.031)	(0.027)	(0.160)
EXT × *WO*				0.038	0.031	−0.032	0.102
				(0.026)	(0.024)	(0.032)	(0.099)
WO × *EXT* × *IT*				0.069***	0.064**	0.077***	0.171**
				(0.026)	(0.026)	(0.023)	(0.066)
Controls	1 digit Industry, Year	1 digit Industry, Year	1 digit Industry, Year	1 digit Industry, Year	1 digit Industry, Year, %Skilled, %Prof	2 digit Industry, Year, %Skilled, %Prof, %High, %Coll	1 digit Industry, Year
Hansen J							0.483
Anderson CC							43.0, $p < 0.000$
Hausman test							0.08
Observations	830	830	830	830	786	674	830
R^2	0.92	0.93	0.92	0.93	0.93	0.96	0.92

Notes. Huber–White robust standard errors are clustered on firm and shown in parentheses. Errors are clustered on firm. *IT employment*, *non-IT employment*, and *capital* are in logs. Dependent variable in all regressions is Log(*value added*). R^2 of first-stage regressions in column (7) vary from a low of 0.12 to a high of 0.23 with a mean of 0.18. The Hansen J statistic tests the null hypothesis that the instrumental variables are uncorrelated with the residual terms (exclusion restriction). The Anderson test tests the correlations between the endogenous regressors and instrumental variables, and therefore, for instrument weakness. The Hausman test tests the null hypothesis that OLS is inconsistent.

*Significant at 10%; **significant at 5%; ***significant at 1%.

($t = 2.19$). However, in our instrumental variable (IV) estimates, decentralization rather than external focus appears to be most closely associated with effective management of the product line ($t = 2.18$). Hausman test statistics from all three IV regressions, displayed at the bottom of Table 8, indicate that we cannot reject the null hypothesis that decentralization and external focus are exogenous to our regression models, consistent with our assumption that organizational factors are difficult to change in the short run.

In aggregate, these results indicate that the ability to exercise product leadership is more closely connected to a firm's ability to capture information from its environment, but its ability to internally process and manage products in a timely manner is governed by its internal information-processing capacity. Competing in quickly changing product environments, therefore, appears to require external receptors in addition to decentralization and technology.

4.3. Full-Sample Regression-Based Productivity Tests

The central hypothesis of this paper is that external focus is an important organizational asset affecting the returns to IT investment, especially when combined with decentralization. Table 9 shows the results from our regressions directly testing this hypothesis in a complementarities framework. All estimates are from pooled OLS regressions, and errors are clustered by firm to provide consistent estimates of the standard errors under repeated sampling of the same firms over time. First, we establish a baseline estimate of the contribution of IT to productivity during our panel (1999–2006). The coefficient estimate on our IT employment variable is about 0.084 ($t = 2.3$), consistent with many pooled OLS regressions of this type that appear in the literature using other sources of data on IT expenditures (e.g., Brynjolfsson and Hitt 1996).

In column (2), we include only decentralization measures, for comparison with earlier studies. Although the coefficient estimate on decentralization is significant ($t = 3.3$), the interaction term between decentralization and IT is insignificant, in contrast with earlier work. This may be because decentralized work practices have more broadly diffused to most IT-intensive firms that can benefit from them, leading to minimal marginal effects on productivity in recent data.[5] The coefficient estimate on IT is slightly smaller but is close to the estimate without any organizational factors explicitly modeled. In column (3), we include only our external focus measure plus an interaction term with IT. The results are similar—the estimate on the external focus measure is significant ($t = 2.08$), but the two-way interaction term between external focus and IT is not.

In our main results, reported in column (4), we include the full set of organizational factors and interaction terms. The coefficient estimates on the three-way interaction term as well as on the decentralization term are positive and significant. For IT returns within our sample range, the estimates imply that IT returns are increasing when EXT and WO are matched in either direction. This is consistent with the interpretation that unless high IT firms have adopted these organizational complements together, adopting only one or the other in isolation may make them worse off than adopting neither. Therefore, IT is complementary with the $EXT \times WO$ combination rather than just WO in isolation. In the cube-based productivity analysis presented later in the paper, we show that of the possibilities for matching EXT and WO for high IT firms—either high-high or low-low—the highest productivity group corresponds to firms that have adopted both practices along with IT, not those that have invested in IT but adopted neither of the two organizational practices. Based on supplemental analysis (see Tambe et al. 2012), these point estimates suggest that complementarities are present among any two factors when the third factor is close to or above the sample mean, and a single factor is complementary to the combination of two other factors when the two factors are above the sample mean. After including the organizational factors and all interaction terms, the IT main effect estimate in column (4) is no longer significantly different from zero. Although our benchmark estimates in column (1) indicate an output elasticity of about 0.08, our column (4) estimates suggest that these benefits are only captured by firms that have also chosen the right combination of decentralization and external focus to match their IT investments.[6]

To gauge the robustness of these results, we re-estimate our model (columns (5) and (6)) including a control for workforce composition (percentage of skilled workers and professionals out of total employment) to account for the fact that human capital is closely related to organizational innovation and technology adoption (Bartel and Lichtenberg 1987). Our coefficient estimates do not change substantively after including these human capital measures or after including more detailed industry dummies. Second, we conduct instrumental variables regressions using our organizational inhibitors measures as instruments for external focus, decentralization, and the interaction terms. The pattern of IV estimates (column (7)) is similar to that in earlier regressions and indicates that our core findings are unlikely to be heavily influenced by the endogeneity of organizational investments. At the bottom of column (7), we report values of the Hansen J-statistic, which tests the instrument exclusion restriction, and the Anderson Canonical Correlation, which tests for weak instruments. The reported values indicate that instrument validity is not likely to be a problem in our IV regression model. A Hausman test is just short of rejecting the null hypothesis that our organizational measures are exogenous with respect to productivity, and that our OLS regressions in columns (1)–(5) produce consistent estimates.

4.4. Sample Difference Tests

We can use a number of contrasts among subsamples of our data to further investigate potential endogeneity or other specification problems. For instance, we construct a measure of adjustment costs by creating a composite scale (comparable to what we did with EXT and WO) for our organizational inhibitor variables, which allows us to segment the sample into firms that have high and low organizational adjustment costs. Firms facing higher adjustment costs are likely to have been endowed with whatever organizational practices we observe, so our quasi-fixed assumption is most likely to be valid, whereas firms with lower adjustment costs are more likely

[5] Estimates from supplementary regressions (not shown) indicate that this complementarity reappears when restricting our estimates to earlier time periods.

[6] We also estimated similar regressions where each of the individual external focus variables is tested individually and where the external focus variable are constructed from different combinations of the individual external focus constructs. The results from these regressions indicate that our external focus measure is not overly sensitive to any of the individual underlying constructs. These results are available in a longer version of the paper (Appendix B of Tambe et al. 2012).

Table 10 Sensitivity Tests of Quasi-Fixed Organizational Assumptions

	1999–2006	1999–2006	1999–2003	1999–2001	2002–2006
	(1)	(2)	(3)	(4)	(5)
Dependent variable: Log(*value added*)	Low adj cost	High adj cost	All	All	All
Log(*capital*)	0.294***	0.341***	0.305***	0.322***	0.322***
	(0.063)	(0.033)	(0.036)	(0.040)	(0.032)
Log(*non-IT emp*)	0.598***	0.547***	0.593***	0.608***	0.575***
	(0.073)	(0.056)	(0.052)	(0.073)	(0.044)
Log(*IT emp*)	0.041	0.082	0.039	0.002	0.056
	(0.056)	(0.050)	(0.040)	(0.055)	(0.037)
EXT	0.003	−0.008	0.013	−0.001	0.019
	(0.061)	(0.050)	(0.040)	(0.048)	(0.043)
WO	0.041	0.117*	0.085**	0.088**	0.072*
	(0.060)	(0.060)	(0.037)	(0.042)	(0.037)
EXT × *WO*	0.031	0.030	0.047	0.056*	0.025
	(0.037)	(0.054)	(0.030)	(0.029)	(0.028)
EXT × *IT*	−0.031	−0.003	−0.046	−0.094*	0.011
	(0.040)	(0.045)	(0.035)	(0.055)	(0.033)
WO × *IT*	0.043	−0.070	0.019	0.031	.003
	(0.041)	(0.046)	(0.031)	(0.043)	(0.026)
WO × *EXT* × *IT*	0.058*	0.106***	0.058**	0.094**	0.064**
	(0.030)	(0.039)	(0.029)	(0.046)	(0.026)
Observations	444	386	539	323	507
R^2	0.92	0.95	0.92	0.91	0.95

Notes. Huber–White robust standard errors are clustered on firm and shown in parentheses. All regressions include controls for one-digit industry and year.
*Significant at 10%; **significant at 5%; ***significant at 1%.

in the midst of change to use more modern work practices. If unusually high performing firms are also likely to be investing in decentralized work practices, we would expect the endogeneity problem to be concentrated in the low adjustment cost firms. In columns (1) and (2) of Table 10, we report regression estimates for the subsamples of firms that have lower-than-average and higher-than-average adjustment costs, respectively, and find results that suggest our analyses are not biased upward by endogeneity. The coefficient estimate on the three-way interaction term for firms with lower organizational adjustment costs is 0.058 ($t = 1.93$), only slightly lower than our baseline estimate, and we cannot reject the hypothesis that the coefficient on the three-way interaction term is the same across the two regressions. The comparable coefficient estimate for firms with high adjustment costs, for whom our assumption of quasi-fixed organizational factors is more likely to be accurate, is 0.106 ($t = 2.72$). Therefore, consistent with our IV estimates, it appears that to the extent that our organizational factors are changing during the sample period, it would introduce a downward bias to our productivity estimates.

We can also test for other specification problems by varying the length and sample frame of our panel. In particular, our organizational practice measures are likely to accurately reflect actual practices in the interval around 2001 and be less accurate in the early and late years. Moreover, if firms adopt these practices over time as IT prices decline, as our theory would predict, we will likely overstate the use of these practices in early periods and understate them in later periods. In column (3), when we restrict the sample to a five-year panel close to 2001, we obtain estimates similar to our full estimates in Table 9, and we cannot reject the hypothesis that the coefficients on the three-way interaction term are the same across the two regressions. In columns (4) and (5), we run separate regressions from 1999 to 2001 and from 2002 to 2006. The higher coefficient estimates on the organizational measures in the 1999–2001 period are consistent with the interpretation that our survey measures understate organizational differences before 2001 and overstate them after 2001. Overall, our estimates in (1)–(5) suggest that even if firms were becoming more externally focused during these years, measurement error in organizational factors is unlikely to have had a significant effect on our productivity estimates.

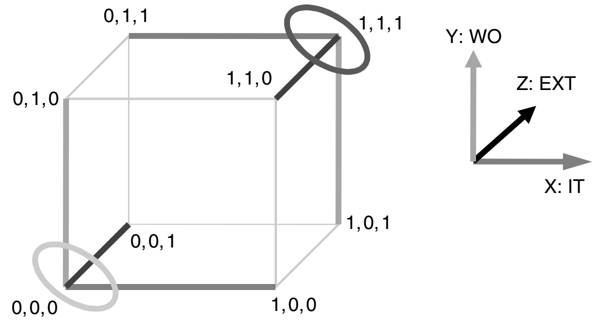
In Table 11, we implement a series of tests for complementarities proposed by Brynjolfsson and Milgrom (2009) that contrast the productivity of firms that have adopted different combinations of IT, EXT,

Table 11 Productivity with Matches and Mismatches on Complements

	EXT	
WO	1	0
	$IT = 1$	
1	0.378*** (0.088) $N = 169$	0.041 (0.106) $N = 65$
0	−0.047 (0.174) $N = 43$	0.078 (0.088) $N = 140$
	$IT = 0$	
1	0.203** (0.088) $N = 145$	0.089 (0.120) $N = 39$
0	−0.010 (0.082) $N = 66$	0 (N/A) $N = 163$

Notes. Huber–White robust standard errors are shown in parentheses and clustered on firm. For $IT = 1$, Pearson chi-sq(1) = 97.5, $p < 0.01$. For $IT = 0$, Pearson chi-sq(1) = 102.0, $p < 0.01$.

Figure 3 Cube View of Complementarities Between IT, WO, and EXT



4 tests of complementarities:

1. IT: $F(1,1,1) - F(0,1,1) > F(1,0,0) - F(0,0,0)$ Fail $p = 0.43$
2. WO: $F(1,1,1) - F(1,0,1) > F(0,1,0) - F(0,0,0)$ Fail $p = 0.11$
3. EXT: $F(1,1,1) - F(1,1,0) > F(0,0,1) - F(0,0,0)$ ✔ $p = 0.01$
4. The system:

$$[F(1,1,1) - F(0,1,1)] + [F(1,1,1) - F(1,0,1)] + [F(1,1,1) - F(1,1,0)] - [F(1,0,0) - F(0,0,0)] + [F(0,1,0) - F(0,0,0)] + [F(0,0,1) - F(0,0,0)] > 0$$

✔ $p = 0.02$

and WO. We first dichotomize each of the three variables, where a 1 represents high levels of the organizational practice and a 0 represents low levels. This yields eight cells ($2 \times 2 \times 2$), one for each possible combination of practices. Each cell in the table is instantiated with average productivity differences of firms in that cell relative to the (0, 0, 0) cell. Unlike the productivity tests shown above, this test distinguishes productivity differences between high IT firms that have invested in EXT and WO and high IT firms that have invested in neither.

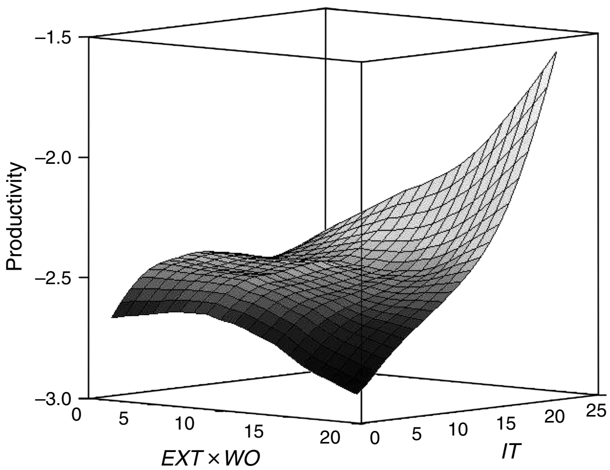
We find that the highest productivity cell is that in which firms invest in all three factors $(1, 1, 1)$. F-tests indicate that the productivity differences between the $(1, 1, 1)$ cell and cells with any combination of two factors are all significant at the 5% level. This pattern of results is what would be predicted by the complementarities story and provides additional evidence that our results are not being driven by endogenous organizational investment. Although reverse causality between performance and organizational investment might explain the $(1, 1, 1)$ quadrant, it does not explain why firms that have neither factor in place would be more productive than those with one but not the other in place. Furthermore, Chi-squared tests (shown with Table 11) indicate that the majority of firms appear to cluster into one of the two main diagonal corners within this group, as would be expected, given the observed productivity differences and the expected clustering of complementary practices. Interestingly, these results also suggest that even for low IT firms, the combination of decentralization and external focus appears to provide benefits that are independent of IT investment levels.

Complementarities arguments also predict that the marginal benefit of adopting a practice should be increasing in the presence of complementary practices. As noted by Aral et al. (2012) and Brynjolfsson and Milgrom (2009), this can be viewed as comparisons along the edges of a cube, where each axis represents one of the (dichotomized) practice measures (see Figure 3). This increasing returns argument implies three specific tests along a pair of edges, plus a fourth test that simultaneously considers all three pairs of edges. For instance, one test is whether the adoption of EXT adds greater benefit in the presence of IT and WO [the comparison of $(1, 1, 0)$ versus $(1, 1, 1)$] than adoption of EXT alone [the comparision of $(0, 0, 0)$ versus $(0, 0, 1)$]. The results of these tests suggest that the benefits of adopting external focus in the presence of IT and decentralization are greater than the benefits of adopting external focus alone ($p < 0.01$). A test of whether the benefits of adopting decentralization are increasing in the presence of IT and external focus falls slightly short of being significant at the 10% level. IT adoption provides greater productivity benefits in the presence of decentralization and external focus, but this is not significant, perhaps because of the substantial complementarity between external focus and decentralization alone.[7] Finally, we reject the null hypothesis of no increasing returns when we consider the most comprehensive test, which examines all three comparisons simultaneously ($p < 0.05$).

The findings from Table 11 and Figure 3 are visually captured in Figure 4, in which we show a plot of fitted values from a regression of organizational and IT inputs on the productivity residuals when other variables have been netted out. Lighter areas in Figure 4

[7] Alternatively, this could reflect lower adjustment costs of IT and a resulting faster adoption rate.

Figure 4 Level Plots of Fitted Values from Regression of Productivity on External Focus, Workplace Organization, and Information Technology



Notes. From authors' regressions. z-axis is log(*value added*).

should correspond to higher productivity values. The surface contours corresponding to changing $EXT \times WO$ while holding IT fixed indicate that high IT firms perform better when EXT and WO are matched. Furthermore, the contours that correspond to changing IT levels with $EXT \times WO$ held fixed indicate that returns to IT increase much more rapidly in firms in which EXT and WO are matched.

5. Conclusion

Our results suggest that a three-way system of complements that includes external focus, decentralization, and IT intensity is associated with productivity in modern firms. IT has the strongest effect on productivity in firms that simultaneously have the right organizational structures in place, whether through wise management or luck. Prior work has demonstrated the importance of decentralization in explaining differences in returns to IT investment, but the central contribution of this paper is the integration of a third variable, external focus, into the IT productivity framework.

Our hypothesis that decentralized decision making and external focus are complementary to IT investment is supported by a number of different analyses. First, these three factors are highly correlated, indicating that firms are likely to invest in them together. This pattern of joint investment is predicted if managers are at least somewhat aware of these complementarities or if competition selects for companies with more productive combinations of practices. We also found evidence that one of the principal mechanisms through which external focus affects productivity is improved product development. Some of the strongest evidence of complementarities comes from our production function estimates—the combination of IT, decentralization, and external focus is positively associated with firm productivity. Moreover, when these complements are included in a production model, main effect estimates of IT and other organizational factors essentially disappear, indicating that firms derive the most benefit from implementing the system of technological and organizational resources, and not IT alone.

From a research perspective, our study contributes to a literature on determinants of IT value, in particular, on IT-related organizational complements. Our findings highlight the benefits of information technologies in an environment in which innovation largely takes place through external linkages with other firms, rather than within insular firms. Information technologies appear to provide greater benefits for firms that must process information effectively to respond to frequent environmental signals. This observation is consistent with recent research suggesting cross-regional variation in returns to IT adoption, because these complementarities are likely to be most valuable when firms are located in information-rich environments. Finally, from a research methods standpoint, we have identified an effective set of instruments for work organization and external focus, providing greater confidence that these and prior results on the benefits of IT-related organizational practices are not driven by endogeneity.

A key managerial implication of our research is that "extroverted" firms are more productive and derive disproportionate benefits from advances in IT and workplace organization. Companies that exploit this opportunity by using more information from customers, suppliers, and competitive benchmarks appear to outperform their rivals. Moreover, theoretical arguments suggest that managers should implement all the elements in a system of complements to realize the maximum benefits (Milgrom and Roberts 1990). Therefore, managers in firms with decentralized structures may not realize productive returns to IT-related investments unless they also find a way to also promote cross-boundary information flows through external practices such as competitive benchmarking and interorganizational product teams. Thus, although the two types of organizational practices are complementary, external focus is distinct from organizational decentralization—both theoretically and empirically. However, it is likely that our measures are only a subset of an even wider set of practices that firms use to bring information into the organization.

Our findings may also have implications for policy makers. There has been recent discussion of why IT appears to have led to greater productivity growth in some regions within the United States than in others and in some parts of the world than others (Dewan and Kraemer 2000, Bloom et al. 2012). Our findings suggest that the degree to which firms are networked with customers, suppliers, and partners is a potentially important factor explaining differences in IT-led productivity growth. Even within the same industry in the United States, scholars have shown that considerable variation can exist among the degree to which firms share information across regions (Saxenian 1996).

There are some important limitations to our study. Because of the research design, we were not able to conduct fixed-effect productivity regressions to determine if changes in organizational assets drive productivity changes. Thus, it is possible that the organizational assets that we have focused on here reflect some unobserved heterogeneity among the firms in our sample. However, we controlled for the most likely candidate, human capital endowments, and supplementary data allowed us to test whether our results were sensitive to this assumption. Furthermore, though heterogeneity could explain correlations between any given practice and our performance measures, it is more difficult to construct a story of heterogeneity that drives correlations with three-way combinations, but not one- or two-way combinations of these practices.

An increasing body of evidence suggests that organizational practices, such as the ones that we identify in this paper, are critical to the success of technological innovation. We expect that future research using more fine-grained measures of organization will continue to identify other organizational and management practices that interact with technology to affect productivity and innovation.

Acknowledgments

The authors thank Anindya Ghose, Natalia Levina, Gary Loveman, Hal Varian, Jeff Wilke, and seminar participants at New York University, Massachusetts Institute of Technology, Harvard Business School, Northwestern University, and the International Conference on Information Systems for helpful comments on this research. This material is based on work supported by the MIT Center for Digital Business and the National Science Foundation [Grant IRI-9733877].

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CORRECTION

In this article, "The Extroverted Firm: How External Information Practices Affect Innovation and Productivity," by Prasanna Tambe, Lorin M. Hitt, and Erik Brynjolfsson (first published in *Articles in Advance*, January 13, 2012, *Management Science*, http://dx.doi.org/10.1287/mnsc.1110.1446), the following sentence, which appears in §4.4, was corrected to read as "Lighter areas in Figure 4 should correspond to higher productivity values."