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Productivity Leadership and Strategic Investments in Innovation: The Adoption of E-Business Capabilities

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March 2009

Abstract:

I investigate whether market leadership predicts adoption of innovations and why. My empirical context is the adoption of e-business practices among U.S. Manufacturing plants in early 2000. Using detailed data from the U.S. Census of Manufactures, I construct two measures of market leadership – a conventional one based on market share and a novel one based on productivity – and investigate how leadership influences the probability of adopting I.T.- driven business process innovations. I find evidence that market leadership is, in general, positively correlated with the use of e-business practices; however, there is an important distinction between e-*buying* and e-*selling*. In e-*buying*, the likelihood of adoption is increasing in all measures of leadership. This result is accentuated in more concentrated markets. This empirical finding conforms to theoretical predictions by Athey and Schmutzler (2001) that leading firms will have incentives to invest in technologies that may help them maintain market dominance in oligopolistic settings. By contrast in e-*selling*, only market share leadership has a positive (and noisy) relationship with adoption. I hypothesize that this difference is consistent with *stand-alone* benefits of adoption that are increasing in output for both technologies, as well as greater *strategic* benefits of adopting that arise primarily in e-buying. I also consider the role that adjustment costs might play in differentiating the two settings.

JEL classifications: L21, O33, D24, M15

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* **Harvard Business School, 431 Morgan Hall, Boston, MA 02153.** I thank Shane Greenstein, Scott Stern, Leemore Dafny, and Ranjay Gulati for excellent guidance and feedback. Useful discussions with participants of the 2007 Colloquium on Competition and Competitiveness and with Allan Collard-Wexler and Steve Kahl are also greatly appreciated. I am indebted to T. Lynn Riggs of the Chicago Census Research Data Center and other members of the Center for Economic Studies for their support, both intellectual and administrative. The research in this paper was conducted while the author was a Special Sworn Status researcher of the U.S. Census Bureau at the Chicago Census Research Data Center. Research results and conclusions expressed are those of the author and do not necessarily reflect the views of the Census Bureau. This paper has been screened to insure that no confidential data are revealed. Support for this research at the Chicago RDC from NSF (awards no. SES-0004335 and ITR-0427889) is also gratefully acknowledged. In addition, I am grateful for financial support from the Census Bureau's Dissertation Fellowship program and the State Farm Companies Foundation Dissertation Award. All errors are my own.

1. INTRODUCTION

Are leading firms likely to raise the bar for competitors by pursuing innovative products and processes? Or, will they remain complacent in their success, thereby inviting incursions by entrepreneurial rivals? The answer to these questions has profound implications for corporate strategy, technological change, and industry evolution. For instance, if market leaders innovate strategically to stay ahead, industries may advance technologically while remaining concentrated among dominant incumbents. Understanding if – and when– this dynamic takes place is of central concern to scholars of firm behavior and policymakers interested in how firms maintain competitive advantage over time.

Distinguishing what makes a firm innovative has been controversial since Joseph Schumpeter posited both that small entrepreneurial firms will be the main locus of innovative activity (1934) and that large firms with some degree of market power will drive technological progress and economic growth (1942). An implication of my work is that research progress may be made by recognizing the duality between organizations and markets in driving technological change. On the one hand, competitive pressure may be crucial for inducing firms to adopt innovative business practices. On the other hand, the market leadership that results may itself spur further innovation. This paper documents the importance of disentangling different incentives for innovative investment and carefully considering both organizational and market characteristics in predicting innovative activity.

In this paper, I investigate whether market leaders are likely to be leading adopters of business process innovations, and why. The particular innovation I study is the adoption of purchasing or selling over a computer network – i.e., e-buying or e-selling – by manufacturing plants in early 2000. Using comprehensive data from the U.S. Census of Manufactures, I construct two measures of leadership to empirically test whether a better market position enhances a firm's propensity to pursue technologically-advanced business practices. The first measure, based on market share, is a conventional definition that ties this investigation to prior literature but may confound the effect of market power with economies of scale in adoption. A novel definition of leadership based on relative productivity within the industry captures competitive interactions between plants while helping to disentangle "high type" plants from those with large output volume.

My approach emphasizes how the position of firms *within* the market structure influences innovative behavior. This constitutes a sharp departure from the large body of work relating aspects of market structure *itself* to technological change .[1] The benefits of this departure are twofold. First, it underscores the importance of firm heterogeneity in determining equilibrium adoption behavior.[2] Second, and perhaps more importantly, it sheds light on important details of how firms compete in the marketplace and brings into focus a potentially important vehicle for long-run technological change.

I exploit an empirical setting with two salient features: 1) unusually rich variation in the observed uses of e-business technology and 2) comprehensive information on plant, firm, and market characteristics. Variation across e-*buying* and e-*selling* in the nature of the market transaction suggests a margin where strategic incentives to innovate are more or less likely to influence firm behavior. This variation helps to empirically identify *strategic* adoption incentives that may be separate from *stand-alone* adoption incentives. It may also point to differential adjustment costs that influence the net benefits of adopting these innovative business processes in different ways.

The comprehensive nature of the Census data makes it possible to directly estimate productivity, situate plants in their respective industry productivity distributions, and accurately

[1] Reviews of this sizeable literature are provided by Kamien and Schwartz (1982), Baldwin and Scott (1987), Cohen and Levin (1989), Reinganum (1989), and Gilbert (2006).

[2] Much of the prior research on the relationship between product market competition and innovation (e.g., Dasgupta and Stiglitz,1980) assumes that competition takes place among symmetric firms. Departures from this symmetry assumption, (e.g., Boone, 2000a & b) demonstrate how different incentives across heterogeneous agents can lead to different optimal choices for agents. It follows that predictions concerning equilibrium market outcomes will depend on the distribution of agent types in a given market.

measure market share. I also leverage the richness of the data to control for heterogeneity among market participants, aiding identification of the core results.

My results indicate that, while the average adoption rate is the same for both e-buying and e-selling, the underlying drivers of adoption differ. In e-*buying*, both market share and productivity leadership measures are positively and robustly correlated with adoption. This empirical finding conforms to theoretical predictions by Athey and Schmutzler (2002) that leading firms have incentives to make investments that may help them maintain market dominance.[3]

By contrast in e-*selling*, only market share leadership has a positive – and noisy – effect on adoption. These results are consistent with stand-alone benefits of adoption that are increasing in output across both settings. Moreover, they are suggestive of *strategic* benefits in the adoption of the particular technology (i.e., e-buying) where there may be more scope for market leaders to deter less-efficient rivals. Differences in adjustment costs for leaders versus lagging firms across the two settings may also play a role.

This paper builds on work in several related literatures. The first is the much-studied relationship between productivity and information technology (I.T.), which has traditionally focused on the impact of information technology *on* productivity.[4] In my work, I reverse this relationship, using relative productivity differences to capture asymmetries among product market rivals that might systematically affect their incentives to adopt frontier technology.[5]

[3] This result is related to the well known "efficiency effect" (Gilbert and Newbery, 1982; Tirole, 1988, chapter 10), but it is more general and extends more naturally to process, as opposed to product, innovation.
[4] Reviews of this literature are provided by Brynjolfsson and Yang (1996) and Brynjolfsson and Hitt (2000). Additional works in this vein include, among others, Athey and Stern (2002), Hubbard (2003), Brynjolfsson and Hitt (2003), Dunne et al. (2004), Atrostic and Nguyen (2005a; 2005b), Rawley and Simcoe (2006), Bloom et al. (2007), and Aral et al. (2007).
[5] In so doing, I borrow from the economic literature on selection and industry dynamics (e.g., Jovanovic, 1982), which has studied productivity as a predictor of firm survival (see Bartelsman and Doms, 2000, for a recent review). However, its use to explain strategic choices of firms is unconventional in the industrial organization and strategy literature.

The second is an empirical literature on innovation which has been overwhelmingly centered on research and development (R&D) investments,[6] primarily in pursuit of new products. Less attention has been devoted to often-incremental but vitally important *process* innovation of the type studied here (Abernathy and Utterback, 1978; Rosenberg, 1982; Klepper, 1996). The focus of my paper is on non-patentable process innovation that requires substantial "co-invention" (Bresnahan and Greenstein, 1996; Forman, 2005) to turn information technology into functioning e-business practices within the firm. [7]

Third, this paper contributes to a small but growing econometric literature on market position and innovation. A few studies have produced results that specifically relate an organization's productivity to its equilibrium I.T. adoption, with contradictory findings (McGuckin, Streitwieser and Doms, 1998; Stolarick, 1999; Atrostic and Nguyen, 2005b). Other works have used different measures of leadership and focus more specifically on *strategic* innovation aimed at deterring competition (Henderson, 1993; Lerner, 1997; Blundell, Griffith, and Van Reenen, 1999; and Aghion and co-authors, 2002 & 2004).[8]

Finally, this paper also informs a large diffusion literature that considers the adoption of related information and communication technologies (for an authoritative review, see Forman and Goldfarb, 2006). However, very little of this research explicitly considers how strategic interactions among product market rivals influence adoption (exceptions include Debruyne and Reibstein, 2005, and Karshenas and Stoneman, 1993).

The rest of this paper proceeds as follows. Section 2 provides details of the empirical setting and phenomenon under study. Section 3 presents my conceptual framework and testable

[6] Aghion and Tirole (1994) refer to tests of the drivers of R&D input and output as the "second most tested set of hypotheses in industrial organization" (p. 1150).

[8] Henderson (1993) distinguishes the market position of incumbents from that of new entrants, Lerner (1997) defines leadership in terms of distance to the technological frontier, and Blundell et al. (1999) define market leadership by market share. Aghion and co-authors (2002; 2004) consider how the market position of firms interacts with competitive pressure to influence innovation. They define leadership in terms of the technology gap between rivals and assume that market leaders are also technological leaders. I expand on this work by evaluating the conditions under which this key assumption is most likely to hold.

hypotheses. Sections 4 and 5 introduce the data and empirical model, respectively. Section 6 discuses the results; section 7 concludes.

2. CONCEPTUAL FRAMEWORK AND HYPOTHESES

To determine whether market leadership ought to have an effect on the incentives to adopt innovative processes, a conceptual foundation for the analysis must first be laid. To that end, I first define what constitutes market "leadership" in the context of this paper and introduce some notation. I then present frameworks from prior theoretical work to provide the economic intuition and articulate testable hypotheses that can be brought to the data. I close this section with a discussion of how possible empirical proxies for leadership relate to the theoretical constructs and their implications for testing particular behavioral mechanisms of interest.

A Note on the Use of "Firm" versus "Plant"

A brief point of clarification regarding terminology is in order at the start of this section. While the relevant theoretical literature deals with the economic and strategic choices of *firms*, the empirical exercise that constitutes the main focus and contribution of this paper will take place at the *plant* level. This is done for compelling theoretical and empirical reasons that will be addressed as they arise. To maintain continuity of the discussion with existing work, however, agents in this and the following section on the phenomenon will be referred to as "firms," whereas plant- and firm-level differences will be explicitly addressed and differentiated in the data and results sections of this paper.

Definition of Market "Leadership", Part 1

Conceptually, it is sufficient to assume that agents posses some sort of "type" that captures differences in competitive advantage, with higher types enjoying better market success.[9]

[9] This notion is common in economic models of firm survival and industry dynamics (e.g, Jovanovic, 1982; Ericson and Pakes, 1995).

Most models of product market competition refer to particular aspects of firm type such as their marginal costs of production or product quality.[10] For now, I abstract away from these details because they are not necessary for the basic intuition. They do, however, become necessary for empirically measuring leadership and interpreting the results, so I will return to this again at the end of the section. For now, let **S** represent a vector of firm-specific state variables, S_i , that captures the relevant elements of competition between firms.

Let the expected net benefit to firm *i* in time *t* of investing in a process innovation that will improve its state be given by $\Pi^i(a_i^t, a_{\sim i}^t, \mathbf{S}^{t-1}) = \pi^i(a_i^t, a_{\sim i}^t, \mathbf{S}^{t-1}) - k(a_i^t, \mathbf{S}^{t-1})$, where $\pi(\cdot)$ is a concave benefits function, $k(\cdot)$ is a convex cost function, a_i^t represents the firm's action, $a_{\sim i}^t$ that of its rivals, and $\mathbf{S}^{t-1}$ the state of the market in the prior period. *Increasing dominance* captures the notion that leading firms (i.e., firms with higher state variables) might have higher marginal incentives than lagging firms to invest in improving their competitive advantage. If $a_i^*(\mathbf{S})$ represents firm *i*'s equilibrium investment decision, increasing dominance describes the case where $S_i \geq S_j$ also implies $a_i^*(\mathbf{S}) \geq a_j^*(\mathbf{S})$ for all *i*, *j*. In the case of smooth functions, this will arise when:

$$\frac{\partial^2 \pi_i}{\partial a_i \partial S_i} \geq 0 \tag{1}$$

Conditions for Increasing Dominance: Athey & Schmutzler (2001)

The many existing theoretical models addressing the relationship between competition and innovation generate contradictory predictions, depending on their particular assumptions (see Reinganum, 1989, for a review and discussion). However, a recent breakthrough by Athey and Schmutzler (2001) derives very general conditions under which increasing dominance is likely to

[10] Other examples of firm type might pertain to the resources (Wernerfelt, 1984) a firm has such as a good brand name or might include a firm's dynamic capabilities (Teece, Pisano and Shuen, 1998; Eisenhardt and Martin, 2000), among others.

arise. While the details go beyond the scope of this paper, the core result is that under certain regularity assumptions and *ignoring adjustment costs*, a sufficient (though not necessary) condition in their model is if investments are strategic substitutes:[11]

$$\frac{\partial^2 \pi_i}{\partial a_i \partial a_{\sim i}} \leq 0 \qquad (2)$$

In words, this means that a rival's investment ($a_{\sim i}$)reduces the marginal return of firm *i*'s investment.

Increasing dominance can also arise if investments are strategic complements, as long as other conditions are met (see Athey and Schmutzler, 2001, for a complete and more technical discussion). The important intuition is that investments cannot be *very strong* strategic complements. If they were, then investment by a leading firm would not deter rivals, but rather it would spur them to make matching investments and increase the competitive pressure in the market. In that case, strategic and direct incentives would work together to reduce the marginal returns to investing for leading firms.[12] Thus, a key condition that must be verified for this model to be empirically appropriate is:

> <u>Assumption 1 (Non-Complementarities in Investment):</u> Firm investments in e-business practices are not strong strategic complements.

I provide empirical support for this condition when I discuss the data in Section 4.

An important assumption of the model is that adjustment costs associated with investments cannot be "too high." The core results depend on the incremental cost of investment not exceeding the incremental benefit for leading firms. To be clear, adjustment costs may be

[11] Conventional substitutes are defined by Bulow et al. (1985) as arising when more "aggressive" behavior (e.g., lowering price or raising quality) reduce a rival's *total* profits, or $\frac{\partial \pi_i}{\partial a_{\sim i}} < 0$. Strategic substitutes arise when rivals' actions influence *marginal* profits.

[12] For another example of how increased investment by leaders can arise with strategic complements and entry by rivals, see the "Fat Cat" example of Fudenberg and Tirole (1984).

higher for leaders than for followers, i.e., $\frac{\partial \pi_i}{\partial S_i} \geq 0$, but the *rate* at which those costs increase cannot exceed the marginal benefit, i.e., $\frac{\partial^2 \pi_i}{\partial a_i \partial S_i} \geq \frac{\partial^2 k_i}{\partial a_i \partial S_i}$. For instance, if both costs and benefits of investment were to be concave in firm state (i.e., increasing at a decreasing rate), but with different slopes of increase, it would be possible for costs to exceed benefits at a certain threshold, violating the assumptions of the model at that particular point. Stated in words:

> Assumption 2 (Adjustment Costs): The rate at which the incremental costs of investment changes as a function of leadership does not exceed the corresponding rate of change in incremental benefits.

In the setting used for this study, I lack the separate information on costs and benefits that would make it possible to empirically verify whether this assumption holds for any particular firm. However, thinking carefully about adjustment costs provides important intuition for when the predictions of the model may be more likely to fail – and may go far towards explaining the observed pattern of results.

Returning to the framework, in the case of a simple incremental investment game where innovations are *non-drastic*[13] and firms' states evolve according to $S_i^t = S_i^{t-1} + a_i^t$, increasing dominance is likely to arise whenever:

$$\frac{\partial^2 \pi_i}{\partial a_i \partial S_i} \geq 0 \text{ and } \frac{\partial^2 \pi_i}{\partial a_i \partial S_{\sim i}} \leq 0 \qquad (3)$$

In words, this states that firms with higher state variables will have higher marginal returns from their own investments and that their returns are decreasing in rivals' investments – the more so the higher their own state variables.

[13] A non-drastic process innovation is one such that the price that would be charged by a monopolist in equilibrium using the new technology is not lower than the marginal cost of production using the old technology (Arrow, 1962). In other words, the old technology remains a viable substitute in the market. Many of the results discussed here do not go through for drastic innovations.

There are many reasons – strategic and otherwise – that the conditions of equation 3 might be satisfied. They need not be enumerated for a high-level test of the received theory to take place. By restricting my analysis to the case of incremental process innovations, Assumptions 1 and 2 provide a sufficient condition for the predictions of the Athey-Schmutzler model to apply. The core testable hypothesis of the model is:

> *Hypothesis 1 (Increasing Dominance):* Market leaders are more likely than market laggards to invest in e-business practices, *ceteris paribus*.

Economic Drivers of Increasing Dominance

It is straightforward to think of cases where a firm's own state variable would increase its marginal returns to investment and where higher levels of an opponent's state variable would decrease its marginal returns (i.e., for equation 3 to hold). For instance, if a higher state variable leads to a higher market share, a leading firm can spread any fixed investment costs across a larger output and enjoy lower average costs from investing.[14] Similarly, any increase in an opponent's market share will lower firm *i*'s output and its marginal returns to investing for the same reason.

This **cost-spreading effect** is particularly important for process innovations, because firms have few ways except through improvements in their own production processes to realize returns – especially for innovations that cannot be patented and licensed in the "market for ideas" (Gans and Stern, 2003; also, Arrow, 1962). This is a key insight of Cohen and Klepper (1996) and Cohen, Levin, and Mowery (1987), who emphasize that the relevant measure of size in this case is output of the business unit, rather than that of the overall firm. This leads to my next set of testable hypotheses:

[14] While assuming that higher state variables lead to higher market share may be useful for establishing some economic intuition, there are straightforward situations that will tend to promote increasing dominance even when a higher state variable does not induce a higher share of the product market. A simple example is provided in Appendix 1.

Hypothesis 2a (Cost-Spreading): Higher market share will be associated with a higher propensity to invest in e-business practices.

Hypothesis 2b (Locus of Scale Economies): The share of the market served by the *plant* will have a greater impact on investment than will the market share of the parent *firm*.

It is important to note two details of the above hypotheses. The first is that they arise out of a particular definition of market leadership: **market share.** The second is that the direct advantage to leaders from cost-spreading favors increasing dominance regardless of any strategic considerations.

The Impact of Strategic Considerations[15]

Existing theoretical predictions regarding the impact of strategic considerations are contradictory (and extremely sensitive to various assumptions that I cannot verify in this broad, cross-industry study). One line of argument maintains that strategic incentives can provide an additional, indirect incentive to market leaders to invest in order to maintain their dominant position. Firms interested in reducing competitive pressure can make expensive investments (even to the point that $\Pi^i(a_i^t, a_{\sim i}^t, \mathbf{S}^{t-1}) < 0$ for a certain period or periods) that commit them to being more aggressive in the product market, thus deterring entry or dampening the competitive reactions of rivals. This effect has largely been explored in terms of capacity investment (e.g., Dixit, 1979 & 1980; Spence, 1977 & 1979), but extends naturally to the case of investing in a process innovation (see Sutton, 1991). For instance, an improvement that reduces the marginal costs of production may make it possible for firms to charge lower prices while earning the same markup or to increase their quantity of output for the same level of production costs. Leading

[15] While the theoretical literature on strategic incentives to blunt or deter competition is well developed (see Reinganum, 1989), the related empirical literature is far less so. Notable exceptions include Ellison and Ellison (2007) in the pharmaceuticals industry and Dafny (2005) in hospital procedure markets.

firms who enjoy higher profits or greater cash flow may be more able to employ this type of "top-dog" strategy (Fudenberg and Tirole, 1984), particularly if investments are quite costly.

In this case, strategic and stand-alone incentives will work in the same direction, tending to promote investment by market leaders. In other words, this would tend to reinforce the prediction of Hypothesis 1.

Another line of reasoning predicts that leading firms in less-competitive markets will be *less* likely to adopt innovative business processes. According to this argument, which arises in the seminal work of Kenneth Arrow (1962), if blunted competitive pressure gives incumbent firms some degree of market power, firms with existing profits face an opportunity cost of innovating that firms in competitive markets or potential entrants do not. This is because the direct benefit of using the new technology must be compared to a firm's pre-innovation profits – and the incremental benefit is higher for firms that are earning lower (or no) profits before the innovation. The extreme case would be that of a monopolist merely "replacing" itself in the market. If, on average, these *replacement effects* dominate, firms with higher market share will, *ceteris paribus*[16], have lower incentives to innovate than will rivals with lower levels of sales.

> *Hypothesis 3 (Replacement Effects)*: Firms with higher market shares are less likely to adopt innovative business practices, *ceteris paribus.*

Note that this hypothesis also explicitly defines leadership in terms of market share and makes a prediction counter to that in Hypothesis 1.

It is worth emphasizing that the cost-spreading effect has to do with the volume of output across which the process innovation will be applied and that the replacement effect has to do with the level of pre-innovation profits a firm enjoys as a function of its market power. To the extent that market share is often the only available empirical proxy for market power, these effects are

[16] In other words, controlling for the idiosyncratic benefits of adoption that a firm may enjoy, apart from considerations arising out of its product market position.

easy to confound. Ideally, a direct measure of a firm's market power, such as firm-specific price-cost margins (see Bresnahan, 1989) could be used to separately identify these effects. As this is beyond the reach of my data across all industries,[17] I instead take advantage of observable differences between the plant-level and firm-level output, as well as other empirical proxies for scale of output, to attempt to disentangle these effects. I elaborate on this further in the Data and Results sections of this paper.

Definition of Leadership, Part 2

Many of the straightforward intuitions from prior work focus on market share as the measure of market leadership. However, as the preceding discussion suggests, there are distinct advantages and disadvantages to using market share as an empirical proxy for competitive advantage. To the extent that market share is arguably related to many different attributes of market leadership (e.g., market power, economies of scale in output, size, etc.) it is a straightforward measure for capturing the underlying "type" of the firm.

However, market share will tend to confound different drivers of firm behavior whose separate mechanisms are important for understanding firm behavior and evaluating the outcome of industry competition. For instance, to the extent that firms with market power and efficiently-run firms will both tend to win larger shares of the product market, a measure of market leadership based solely on market share will tend to confound market power with market effectiveness. This distinction is important to many scholars and policymakers (see, e.g., Demsetz, 1973).

Moreover, market share is not (at least in the short term) a choice variable of firms. Rather, it is the outcome of a competitive equilibrium determined by other characteristics of competitors that are arguably more within their control, such as production costs and quality.

[17] Foster, Haltiwanger, and Syverson (forthcoming) estimate this margin for certain industries using data from the U.S. Census of Manufactures, but their results require a great deal of physical homogeneity among products and thus limit their study to eleven industries such as boxes, carbon black, gasoline, and sugar.

Finally, there are straightforward situations that will tend to promote increasing dominance even when a higher state variable does not induce a higher share of the product market. If these types of situations arise with sufficient empirical frequency, any test that measures market leadership solely in terms of market share will tend to reject the predictions of the model, even if the underlying positive relationship between a higher state variable and higher investment incentives holds. A simple example is provided in Appendix 1.

For these reasons, I propose a less-conventional measure of leadership: productivity of the firm relative to its rivals in the product market. While the empirical literature on industry dynamics and firm survival has made extensive use of productivity as an empirical proxy for firm type (see Bartelsman and Doms, 2000, for a recent review), its use as a predictor of strategic firm decisions is novel, to my knowledge. This is likely due to the stringent data requirements associated with accurately calculating productivity.

3. PHENONMENON: E-BUSINESS PRACTICES IN U.S. MANFUACTURING

The specific context in which I investigate the relationship between market leadership and business process innovation is the adoption of e-business practices among U.S. manufacturing plants at the end of 1999 and early 2000. "E-commerce" has received a great deal of attention in the popular press over the past decade, due in part to the dot-com bubble, but also due to the very real potential of networked computers and automated transactions to streamline and transform inefficient business processes. This section describes the salient features of the phenomenon and makes the case for why this is a useful context in which to study how market position influences innovation and to what extent strategic considerations play a role.

At the outset, it is important to distinguish the business-to-business ("B2B") transactions that are the subject of this investigation from the business-to-consumer ("B2C) e-commerce conducted by firms such as Amazon.com and Ebay. New e-commerce start-ups that leveraged the

Internet to provide a new sales and marketing channel are excluded from this study. More details on my sample are included below and in Section 4.

Benefits of E-Business

At the most basic level, electronic commerce merely entails moving the communications and transactions associated with buying and selling goods from traditional technologies – such as telephone, fax, and face-to-face interactions – to an electronic communication network such as (but not limited to) the Internet.[18] An example of e-buying in manufacturing would be a purchasing manager using a desktop computer to access a list of approved vendors from an internal company website, linking to the vendors' online catalogs, selecting and comparing a list of items, adding items to an electronic shopping cart, and issuing an online requisition that is forwarded to a supervisor for approval or converted to a purchase order that is sent electronically to the supplier. An example of e-selling in manufacturing would be a back-end manufacturing resource planning (MRP) system receiving electronic purchase order information from an existing customer, checking internal inventory records, and generating an advance shipping notification (ASN) of when product could be expected to arrive. An automatic invoice or updated production plan might also be generated as part of the process, or employees of the accounting or planning departments might have to manually integrate this information into their normal workflows.

This type of process innovation appears deceptively straightforward. Many different steps of the process can be automated and integrated together; or, some steps of the process can be automated while others are still managed manually. At a very basic level, automated communication has many advantages over more-traditional methods of communication,

[18] Business-to-business electronic commerce did not originate with the Internet. Electronic Data Interchange (EDI) technology began to diffuse in the 1970s and 1980s, allowing businesses to exchange documents such as purchase orders and invoices. By 2000, a large proportion of e-selling in my sample took place using EDI technology. However it would be incorrect to say that EDI had diffused widely at the time, and an exploration of my main results suggests that they are not biased by particularities of EDI versus the Internet in e-selling. I address this more fully in Section 6.

including: improved speed and accuracy, less redundant data entry, asynchronous interactions, richness of communication, and automated transaction management (Saloner and Spence, 2002). Applying these advantages to the purchase of materials or the sale of products, firms can dramatically cut their average variable costs of production by removing time and labor associated with order management and by reducing latency and uncertainty in their supply chains.[19] On the procurement side, firms can also benefit from consolidating and centrally managing purchasing to exploit volume discounts and maintain oversight. On the sales side, firms can use e-commerce to improve the quality of their goods and services through improved responsiveness to customer changes (AMR Research, October 1st, 1999).

Costs and Co-Invention

Deploying e-commerce practices in manufacturing is not a straightforward adoption of existing technology solutions. To begin, these are complex enterprise software applications – and priced accordingly.   High-end procurement software applications from leading vendors such as Ariba or Commerce One cost as much as $500,000 to $4 million (Waltner, 1999).

More importantly for the purposes of this paper, the process of customizing the software to match a firm's business requirements and training users is often just as expensive – or more so – than the price of the software license.[20] To enjoy the benefits associated with automated management and execution of orders, firms must adjust their existing information technology infrastructure, their existing business practices – and possibly even their trading relationships – to integrate e-commerce into their organizations. The best way to do this varies by organization, and both the steps to be taken and the costs associated with achieving successful deployment of the

[19] Timely information exchange can eliminate large build-ups of buffer inventories and costly stockouts known as the "bullwhip effect." See Lee et al. (1997) and Lee and Whang (2001) for research on this effect and how information technology can mitigate it.
[20] One study by Gartner Group (Cappucio, Keyworth and Kirwin, 1996) estimates that only 20% of the total cost of ownership for enterprise I.T. lies in acquisition costs.

new technology are generally uncertain. Bresnahan and Greenstein (1996) use the term "co-invention" to describe this type of innovative activity.

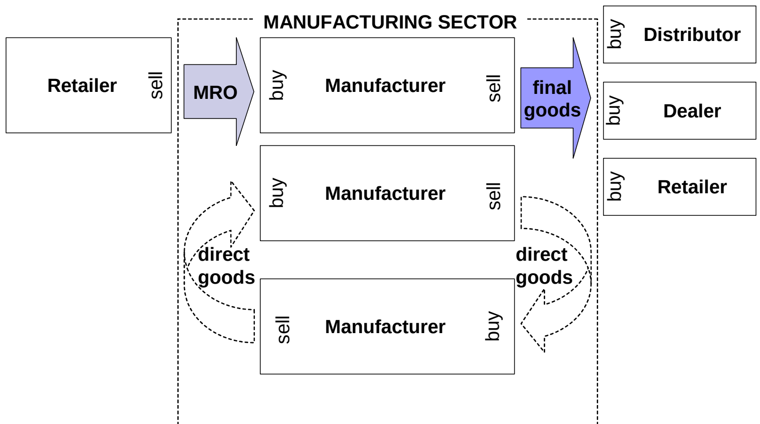
E-Buying vs. E-Selling in Manufacturing at the Start of 2000

In early 2000, e-commerce software applications were available that only addressed indirect and finished goods. *Indirect* goods are materials used by the manufacturing firm but not used as part of the product. Standard examples are maintenance, repair, and organization (MRO) goods such as machine lubricant or pens and pencils. In contrast, d*irect* goods are products required by the production plan, such as raw materials or intermediate components. *Finished* goods are manufactured goods ready for consumption by end-users. Examples include computers or toys destined for shelves in retail stores.

At the time, Ariba, Commerce One and similar vendors of "procurement" applications had well-defined offerings for MRO procurement. Firms such as Mercado and QRS specialized in meeting the needs of retailers to manage the flow of finished goods and had begun to extend their offerings into manufacturing. But very little headway had been made in terms of offering a procurement solution that could effectively manage direct procurement (AMR Research, 1999; PRTM, 2000; Stephens, Inc., 2001).

The limitations of the software solutions available at the time meant that a survey of e-business practices among manufacturers in 2000 would observe *e-buying of indirect materials* and *e-selling of finished goods*. This particular relationship between the practice (e-buying or e-selling) and the type of good (indirect or finished) in this sector was due to the position of manufacturing firms in the value chain. Only direct goods, for which no software solutions were widely available, tend to be both bought and sold among manufacturers. In contrast, manufacturing firms purchase indirect goods from – and sell finished goods to – retailers, wholesalers, distributors, and other firms *outside of the manufacturing sector.* See Figure 1, below. So, while there was certainly e-*selling* of indirect goods and e-*buying* of finished goods in the overall economy in early 2000, the restriction of my sample to manufacturing entities excludes these from my data.

Figure 1. E-buying vs. E-Selling



Moreover, because e-*buying* and e-*selling* concerned very different types of goods, they took place in very different competitive environments. The fungible nature of MRO and other indirect goods means that transactions (both off- and on-line) take place in an arms-length fashion. “Opportunistic buying” to take advantage of one-time discounts was not uncommon at the time (Waltner, 1999). The key point to note for the purposes of this paper is the lack of an ongoing relationship or any relationship-specific investments between trading partners in MRO procurement.

In contrast, vendors of final manufactured goods destined for distributors, dealers, and retailers (on the way to the end consumer) are, in general, more likely to have long-term, repeated interactions with their customers that promote relationship-specific investments (Ring and Van De Ven, 1992) or possibly exclusive production (Katz, 1989). These investments tend to be difficult for rivals to replicate, thereby blunting product market competition among potential adopters of e-selling, at least in the short run.

Thus, due to the combined effect of the peculiarities of software application development at the time, my data’s sampling frame, and institutional details governing transactions over certain types of goods, I argue that the competitive pressure and scope for strategic use of this type of technology faced by manufacturing firms in the context of e-*buying* was higher than that for e-*selling*. Moreover, this difference is exogenous, being driven by conditions external to the firm.

Adjustment Costs in E-Selling

Another important difference between e-*buying* and e-*selling* was the locus of the innovation with respect to the firm's product market offerings and the impact of the technology on customers. While both technologies offered similar supply chain efficiency benefits, the adoption of e- *buying* removed costs from the production of products that arrived in the market in the same fashion they did prior to the process innovation. The adoption of e-*selling*, on the other hand, meant that goods arrived at the conclusion of a very different type of transaction. Importantly, it generally required some type of participation on the part of customers who would access a firm's online selling capabilities, thus disrupting and potentially even cannibalizing existing sales (particularly if existing customers resisted this innovation for reasons of their own). Thus the costs of adopting e-*selling* were likely much more closely tied to the number of customers a potential adopter had – a link that could conceivably increase the costs of this process innovation proportionately with output, potentially in violation of the adjustment costs assumption (Assumption #2) outlined in the previous section.

Usefulness of the Empirical Context

E-business practices among manufacturing firms in 2000 serve as a useful context in which to test the impact of market position on innovation and how competitive concerns interact with these effects. There are two main reasons for this:

- The significant cross-industry variation within the manufacturing sector means that results will not be driven by the peculiarities of a single industry.
- The exogenous variation in competitive pressure between e-buying and e-selling makes it possible to find some evidence for the presence of strategic investment behavior. This is because, although they had very similar direct value propositions, historical variation in the institutional details of these practices gave rise to differences in their strategic importance.

4. DATA

E-Business Practices

My dependent variables come from the Computer Network Use Supplement (CNUS) which was mailed in June of 2000 to all plants in the 1999 Annual Survey of Manufactures (ASM) sample. The ASM is sent by the U.S. Census Bureau to a 10% sample of all manufacturing plants in the United States, with extra sampling weights assigned to large manufacturing plants to ensure their inclusion in every ASM year (at the expense of smaller plants). The approximately 30,000 plants included in my sample account for a substantial fraction – over 50% – of U.S. manufacturing employment and output in 2000.

The CNUS contains extremely detailed information on plant use of a variety of e-business practices. Examples range from e-mail to online catalogs to network-enabled vendor managed inventory practices. In particular, plants identify whether or not they place or accept orders for goods or services over a computer network.

Summary Statistics

In 2000, e-buying and e-selling represent a small but growing fraction of business conducted in the U.S. manufacturing sector. Online purchases account for 11 percent ($231 billion) of the cost of materials at all manufacturing plants; 12 percent ($485 billion) of all sales orders are accepted online (U.S. Department of Commerce, *E-Stats*, 2004)

The reach of e-business capabilities among plants is far: e-commerce takes place in every manufacturing subsector and at every point of the size distribution. over 40% of manufacturing plants either place or accept orders over a computer network.

E-business Practice	**% of Plants in Weighted Sample**[21]
Place orders online	25%
Accept orders online	27%
Place OR accept orders online	41%
Place AND accept orders online	14%

Beyond these high-level summary statistics, however, there is a great deal of heterogeneity in the use of technology. First of all, due to the reasons discussed in Section 2, plants tend to specialize in their e-business practices: only 14% both accept and place orders online. Also, industries vary a lot in terms of how prevalent the use of e-commerce is. Transportation Equipment has both the largest percentage of value shipped (40%) as well as high penetration of e-commerce (roughly 50% of plants place or accept orders online). Among Computer and Electronic Products plants, approximately 52% place orders online and 41% accept online orders. Wood Products plants lag with 26% and 18% adoption of e-buying and e-selling, respectively (U.S. Department of Commerce, *E-Stats*, 2004).

[21] These numbers represent responses from plants for which production information in 1997 is available, weighted using the Census Bureau's ASM sampling weights. For more information, see the Data Appendix.

Figures 2 & 3 (*Not Yet Cleared for Disclosure)* provide histograms of the mean adoption of electronic buying and electronic selling for most 4-digit SIC code industries in the manufacturing sector. The notable feature of these graphs is that there is no clustering in adoption among firms at either 0 or 100%. This establishes the lack of strong strategic complementarity in the adoption of e-business practices (Assymption 1) that is needed for the overall theoretical model to apply in this particular context.

Leadership

Various proxies for competitive advantage have been used in related empirical work, depending on the theoretical justification or merely due to data limitations. Popular examples include firm size, market share, and proxies for monopoly power (see Cohen and Levin, 1989, for a review). In the empirical work to follow, I will explore the theoretical relationship between leadership and innovation using both productivity leadership within the industry and market share as measures of relative position in the product market.

I explore the relationship between productivity leadership and the adoption of IT-driven process innovation by calculating total factor productivity (TFP) at the plant level. As previously discussed, there are important conceptual justifications for measuring key firm attributes at the business unit level (see Section 3). Moreover, the data required for a careful TFP calculation is collected at the plant level in the 1997 Census of Manufactures (CMF). Therefore, I conduct the empirical analysis at the plant level.

Data collected in the CMF includes the annual total value of shipments by product category, production worker and non-production worker employment and salaries, book values of equipment and structures, and cost of materials. With this information, I calculate a measure of TFP by estimating the residual of a log-linear production function that regresses capital (K), labor (L), and materials (M) on gross output (Q) at the plant. Lower-case letters indicate logarithms of plant-level measures:

$$TFP_i = q_i - [\beta_k k_i + \beta_l l_i + \beta_m m_i] \tag{5}$$

Capital is measured by the book value of buildings and machinery at the plant at the end of 1997. Labor is measured in total hours.[22] Materials are the total reported cost of direct parts and materials. The β_j 's ($j=k,l,m$) are industry-specific factor elasticities where industry is defined by 4-digit SIC code.

To test the importance of productivity leadership in explaining e-commerce adoption, I use the entire CMF (not just those plants that responded to the CNUS survey) to rank plants according to their productivity *relative* to other plant in the same industry (as defined by 4-digit SIC code).

Market Share

Because the 1997 CMF covers the entire manufacturing sector, I can accurately measure the value of shipments in each industry and the share of that value shipped by every plant in my data set. I identify the relevant market as the total value of shipments coded as primary product shipments in the same 4-digit SIC industry code as the plant of interest. Plant market share is the percentage of this market shipped from the individual plant.

Since the majority of existing work on how size influences incentives to innovate focuses on output at the firm level, I also calculate market share for the parent firm.[23] This is calculated as the percentage of value in a 4-digit SIC industry code shipped from all of the plants belonging to the same firm to which the plant of interest belongs.

[22] To be precise, labor is measured in "production-worker-equivalent" hours. See Data Appendix for details.

[23] According to these arguments, larger firms have more internal resources to devote to innovation that might be difficult to acquire in the market. The focus is generally on the need for capital to devote to R&D and the role that large firm size may play in overcoming capital market imperfections, though the logical extension to other firm resources that might more directly influence co-inventive activity, is not difficult to imagine. For a review of the large literature on firm size and R&D see Cohen and Levin (1989). For a treatment of how internal firm resources substitute for market resources in the adoption of information technology, see Forman, et al. (2006).

Controls for Confounding Influences

The CMF also provides a rich set of variables to control for potentially confounding drivers of investment in e-commerce capabilities. These controls are critical for separately identifying the effects of leadership from other known or suspected drivers of information technology adoption (see Forman and Goldfarb, 2006; and Forman, 2005). Examples of controls used in my analysis include:

- *Plant Size:* A great deal of existing work has tested the relationship between size and innovation (e.g., Cohen et al., 1987;Cohen and Klepper, 1996; and studies reviewed in Cohen and Levin, 1989 and Gilbert, 2006) as well as the relationship between size and I.T. adoption (e.g., Astebro, 2002). I address the very skewed distribution of the number of employees at the plant by using the log of employees as my empirical proxy for size.
- *Age*: Existing literature (e.g., Rogers, 1995) indicates that age is an important predictor of firm IT choices. Also, newer firms may be more likely to enter with new technology, in a classic vintage capital effect (Solow 1960; and Chari and Hopenhayn 1991). This effect is controlled for with a dummy for whether the plant is 10 or fewer years old.
- *Complementary Skilled Labor*: Bresnahan, Brynjolfsson, and Hitt (2002) find evidence that information technology and skilled labor are complements. Under the assumption that non-production workers tend to be higher-skilled white collar workers, I control for the skill mix of employees at the plant by taking the ratio of non-production workers wages to total salaries and wages at the plant.
- *Multi-Establishment Status*: Plants belonging to multi-establishment (i.e., multi-plant) firms may enjoy access to additional resources for making IT investments as well as additional economies of scale if there are large sunk costs at the firm level. At the same time, the more complex organizational structure may increase co-invention costs. I do not take a stand on which may dominate in this setting, but control for this potentially important effect. A dummy variable denotes plants belonging to multi-establishment firms.
- *Local Population Density:* Prior work suggests that the local market characteristics, such as local population density, may tend to influence the net

benefits of adopting information technology (Forman et al., 2006; Forman, Goldfarb and Greenstein, 2005). I include a dummy for whether the plant is located in a metropolitan statistical area (MSA) with greater than 10 million people.

- *Industry*: Controls for industry-specific drivers of e-business adoption are included for all 4-digit SIC code industry groupings.

5. EMPIRICAL MODEL

5A. PROBIT MODEL OF ADOPTION

In the theoretical model, asymmetries between potential adopters were restricted to their relative state variables (i.e., relative costs of production or relative quality). For the empirical estimation, I relax this assumption and allow the benefits and costs of adopting e-business practices to vary by other characteristics of the firm that might influence adoption (and which were described in the previous section).

Since I do not directly observe the costs and benefits of adopting e-business practices, but rather observable characteristics of plants that arguably shift costs and benefits in ways defined by the theoretical model and prior work, I re-state the objective function in equation (1) in terms of the net benefits (*NB*) a plant enjoys from adopting, as a function of its relative market position (MP_i), share of the product market (MS_i), observable plant-specific characteristics (X_i),industry-specific conditions (IND_i), and unobserved plant-specific "shocks" (ε_i).

$$\max_{a_i \in \{0,1\}} \Pi^i = NB(a_i, MP_i, MS_i, X_i, IND_i) + \varepsilon_i \tag{6}$$

Plants will choose to adopt ($a_i = 1$) a particular e-business practice if the net benefits of doing so are positive. Assuming that the plant-specific errors follow a standard normal distribution, the probability of adopting a particular business practice can be estimated using a standard probit model (David, 1969):

$$\Pr(a_i = 1) = f(MP_{i,} MS_i, X_i, IND_i) \tag{7}$$

where *f* is the standard normal CDF.

5B. IDENTIFICATION

Identification in this model requires that market position, market share, plant size and other explanatory variables not be simultaneously determined with adoption. I use lagged values of the explanatory variables to reduce simultaneity. Moreover, I include a rich set of controls for possible drivers of IT adoption that might confound the empirical results if not explicitly accounted for in the specification. As mentioned previously, prior research finds strong effects of firm size, age, location, and complementary skilled labor in IT adoption decisions. These and other observable plant characteristics are used to refine and test the robustness of the coefficient estimates in the next section.

However, if there are omitted variables that influence, for example, both adoption and productivity, then this specification will still introduce bias in the estimates of the coefficients on relative productivity and market share. While this cannot be entirely ruled out as long as the explanatory variables exist only in a cross-section, there are some mitigating circumstances that should increase our confidence in the results.

To begin, prior research (e.g., Baily, Hulten and Campbell, 1992) suggests that there is a persistent component of plant productivity that strongly influences plant survival and industry dynamics. If this is the case, my results are unlikely to be affected by an unobserved shock that moves both productivity and adoption together in such a way as to create a spurious empirical relationship between productivity leadership and propensity to innovate. There may still be an unobserved factor that contributes both to productivity persistence and a tendency to pursue cutting-edge technological capabilities. In this case, the proper way to interpret this possibility is that productivity serves as a proxy for this other, harder-to-observe facet of market "leadership", leaving our basic intuition about how leadership influences firm behavior unchanged.

Finally, the influence of an unobserved variable that raises both productivity and the tendency to adopt cutting edge information technology, such as the recent introduction of better managers, should generate a positive relationship between productivity and adoption across all types of e-business practices. As will be seen in the next section, this is not the case here.

6. RESULTS

Although the average adoption rate is the same for both e-*buying* and e-*selling*, I find that productivity leadership is positively correlated with the adoption of e-buying process innovations but not with e-selling. Market share leadership has a positive effect on the adoption of both practices, though the effect is larger and more robust for e-buying than for e-selling. These results are consistent with increasing dominance: leading firms are associated with a higher probability of adopting business process innovations. In addition, I hypothesize that the pattern of results is suggestive of the presence of strategic incentives to adopt that go beyond the stand-alone benefits of the technology. It is also consistent with higher adjustment costs in e-selling that violate the assumptions necessary for the prediction of increasing dominance to hold.

This section presents the empirical results for both types of business process innovations and compares the magnitude of different explanatory variables in the model. Differences across the two types of e-business practices are discussed and used to make a case for why these results can be taken as evidence of strategic behavior on the part of firms.

6A. E-Buying Results

According to the empirical results, market leaders are more likely to purchase goods and services over a computer network, consistent with Hypothesis 1. Moreover, this holds for different measures of market leadership. Being at the top of the industry productivity distribution has an economically and statistically significant correlation with the propensity to adopt e-buying. The effect of market share leadership is also positive and large. Table 3 presents these findings.

Productivity Leadership

The average rate of adoption of e-buying across all manufacturing industries is 26%. Comparing productivity leaders to laggards with no other controls, plants in the top 20% of the productivity distribution for their industries are 2.4 percentage points, or 9.2% more likely, on average, to practice e-buying than are plants in the lowest 20% . As the same is true for plants in the adjacent quintile of the productivity distribution, these plants are all grouped together as "Productivity Leaders" (Column 1 of Table 3). Adoption is increasing in productivity, with average productivity plants more likely than the least-productive plants to adopt. However, the coefficient for this group of plants is not measured very precisely. When the top plants are compared to *all* other rivals (including average plants), the coefficient on leadership is a bit lower, at 1.6 percentage points, or a 6% increase in adoption on average (see Column 2 of Table 3). The effect of productivity leadership is robust to the inclusion of many other controls, including industry-specific effects at the level of four-digit SIC Code (see Column 3 of Table 3).

Scale Effects and the Role of Market Share

Columns 4 and 5 of Table 3 demonstrate the importance of controlling for the scale of output at the plant. An increase in a plant's share of the market by 1 percentage point (i.e., a one-standard-deviation increase) at the mean value of 0.3% is associated with a 4.01 percentage-point increase in the likelihood of adoption, all else equal. At the mean, this represents a 15.4% increase in the likelihood of online buying. In contrast, the same percentage-point increase in market share at the firm level only generates a 3.9% increase in the adoption probability. These results are consistent with Hypothesis 2 on cost-spreading: output at the plant level has more explanatory power than the market share of the parent firm.

Including market share in the specification dramatically reduces both the size and the significance of the productivity leadership coefficients. One possible explanation is that this other definition of leadership *mediates* (Kenny, Kashy and Bolger, 1998; Shrout and Bolger, 2002) the effect of productivity leadership on the propensity to innovate. If this framing is correct, the *primary* mechanism by which productivity drives innovation is *through* its tendency to increase market share. In this case, studying productivity leadership may still reveal something about a root cause by which firms with high market share have a higher propensity to adopt, providing insight into the underlying mechanism. It will not, however, offer any empirical insights that market share does not.

Under this assumption, market share would be a sufficient proxy for the underlying "type" of the firm and could prove useful in contexts where the detailed data necessary to directly estimate productivity are unavailable. It also means that the practically useful measure of the effect of leadership is the market share coefficient, which is large by any definition.

Another possibility is that there are important differences between market share leadership and productivity leadership that are being masked by the high collinearity between the empirical proxies in this specification. Conditional on industry-specific controls, there is a very high empirical correlation between productivity and market share, particularly market share defined at the plant level (see Table 2B).

Additional support for model misspecification in Columns 4 & 5 comes from the small and insignificant coefficient on firm age. Plant age varies a great deal across the Census of Manufactures, and a classic vintage capital argument indicates that age should be a significant predictor of firm behavior in this type of context.

A possible remedy lies in finding a proxy for scale of output that is less highly correlated with the total factor productivity measure. The model in Column 6 of Table 3 uses plant size as measured by the log of the number of employees as an empirical proxy for scale.[24] The correlation between total factor productivity and the log of employees is small (and slightly

[24] This may more accurately be described as a proxy for the cost-spreading effect of Cohen and Klepper (1996), but the cost is being spread across employees, not units of output, although the two are positively and significantly correlated (see Table 2).

negative), even controlling for industry fixed-effects (see Tables 2A & 2B). When plant size is used in place of market share, the coefficients on both productivity leadership and age increase dramatically. The explanatory power of the overall model goes up, as well. Under this specification, productivity leaders are 13.5% more likely to adopt e-buying than are their least-productive rivals.

Column 7 presents the results when productivity leadership, market share, and logged number of employees are all included in the same model. This is not my preferred specification due to multicollinearity among the explanatory variables (see Table 2A), however, it provides further support for the notion that being "good" (i.e., productive) and being "big" (either in terms of plant size or scale of output) have different effects on firm behavior. In other words, the definition of leadership matters for predicting firm behavior in this setting.

Notwithstanding concerns about the overall specification, the coefficient on productivity leadership remains robust to this inclusive approach, with leaders nearly 12.7% more likely to adopt than laggards. Market share leaders are marginally more likely to adopt as well, though with a quarter of effect estimated in Column 4.

How Important is Market Leadership? A Comparison of Effects

While all of these market leadership coefficients are statistically significant at conventional (or higher) levels, it is important to question whether these are economically significant results. Since one goal of this paper is to disentangle the strategic incentives to pursue I.T.-driven process innovation from the stand-alone benefits firms derive from adoption, I calculate the impact that small changes in observable plant characteristics have on the probability of adopting e-commerce and compare their magnitudes.

The average plant[25] in my sample has: $e^{3.6}$, or roughly 37 employees, is 34% likely to belong to a multi-establishment firm, spends 38% of its payroll on non-production workers (e.g., managers and other white-collar workers), is a little over 16 years old, and is probably located in an urban area (80% of the sample is in a Metropolitan Statistical Area).[26] However, it has only a 10-percent probability of being located in an MSA with more than 5 million inhabitants in 1990.

Plant size as defined by number of employees has a very large effect on the adoption of e-buying. Using the model in Column 6 as my preferred specification, and holding all else constant at their estimated mean values, a plant with approximately one hundred more employees has a 10-percentage-point, or 39% higher probability of adopting e-buying than a plant at the mean of the distribution.[27] Plant age is another significant determinant of technology adoption. A plant that is ten or fewer years old in 2000 is 20% more likely to practice e-buying.

The impact of other observable characteristics of plants is much smaller. Controlling for economies of scale in the number of employees, a plant that belongs to a multi-establishment firm is 2.4 percentage points, or 9.2% more likely to practice e-buying than a plant with equivalent characteristics that does not belong to a larger entity. The same plant with a higher share of payroll going to non-production workers, say 50% instead of the mean of 38%, increases its likelihood of e-buying by 2.4%.[28] The effect of being in a very densely-populated area reduces the likelihood of e-buying by roughly 9.6%, although this coefficient is less precisely measured in the more richly-controlled specifications.

[25] In order to prevent disclosure of the identity of any firm in my sample, this description applies to no actual plant in the sample, but represents the weighted averages of these variables across the entire sample of over 30,000 plants using the Census Bureau ASM sampling weights.

[27] This derivation comes from multiplying the marginal coefficient of logged employees, .078, by 1.325, which is the increase in x necessary to shift e^x from the mean value of logged employees (which is $e^{3.6} = 36.6$ employees) by 100, to 137. This is slightly more than a one-standard-deviation increase, which would result in a 36% higher propensity to adopt from an increase of roughly 85 employees.

[28] This is calculated by taking the difference between .50 and the mean value of .38, or .12, times the marginal coefficient of .048.

Putting it all together, it is clear that the effects of plant size and age generate firm-specific benefits from adopting e-buying that overshadow the increasing dominance effect as measured by productivity or market share leadership. This is not surprising given the existing evidence on the importance of organization size in information technology adoption (e.g., Rogers, 1995; Kimberly and Evanisko, 1981; Forman, 2005). However, the effect of market leadership measured in different ways across different specifications is comparable – and, in some cases, even larger than – the other statistically significant drivers of plant behavior.

6B. E-Selling Results

The effect of market leadership in e-*selling* is dramatically different than in e-buying. The effect of productivity leadership is not statistically different from zero in any specification. In fact, market share of the parent firm is negatively associated with adoption in certain specifications, consistent with Hypothesis 3 on replacement effects.

As previously discussed, this could be due to competitive pressure being blunted in the context of e-selling due to relationship-specific investments trading partners undertake in the relationships surrounding the sale and purchase of finished goods. It could also be a result of adjustment costs being tied to the scale of output (i.e., through the number of customers) such that the increasing dominance prediction is overturned. These results are presented in Table 4.

The effect of market share is significantly smaller in e-selling than in e-buying, but the results remain consistent with a cost-spreading effect: plants with larger scales of output are more likely to pursue e-selling, and the plant market share has a larger effect than does market share of the parent firm. A one-percentage point (i.e., one-standard-deviation) increase in plant market share is associated with a 9% higher probability of adopting e-selling (Column 3, Table 4). While the coefficient on firm market share is statistically significant, a one-percentage point (one-fourth of a standard deviation) increase in firm market share only increases the likelihood of e-selling by 1% (Column 4, Table 4).

One possibility is that the cost-spreading benefits (i.e., direct, stand-alone benefits) of adopting e-selling are greater for larger plants, but that the strategic benefits (i.e., indirect benefits) actually work in the opposite direction. A firm that enjoys some market power due to blunted competition (as I hypothesize ought to be more likely to exist in e-selling than in e-buying) will be more likely to experience an "Arrow replacement effect" (1962), as outlined in the conceptual framework. In this case, the net effect of firm market share ought to be reduced and could even be cancelled out if the magnitude of these competing effects is sufficiently equivalent.

Some tentative evidence for this is provided in Column 7 of Table 4. While it is risky to draw too many conclusions from a specification with correlated explanatory variables – in particular, size of plant and market share – the results of a very full specification proxying separately for plant size and market power (using the share of the output market controlled by the parent firm) suggest that, controlling for economies of scale in adoption, firm market share actually has a slightly negative effect on the likelihood of e-selling. A one-standard-deviation increase in firm market share (which is 4 percentage point gain) is associated with a 3% lower probability of e-selling.

Further evidence for economies of scale in adoption is provided by the large positive coefficient on the number of employees. An increase in the number of employees by 100 is associated with an approximately 41% percent higher probability of adopting e-buying – almost identical to the magnitude of the effect for e-buying (Column 5, Table 4)

Is This Behavior Strategic?

Controlling for idiosyncratic benefits of adopting e-business practices that reduce plant production costs such as plant size and age, the coefficients on different measures of market leadership are consistent with the predictions of a model of strategic interaction between firms that generates higher incentives to innovate for leading firms. Moreover, my preferred empirical proxy for market leadership – productivity leadership – is based on the *relative* position among firms in the market structure, not *absolute* productivity levels. So in that sense, as well, it captures competitive rivalry between firms that cannot be captured by looking at stand-alone characteristics of potential adopters.

The main evidence of strategic behavior among rivals in the product market is the difference in behavior across e-*buying* and e-*selling*. The two business practices share the same mean rate of adoption: 26-27%, which implies comparable net benefits of adoption (under the assumptions of a probit model of adoption). Moreover, many of the stand-alone benefits for adopters of the two types of technology are of the same nature (though not necessarily of identical magnitudes), in terms of increased speed and accuracy of transactions and removing latency in the supply chain. The important difference between e-*buying* and e-*selling*, I argue, is a difference in the degree of competitive pressure across the two settings. If the strategic incentive to invest is blunted due to the relationship-specific investments made by trading partners transacting on strategic inputs to the manufacturing process, then strategic incentives will be present in e-buying and not in e-selling. Under this hypothesis, the discrepancy in the effect of market leadership across the two settings would constitute empirical support for strategic investment in innovative e-business processes that exceeds what would be expected due to stand-alone benefits from adoption.

6C. ROBUSTNESS CHECKS

The results discussed thus far are robust to a number of perturbations in the specification and the inclusion of other controls for unobserved heterogeneity among plants. Controls that have been explored include: exports as a share of total value shipped; growth in total value shipped from 1992 to 1997; complementary IT investments (Forman, 2005) including enterprise resource planning (ERP) software and a dummy for whether or not there was prior software investment in 1992; capital intensity (i.e., the log of capital assets at the plant).[29]

In addition, a variety of calculations of productivity were tested, with no effect on the core results. In the TFP estimation, measuring labor using plant hours, total number of employees, and excluding contract worker labor had almost no measurable effect. Using value added per employee as the productivity measure greatly enhances the effect of productivity leadership. However, in the interest of presenting conservative estimates and concern about measurement error (see Atrostic and Nguyen, 2005b) in this approach, I omit these results from the final presentation.

Another concern for these results is the possibility of confounding frontier technology (i.e., Internet-based e-business practices) with older technology (i.e., electronic data interchange, or EDI). This is a particular concern for e-selling, where EDI is the primary network for conducting sales for roughly half of the plants in my sample. Table 5 presents the results for the same regression models in Table 4, but restricting the dependent variable to online sales that are conducted *primarily* over the Internet. While there are some interesting differences in the coefficients for the control variables, the results for productivity leadership remain materially unchanged. Interestingly, the effect of market share is negative in every specification, indicating that any economies of scale in adoption of Internet-only e-selling may only relate to the number of employees at the plant – and not the total output. An alternative interpretation is that the Arrow replacement effect is even stronger for Internet-only e-selling.

Further investigation of the robustness of these results is warranted. For instance, I plan to investigate how controls for industry concentration affect these results and to run bootstrap estimates to calculate more accurate standard errors (the current specifications include TFP,

[29] These other variables have been excluded from the final results either for the sake of parsimony, because they cause specification problems (e.g., capital is highly correlated with the number of employees at the plant) or because they rely on a subsample of plants that were extant in 1992, which significantly reduces the sample size without improving the estimates and also may introduce some undesirable survivor bias.

which is a generated regressor, so the current standard errors are likely underestimating the variance of these coefficients).

7. CONCLUSION & IMPLICATIONS

In this paper, I empirically test whether market leaders are likely to be leading adopters of economically important business process innovations. I use a novel definition of leadership – relative productivity in the industry – to help disentangle strategic and stand-alone adoption incentives and differentiate market effectiveness from market power in the behavioral mechanism. My use of a conventional definition of leadership – market share – ties this investigation to prior empirical and theoretical work and provides evidence for stand-alone benefits of adoption that are increasing in firm output. I leverage exogenous differences in the market environments of e-*buying* versus e-*selling* to identify whether strategic motivations to blunt or deter competition play a role in this behavior.

Using this analytical framework and rich data from the U.S. Census of Manufactures, I find evidence that productivity leaders are more likely than laggards to adopt e-*buying*, but that productivity leadership has no effect for e-*selling.* I argue that this is consistent with strategic innovation, under the assumption that competitive pressure is blunted in e-*selling* vis-à-vis e-*buying*. This empirical finding conforms to theoretical predictions by Athey and Schmutzler (2002) that leading firms have incentives to invest in maintaining market dominance.[30] However, the results suggest that market power is not necessary for this effect to take place -- more-productive firms have a tendency to pursue certain cost-saving innovations, even controlling for market share.

Overall, these results have interesting implications for industry dynamics. For instance, if leading firms are able to leverage these types of technologies to actually increase their market

[30] This result is related to the well known "efficiency effect" (Gilbert and Newbery, 1982; Tirole, 1988, chapter 10), but it is more general and extends more naturally to process, as opposed to product, innovation.

share, then industry evolution will be characterized by increased concentration among dominant firms.

However, the implications of this for welfare and public policy are unclear. To begin, the process innovations of interest in this study tend to promote outcomes that are beneficial to consumers, such as reductions in production costs (which can lead to lower market prices) and quality improvements (see Bagwell, Ramey and Spulber, 1997 for a nuanced discussion). Moreover, the increase in market concentration brought about by these higher market shares will be associated with higher rates of technological advance. Currently, a main concern among antitrust regulators is that increased industry concentration may harm long-term growth by stymieing innovation (Katz and Shelanski, 2007). These results contribute to the ongoing body of empirical and theoretical scholarship calling for more careful examination of the relationship between market concentration, competition, and economic growth.

This paper also provides a complementary viewpoint to the literature focused on organizational drivers of technological change (e.g., Attewell, 1992; Fichman, 1992; Fichman and Kemerer, 1997; Brynjolfsson, Hitt and Yang, 2002). In the model of technology adoption presented here, market-based pressure to adopt innovative business practices provides incentives for firms to adjust their core business practices. Certainly, the story does not end here. Organizations' willingness to pursue new process innovations will depend on factors other than their relative position in the product market. However, this paper can provide a useful point of departure for further investigations into organizational characteristics that tend to enhance or mitigate the behavioral mechanisms explored in this paper.

Figure 2 and Figure 3.

(Pending Disclosure Review)

Table 1. Definitions, Means, and Standard Deviations of Variables

Variable	Definition/Variable Name	Estimated Population Mean	Estimated population S.D.
E-Buying	= 1 if the plant reports buying online; 0 else.	.26 (.004)	.44
E-Selling	= 1 if the plant reports selling online; 0 else	.27 (.005)	.45
Productivity	$TFP_i = \ln(Q_i) - [\beta_K(\ln K_i) + \beta_L(\ln L_i) + \beta_M(\ln M_i)]$ (OLS estimation) from 1997 CMF	.024 (.005)	.40
Productivity Leader	=1 if plant is in the 4th or 5th quintile of its industry's productivity distribution	.44 (.005)	.50
Average Productivity	=1 if plant is in the 2nd or 3rd quintile of its industry's productivity distribution	.38 (.005)	.49
Market Share of Parent Firm	$\dfrac{\sum_{\text{all plants in firm}} \text{PPS}_{\text{plant in SIC4}}}{\sum_{\text{all plants in SIC4}} \text{PPS}_{\text{plant in SIC4}}}$ in 1997	.01 (.0002)	.04
Market Share of Plant	$\dfrac{\text{PPS}_{\text{plant}}}{\sum_{\text{all plants in SIC4}} \text{PPS}_{\text{plant in SIC4}}}$ in 1997	.003 (.00004)	.01
Herfindahl	Sum of squared market shares of firms in the SIC4 industry in 1997	.03 (.0004)	.05
LNEMP	Log of total employees at the plant in 1997	3.6 (013)	1.2
LNEMP^2	Square of log of total employees at the plant in 1997	14.4 (.086)	9.7
MU	=1 if plant is owned by a multiple-establishment firm	.34 (.005)	.47
Skill Mix	Share of non-production worker wages to total salaries and wages in 1997	.38 (.002)	.19
Age	Age of the plant in 2000.	N/A[31]	N/A
AGE_10	=1 if the plant is ten or fewer years old in 2000	.27 (.005)	.44
Big Pop	> 5 Million in MSA	.10 (.003)	.30
Industry	4-digit SIC Code	N/A	N/A

Variable Definitions (see Data Appendix for details):

Q= Total value of shipments
K = Total book value of capital at the plant.
L= Production-worker-equivalent hours.
M = Total cost of materials.
PPS = Total value of shipments from plant in its primary industry.

[31] An unbiased estimate of the average plant age in the sample is currently unavailable due to the truncation of this variable at 24 in the current Longitudinal Business Database. This information is used solely to control for unobserved heterogeneity in specifications that do not admit a dummy variable for age due to disclosure risks.

Table 2. Variable Correlations

	TFP	Firm MS	Plant MS	Log (employees)	Multi-Unit	Skill Mix	Age	High Pop	Log (K)
TFP	1								
Firm Market Share	.066	1							
Plant Market Share	.067	**.483**	1						
Log (employees)	-.071	**.258**	**.371**	1					
Multi-Unit Flag	.044	**.312**	.187	**.401**	1				
Skill Mix	-.078	-.115	-.039	-.064	-.123	1			
Age	-.027	.088	.099	**.227**	.106	.009	1		
High Population	.009	-.053	-.021	-.046	-.108	.066	.022	1	
Log (K)	-.070	.291	-.300	**.300**	**.444**	-.061	.225	-.080	1

X	**Linear regression coefficient of X regressed on TFP, controlling for SIC4 Industry**
Market Share of Plant	2.71*** (.233)
Market Share of Parent Firm	.282*** (.078)
Log of Employees	-.019*** (.004)

Table 3. Competitive Setting: Plant Adoption of E-Buying
(Base category contains plants in the lowest 20% of their industry productivity distribution)

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Productivity Leader	**.024*** **(.013)**	**.016*** **(.009)**	**.023*** **(.012)**			**.035***** **(.012)**	**.033***** **(.012)**
Average Productivity Plants	.013 (.013)		.013 (.013)			.018 (.013)	.017 (.013)
Market Share of Plant				**4.01***** **(.341)**			**1.10***** **(.274)**
Market Share of Firm					**1.02***** **(.098)**		
Log of Employees						**.078***** **(.021)**	**.090***** **(.022)**
(Log of Employees)^2						.0004 (.002)	-.001 (.003)
Multi-Establishment Flag			.097*** (.010)	.081*** (.010)	.079*** (.010)	.024** (.011)	.024** (.011)
Skill Mix			.040* (.025)	.043* (.025)	.054** (.025)	.048* (.025)	.047* (.025)
Age <= 10 Years			.017 (.011)	.021* (.012)	.020* (.012)	.053*** (.012)	.053*** (.012)
High Population MSA			-.030* (.015)	-.029* (.015)	-.028* (.015)	-.025 (.015)	-.025 (.015)
Industry Controls (453 SIC4 Dummies)	No	No	Yes	Yes	Yes	Yes	Yes
N	~33,000	~33,000	~33,000	~33,000	~33,000	~33,000	~33,000
Pseudo R^2	.0003	.0003	.0638	.0757	.0758	.0946	.0962
Predicted Pr(Y=1) at x-bar	.26	.26	.25	.25	.25	.24	.24

Weighted maximum-likelihood probit estimation, reporting estimated marginal effects for continuous variables and discrete change from 0 to 1 for dummy variables. Robust standard errors are clustered by firm and are included in parentheses. Significance levels are denoted as follows: *10%, **5%, ***1%.

Table 4. Blunted Competition: Plant Adoption of E-Selling
(Base category contains plants in the lowest 20% of their industry productivity distribution)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Productivity Leader	-.008 (.014)	-.009 (.013)					
Average Productivity Plants	-.012 (.014)	-.011 (.014)					
Market Share of Plant			**2.42**** **(.288)**			.343 (.259)	
Market Share of Firm				**.19***** **(.092)**			**-.18***** **(.086)**
Log of Employees					**.080***** **(.021)**	**.083***** **(.021)**	**.075***** **(.021)**
(Log of Employees)^2					-.002 (.002)	-.002 (.002)	-.001 (.003)
Multi-Establishment Flag		.05*** (.010)	.04*** (.010)	.05*** (.010)	-.007 (.011)	-.007 (.011)	-.006 (.011)
Skill Mix		.08*** (.025)	.09*** (.025)	.09*** (.025)	.09*** (.025)	.09*** (.025)	.09*** (.025)
Age <= 10 Years		-.021* (.011)	-.02 (.011)	-.02* (.011)	.006 (.012)	.006 (.012)	.006 (.011)
High Population MSA		-.043*** (.015)	-.04*** (.015)	-.04*** (.015)	-.04*** (.015)	-.04*** (.015)	-.039*** (.015)
Industry Controls (453 SIC4 Dummies)	No	Yes	Yes	Yes	Yes	Yes	Yes
N	~33,000	~33,000	~33,000	~33,000	~33,000	~33,000	~33,000
Pseudo R^2	.0001	.0906	.0924	.0908	.1058	.1058	.1059
Predicted Pr(Y=1) at x-bar	.27	.25	.25	.25	.26	.25	.25

Weighted maximum-likelihood probit estimation, reporting estimated marginal effects for continuous variables and discrete change from 0 to 1 for dummy variables. Robust standard errors are clustered by firm and are included in parentheses. Significance levels are denoted as follows: *10%, **5%, ***1%.

Table 5. Robustness Check: Internet-Only E-Selling
(Base category contains plants in the lowest 20% of their industry productivity distribution)

	(1)	(2)	(3)	(4)
Market Share of Plant	**-1.21*** (.340)**			
Market Share of Firm		**-.553*** (.089)**		**-.350*** (.086)**
Log of Employees			**.090*** (.018)**	**.084*** (.018)**
(Log of Employees)^2			**-.012***** (.002)	**-.011***** (.002)
Multi-Establishment Flag	-.063*** (.008)	-.060*** (.008)	-.056*** (.008)	-.053*** (.008)
Skill Mix	.031* (.019)	.027 (.019)	.025 (.019)	.023 (.019)
Age <= 10 Years	.007 (.009)	.007 (.009)	.007 (.009)	.007 (.009)
High Population MSA	-.027** (.011)	-.027** (.011)	-.026** (.011)	-.027** (.011)
Industry Controls (453 SIC4 Dummies)	Yes	Yes	Yes	Yes
N	~32,000	~32,000	~32,000	~32,000
Pseudo R^2	.1109	.1118	.1143	.1148
Predicted Pr(Y=1) at x-bar	.12	.12	.12	.12

Weighted maximum-likelihood probit estimation, reporting estimated marginal effects for continuous variables and discrete change from 0 to 1 for dummy variables. Robust standard errors are clustered by firm and are included in parentheses. Significance levels are denoted as follows: *10%, **5%, ***1%.

Appendix 1.

Consider two firms at time *t-1* facing a downward-sloping demand curve with equal initial market shares ($D_i = D_j = D$), equal marginal costs ($c = c_i = c_j$) but differences in a state variable, $S_i > S_j$, that captures the price they are able to charge in equilibrium (e.g., a firm with higher quality may be able to charge a higher price for the same level of sales). Thus $S_i > S_j \not\Rightarrow D_i > D_j$, in violation of assumption (1). Because both firms begin at the same point on the demand curve, the slope with respect to price is identical for both firms: $\frac{dD_i}{dS_i} = \frac{dD_j}{dS_j} = \frac{dD}{dS}$.

Next consider an innovation that lowers production costs, but at a decreasing rate. In terms of the markup a firm can charge, this is captured mathematically by $\frac{dM_i}{da_i} \geq 0$ and $\frac{d^2 M_i}{da_i^2} \leq 0$. Again assuming an incremental investment scenario where $S^t = S^{t-1} + a^t$, this generates the key condition:

$$\frac{dM_i}{dS_i} \geq 0 \text{ and } \frac{d^2 M_i}{dS_i^2} \leq 0 \tag{4}$$

Ignoring adjustment costs, profits for firm *i* are defined by markup times demand:

$$\pi_i = D_i(S)_i \times M_i(S_i) \tag{5}$$

Then the difference in marginal incentives between leading firms and lagging firms, where $S_i > S_j$ is:

$$\frac{d\pi_i}{dS_i} - \frac{d\pi_j}{dS_j}$$

$$= \left[\frac{dD_i}{dS_i} M_i - \frac{dM_i}{dS_i} D_i \right] - \left[\frac{dD_j}{dS_j} M_j - \frac{dM_j}{dS_j} D_j \right]$$

$$= \frac{dD}{dS} \underbrace{(M_i - M_j)}_{>0 \text{ by (4)}} - D \underbrace{\left(\frac{dM_i}{dS_i} - \frac{dM_j}{dS_j} \right)}_{<0 \text{ by (4)}}$$

Assuming that market demand is not decreasing in the firms' cost reduction (i.e., $\frac{dD}{dS} \geq 0$), this value is greater than zero, and leading firms have a higher marginal return to investing in the cost-saving innovation.

Thus, this example demonstrates one case whereby firms with higher market states may have higher marginal incentives to invest in state-enhancing technologies without any differences in initial market share.

Appendix 2: Data Appendix

The Census of Manufactures is conducted quinquennially and covers all manufacturing plants in the United States in years ending in ‘2 and ‘7. This appendix discusses key variables used in this study and what they mean.

A. TFP CALCULATION

- Output (Q): This gross output measure is the total value of shipments (across all industries) reported by the plant.
- Capital (K): Capital inputs are plants’ reported book values for their structure and equipment capital stocks.
- Labor (L): Since hours of work are only reported for production workers in the 1997 CMF, the equivalent hours for all production and non-production workers must be imputed. A measure of “production-worker-equivalent hours” is constructed following the method of Baily, Hulten and Campbell (1992). This involves multiplying the production-worker hours reported by the plant by the ratio of total payroll (salaries and wages plus cost of contract work) to payroll for production workers. Prior work has shown this measure to be highly correlated with Davis and Haltiwanger’s (1991) more direct imputation of non-production workers, which multiplies a plant’s number of non-production workers by the average annual hours for non-production workers in the corresponding two-digit industry calculated from the CPS.
- Materials (M): Materials are plants’ reported expenditures on parts, and materials.

B. OTHER CONTROLS

- **Market Share of Parent Firm:** Diversified firms have shares of different output markets. Since the unit of observation in this study is the plant, however, no effort is made to calculate an aggregate “market share” measure for the parent firm. Rather, all shipments made by other plants that have been assigned the same primary industry code (SIC4) and belong to the same firm are summed up and then divided by the total of primary product shipments for that industry across the entire Census. In order to have accurate industry totals, shipments for plants have been imputed from administrative records data are included in the totals. This is the only place where imputed data is used, due to concerns about the accuracy of current Census imputation methods.

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