Market Returns to Digital Innovations: A Group Based Trajectory Approach

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Abstract

A rich body of prior work documents the factors that condition organizational response to technological innovation and the performance consequences thereof. Our study addresses three important limitations in this literature. First, a bulk of the literature has focused on the constraints imposed by internal characteristics of firms in responding to technological innovation and change. Consistent with an agency model that dominates corporate governance and control in modern organizations, we examine how stock market valuation and expectations of future growth versus current period performance determine investments in technological innovation. Second, opposing views in the literature on strategic response to technological change emphasize underlying heterogeneity in firms that is unobserved and difficult to theoretically predict ex ante. We use group-based trajectory (GBT) models to identify heterogeneous firm types based on firms' market performance and descriptively derive the underlying strategic position that conditions their response to technological change. Finally, the endogenous relationship between technological innovation and performance makes it hard to disentangle the effects of one on the other. In this study, we use GBT models along with propensity score matching to identify returns to technological innovation, contingent on the prior performance of the firms. We develop and test hypotheses in the context of the systematic and pervasive shift towards digital innovation. The latter is reflected in growing stocks of Information and Communication Technology (ICT) patents and increasing backward citations to ICT patents in firms. We find that firms with greater market valuation and expectations of growth versus current period profitability are more likely to engage in digital innovation and obtain higher ex post market valuations. We discuss the scholarly and managerial implications of these results.

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1. Introduction

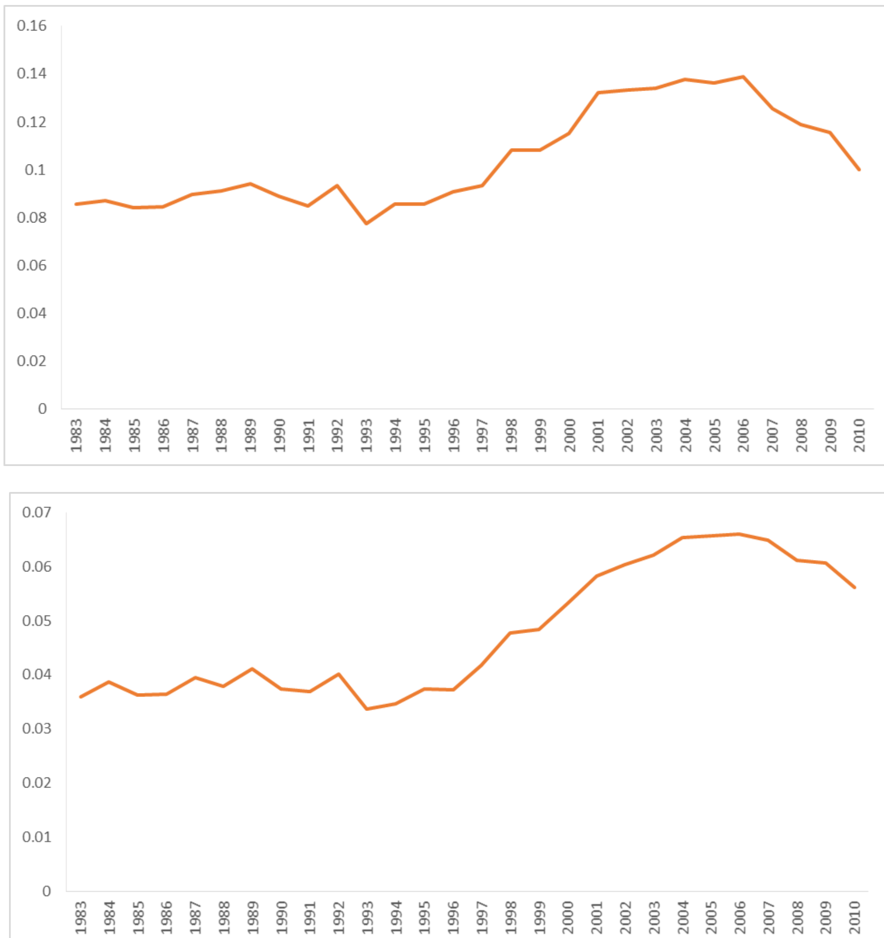
Businesses across a variety of industries are experiencing a significant and pervasive shift toward more digitally based innovation (Yoo et al. 2012). The rapid digitization of all forms of data and the concomitant acceleration in processing and storage capacities has opened up new opportunities for innovation that combine physical and digital components in products and services (Henfridsson et al. 2014; Yoo et al. 2012). Embedded digital components enable firms to augment traditional products with online and mobile services that utilize the data generated to offer further innovative services (Bharadwaj et al. 2013). For example, today's automobiles incorporate a variety of software to run engines, control safety features, identify current coordinates of drivers and guide them to their destinations, and integrate with satellite, mobile and GPS networks. Emergent innovations such as driverless cars and business model innovations based on sharing-economy principles further emphasize this shift. Similar examples abound in diverse industries ranging from defense to pharmaceuticals and financial services.

Beyond the numerous anecdotes, the shift toward a more digital centric innovation can also be observed through patenting activity in ICT related patent classes[2]. Patents, besides being used as visible proxies of R&D productivity at the firm level, also serve as signals of broad shifts in the loci of the underlying technologies (Chien, 2016). Using both raw counts as well as citation weighted counts of patents, we observe overall growth in the proportion of ICT patents to the total patent portfolio, from roughly 8% in 1983 to over 11% in 2009. The pattern of growth in the stock of and citations to ICT patents remain qualitatively similar in the ICT producing as well as in ICT consuming sectors, lending credence to the

[2] We use the IPC classes identified in Corrocher et al. (2007) to classify patents as ICT related. The classification is based on patent abstracts to detect important technological applications in the ICT field

notion that digitally biased shifts in innovation have been broad-based and have occurred across many sectors of the economy.

Figure 1 – Proportion of citation-weighted ICT Patents (top) and ICT Backward Citations (bottom) to Totals



The observable macro-level shift toward more digitally-biased innovation, however raises new questions as to which firms have been able to strategically respond to the opportunities of digital innovation and how the responses have shaped subsequent performance. Past studies have shown that even as new technologies become ubiquitous, not all firms benefit equally from them (Abernathy and Utterback 1978; Tushman and Anderson 1986). Heterogeneities in innovation adoption propensity as well as in the subsequent ability to extract rents are well known and have been attributed to a variety of internal (firm) and external (market and competition) factors. Firms differ in their resource endowments (Wernerfelt 1984; Barney 1991), dynamic capabilities (Eisenhardt and Martin 2000; Winter 2003), absorptive capacities (Cohen and Levinthal 1990; Zahra and George 2002) and routines (Nelson and Winter 1982) all of which can cause a great deal of unevenness in their propensity to adopt innovations in the first place. Even with similar levels of innovation adoption, the subsequent value of innovations can also be different for different firms (Henderson and Clark 1996). Benefits may depend upon complementary adjustments within the firm (Milgrom and Roberts 1990) or value chain (McElheran 2015). Additional external factors can further complicate the value dimension. This is especially true in the digital context, where innovation value is impacted by factors such as network-effects and winner-take-all markets (Brian Arthur 1996; Varian and Shapiro 1999; Parker, Van-Alstyne and Choudhary 2016). Therefore there are several good reasons to expect considerable variation not only in the adoption propensities but also in the subsequent performance consequences of digital innovations.

Although most prior work on innovation and performance has focused on how capabilities internal to the firm will determine its innovation adoption propensity (McElheran 2015), new insights can emerge from an examination of the role that financial markets may play in shaping the strategic choices of firms. Stock market valuations provide firms with access to the needed capital to finance innovation efforts and therefore firms respond to investor expectations underlying the firm's valuation (Christensen 1997). For example, a range of evidence and arguments have been offered to suggest that top management focus on achieving high stock prices can induce them to behave myopically, inflating current earnings at the expense of longer term benefits (e.g., Jensen 1986; Hansen and Hill 1991; Samuel 2000). Specifically, managers have been implicated for viewing R&D as an earnings management tool and for the associated moral hazards (Hall 2002). Notwithstanding the efficiency of managerial focus on stock prices and the optimality of outcomes, it is nevertheless true that such focus shapes strategic decision making. However, the role of financial markets in shaping firm level choices for digital innovation and performance has not been examined empirically and forms the primary focus of this study. Research in finance further suggests that market expectations of firm performance may be based on growth or based on current period profitability (Daniel and Titman 2006). Therefore, in addition to examining valuations, we investigate the expectations of growth versus profitability underlying the valuation and how these in turn drive propensity for digital innovation and subsequent impact.

We measure a firm's digital innovations as reflected in the stock and quality of its information and communication technologies centered patents (*ICT patents*). The value and returns to ICT patents are measured using the *Tobin's q* ratio, which serves as a broad market based measure of firm value and has been used in prior literature to discern the value of ICT (Bharadwaj et al. 1999; Mani et al. 2009). However, in attempting to untangle the relationship between digital innovation and market performance, we face two empirical challenges. The first is the aforementioned heterogeneities in innovation adoption propensity and performance. This line of reasoning suggests that firms may belong to heterogeneous groups or *firm types* based on how they are valued by the financial markets for growth versus profitability. Any assessment of performance effects of innovation would therefore need to take into account the *ex ante* propensity of a firm to pursue digital innovation. Second, even after accounting for the underlying heterogeneity in prior performance, we are faced with the fact there is an endogenous relationship between innovation and performance, such that the high digital innovators within each performance group are also likely to be the ones that are most responsive to financial gains. We attempt to address both these challenges through the use of an empirical technique called Group Based Trajectory Modeling (GBTM). The method, originally developed to study developmental trajectories in a clinical setting (Nagin and Land 1993) has been shown to be applicable in strategy research for analyzing firm performance (Mani and Nandkumar 2016).

Extant research has adopted two different ways to address such problems of endogeneity. The typical approach for dealing with the issue of endogeneity would be to use an instrument variable that is correlated with the endogenous regressor but uncorrelated with the dependent variable of interest. When constructing or finding instruments are difficult, as is the case in our context, many studies have relied on matched samples based on propensity score matching (Rosenbaum and Rubin, 1983). Matched sampling techniques rely on grouping firms based similar on observable attributes, to construct the correct counter-factual to estimate the treatment effects. However, one criticism of matched sampling techniques is the fact that it relies on constructing the correct counter-factual based on the observable attributes of a firm. It is however plausible that unobservable attributes of firms may drive their selection into the treatment or control group. The use of GBTM along with propensity score matching (Haviland and Nagin, 2005) enables us to also account for the fact that the selection into treatment or control groups may also be driven by unobservable attributes of firms. To the extent that a firm's ex-ante performance is driven by these unobservable attributes, additionally conditioning on groups' of ex-ante (prior to adoption) performance group enables us to account for the possibility that selection may also be driven by unobservable differences between firms.

We obtain patent data from the Google patent database and combine this with data on financials and other firm and market performance from COMPUSTAT and CRSP. For all patents granted between our sample years 1981-2010, we obtain data on citations, grant years, application years, and patent technology classes (IPC classes). Using Tobin's q as the performance metric, we employ GBTM to first identify firms that are in similar in their ex-ante performance between the years 1981-1996. In this step we identify firms that are similar in their performance trajectories prior to the adoption of digital innovations. The underlying assumption here is that the rapid diffusion of the internet in US firms that took place starting in 1996, fundamentally changed the opportunities for digital innovation for all firms. We then use a variety of firm attributes particularly the extent to which a firm is valued by the investors based on their growth versus profitability to analyze how firms in the trajectory groups differ from each other.

Since the literature on innovation has argued that prior performance itself may drive adoption, the data driven trajectory groups obtained using GBTM helps us to categorize firms into groups using which we explore their subsequent propensities to adopt digital innovations. To examine the impact of digital innovations on subsequent performance, we compare the ex-post performance of firms, in the period 1997-2010, and within each trajectory group by constructing a matched sample, which matches high adopters (treatment) with low adopters (control) within each trajectory. As alluded to before, the use of a matched sample along with the GTBM enables us to control a sample that closely resembles a natural experiment. The results obtained through this analysis hence helps us to make causal inferences about substantively meaningful collections of firms on similar pre performance trajectories.

2. Theory

2.1. The shift toward digital innovation

Recent years have witnessed the widespread application of ICT to innovation processes and outcomes (Yoo et al. 2012; Branstetter et al. 2015). Much scholarly attention has focused on how ICT has reshaped innovation processes by improving the production and distribution of innovation knowledge, both within the firm and through external networks and collaborations. The application of ICT for innovation has been particularly valuable to firms in providing the links for effective information sharing and seamless coordination across knowledge boundaries and for effective monitoring of the innovation tasks such as design and prototype development (Kleis et al. 2012). The corresponding empirical literature has also documented the value potential and the benefits that accrued to firms that made IT investments for reshaping and improving their R&D processes (Mani et al. 2014; Bardhan et al. 2013).

In short, the role of ICT in improving the efficiency and effectiveness of innovation processes is well established in the academic literature. However, a more significant and pervasive shift in the nature and scope of innovation outputs has been documented across several industries. Beyond using ICT to speed up and make innovation processes more efficient, firms are applying ICT to *digitize* their products, services, and even entire business models. In industries as diverse as auto manufacturing, defense, aerospace, medical devices, financial services, and retail, to name a few, innovators are increasingly looking to ICTs (e.g. software, hardware, electronics, wireless, networking, communication and mobile technologies) to fundamentally redesign traditional products and services and for new opportunities rooted in embedded digital capabilities (Yoo et al. 2016).

Academic scholars and industry practitioners have noted an acceleration in the digitally-biased shift in product and service innovation with the growth of the internet (Brian Arthur 2011, Brynjolfsson and McAfee, 2017). Forman and van Zeebroeck (2012) record the period between 1996 and 1998 as the time when the rapid diffusion of internet as a commercial technology occurred in US firms. This period also marked significant investments by ICT producers in fundamental infrastructure and communication technologies that enabled the storage and rapid movements of a large amounts of data across organizational and national boundaries. As a general purpose technology (Bresnahan and Trajtenberg 1995), the internet provided new opportunities for firms to grow and to differentiate themselves from competition. The remarkable growth of the internet has therefore been chronicled as marking a significant turning point in the innovation trajectory as firms in diverse industries sought to leverage ICT to redesign their core products and service offerings (Branstetter et al. 2015).

2.2. Digital innovation propensity and value

As the examples above illustrate, the potential of ICT for innovation has been documented extensively. However, many of these are based on anecdotal case studies of companies that came up with winning ideas for digital transformations. More systematic, empirically based evidence of the impacts of ICT innovation on firm level performance is just starting to emerge. In a recent study that examined software patenting as the 'instrument of digital change' the authors document the rise in software patenting (as a proportion of the total innovation output of firms) and show that firms that adopted a more software intensive approach to product innovation significantly outperformed their industry peers in overall innovation productivity and in the financial market's valuation of their innovations (Branstetter et al. 2015). However, this study examined only the average effects due to software patents and did not include other ICT related patents such as hardware, networking, telecomm, etc. Furthermore, the study was limited to only four manufacturing industries (automobile, defense, pharmaceuticals and medical devices) and the question remains as to whether the results obtained in this study extend broadly to other ICT consuming industries as well.

Beyond an examination of the average performance effects of ICT based innovations, there are several reasons to expect considerable firm level heterogeneity both in the propensity to exploit the opportunities for digital innovation as well as in the value realized from such innovations by different firms. As noted earlier, these heterogeneities can stem from differences in firm level resource endowments, but importantly, can accrue as well due to differences in how the financial markets value the firm's performance potential. While the former has been examined in prior studies, the latter has been relatively under emphasized and lacks empirical testing. In other words, our thesis is that firms exhibit considerable variation in their digital innovation propensities and in the subsequent performance consequences due to differences in how they are valued by the financial markets. We examine these issues next.

2.3. Heterogeneity in Propensity for Technological Change

A digital or ICT-based innovation is the ability of firms to innovate with digital technologies. Examples of digital innovations include, among others, a) creating completely new digital products and services (e.g. e-books, digital music); b) creating new digital channels for price discovery and delivery (e.g. electronic markets and auction mechanisms); c) augmenting existing products and services with embedded digital functionality (e.g. self-driving cars, online reviews for restaurants) and; d) new digitally based business models that leverage traditional assets in more efficient ways (e.g. platform businesses such as Airbnb, Uber).

An emergent body of work focuses on market related factors including labor markets (Branstetter et al. 2015) and markets for technology (Mani and Nandkumar 2015) as sources of variation in firm level choices to innovate with ICT. For example, there is some evidence that firms that are distant from labor pools with expertise in software engineering and related technological fields are slow to innovate with ICT (Arora, Branstetter and Dev 2013). Similarly, markets for technology, or the opportunities to create and trade technologies are themselves heterogeneous and create asymmetric firm level choices regarding technology capabilities (Zahra and Covin 1995; Mani and Nandakumar 2015).

In general, prior research attributes differences across firms in their ability to pursue digital innovation to key differences in their resource endowments and capabilities (Pfeffer and Salancik 1978). Forman (2005) showed that in the early years of internet diffusion, firms differed substantially in their ability to adopt basic and subsequently more complex internet applications based on the compatibility and sophistication of their existing infrastructure. These early differences in starting conditions can accrete over time, resulting in different trajectories of innovation adoption, both in terms of quality and speed of adoption. Others have argued that steeper learning curves (Attwell 1992) and other investment costs such as in revamping existing infrastructure and in subsequent training (Breshnahan 199x) impede firms for whom the new inventions are radically different from their existing prior expertise and knowledge bases. Management research has also implicated managerial traits such as the fixed mind-sets of top management (Bettis and Hitt 1995) as factors that contribute to why some firms lag significantly in their ability to innovate with technology.

A bulk of the above literature focuses on the role of resources and capabilities *internal* to the firm in conditioning response to technological change. Christensen (1997), while acknowledging the importance of differences in resource endowments across firms, extends the focus of this literature to factors external to the firm to argue that incumbents are trapped in a sustaining trajectory of innovations that made them successful in the first place, with little ability or incentive to respond to technological change. Specifically, he argues that the two key *external* stakeholders in a firm, *customers* and *investors*, who provide the necessary resources for firms to innovate, are an important determinant of incumbents' response to technological innovation and change. In the case of firms with a successful track record of products and services that are valued by their customers, their successful prior performance prevents these firms from embracing potentially disruptive technologies such as the Internet.

The equivalent constraints posed by investors on firms is relatively unexamined in the literature (King and Baatartoghtokh, 2015). Yet, several studies have documented a significant shift in the early eighties in the institutional logics of firms towards an agency model of corporate governance and control (e.g. Zajac and Westphal 1995, 2004; Graham et al. 2006). Indeed, American corporate managers consistently rank share price increases and shareholder value maximization as dominant business objectives for the firm. For example, in their survey of over 500 major U.S. and Japanese companies, Abegglen and Stalk (1985) find that U.S. executives rank share price increase as the second most important objective ahead of other alternatives such as product portfolio and company image. This was in contrast to Japanese executives, who ranked share price increase as the least important of all objectives.

This shift towards the agency model is enabled through incentives that tie executive compensation directly to share prices (Frydman and Jenter 2010; Chakravarthy and Grewal 2011; Bartov and Mohanram 2004), penalties for not preserving market value (e.g., Fisher and Govindarajan 1992), and an efficient market for corporate control (Markovitch et al 2005). Despite the wide acknowledgment of these studies that stock markets impact strategic decisions, the nature of such impact, especially as it pertains to long-term investments such as R&D and innovation, remains an open question. One school of research (e.g. Hirshleifer 2016) suggests that higher market valuations reflect access to equity capital at lower costs. The greater the catering incentives, capital constraints, or inability to internalize network externalities, the greater is the influence of higher valuations on propensity to innovate and adopt technological change. Another view (Narayanan 1985; Stein 1988, 1989; Bresnahan et al. 1990) suggests that high market valuations constrain firms to a trajectory of sustaining innovations. Imperfect information, together with managerial emphasis on stock market valuations, leads to underinvestment in long-run projects, including technological innovation. In turn, some of these studies (e.g. Dechow and Sloan, 1991; Cheng, 2004) view innovative activity as a real earnings management tool. These opposing views point to heterogeneity in the effects of stock market pressures on firm strategy. However, there is little theoretical guidance on the nature of such heterogeneity, rendering the identification of such heterogeneity an empirical question.

We use group based trajectory (GBT) models to identify trajectories of market performance and descriptive characteristics of these trajectories to deduce strategic positions that inform propensity to innovate. Prior research (Daniel and Titman 2006) suggests that market valuations and returns may be decomposed into two components – one, the component of past returns that is explained solely by past fundamental growth measures and another, the component of past returns that remains unexplained, and presumably, is an outcome of investor response to information not contained in accounting growth measures. They define the former as a firm's tangible returns and the latter as its intangible returns. Intangible returns reflect market expectations about future growth prospects of the firm relative to current period fundamentals. It is likely that for a given valuation, firms with growth pressures (as reflected in greater intangible returns) are more likely to change the content and trajectory of their innovation. Therefore, in discerning heterogeneity in market valuation, we assess the underlying market expectations of the firm that might drive propensity to innovate.

2.4. Heterogeneity in the Value Implications of Technological Change

There is little consensus in the expansive literature that documents gains to firms from frontier technological opportunities and technological change in the presence of the above-mentioned constraints (see Cohen 2010 for a review of the literature). One school of research in the tradition of Galbraith (1952) suggests that a firm's existing resources and capabilities play a critical role in adaptation to technological change. For example, a large asset base is correlated with availability and stability of internally generated funds. Similarly, firms with a larger base of assets and resources are able to generate scale economies from innovation. Well-developed competences of the firm such as marketing and financial planning are complementary to R&D and innovation and therefore, critical to appropriating value from technological change. Well-established firms are also more likely to have dedicated resources for change management and abilities to reduce the risk associated with prospective returns to innovation.

A contrasting view is that the existing resources and capabilities of a firm constrain its ability to gain from technological change (Christensen and Rosenbloom 1995; Christensen and Raynor 2003). These studies present the constraints posed by the value network of a firm or the "*context within which the firm identifies and responds to its customers' needs, solves problems, procures input, reacts to competitors, and strives for profit*" (Christensen and Rosenbloom 1995, p.234). A key determinant of the success of technological innovation or change effected by a firm is therefore, the extent to which the change or innovation addresses the needs of the actors in the incumbent firm's value network. These opposing views emphasize likely heterogeneity across incumbents not just in in their response to technological change but also benefits from such change.

Our discussion so far can be summed up succinctly as follows. With the rapid diffusion of the commercial internet, which served as an exogenous shock to firms, the opportunity set for innovating with ICT substantially changed for all firms and across all industries. However, as we begin to study the broad effects of this transformative change, prior theory only provides weak guidance as to the set of variables that might explain the inherent heterogeneity both in the propensity of firms to innovate with ICT as well as in the heterogeneity in valuation that accrues to inventing firms. Studies that have attempted a comprehensive assessment that takes into account all known factors that impact innovation value have found that only a small percentage of the variance in value are explained by these known factors (Bessen 2006). Moreover, these studies have mostly focused on a specific sub-class of ICT patents (e.g. software) or on a specific set of industries (e.g. Branstetter et al. 2015) within which these effects have been examined.

In contrast, our interest in this study is to examine the full gamut of ICT related patents filed by publicly listed firms across all industries over a time period that spans nearly three decades, to see how market expectations drives adoption of digital and how that impacts subsequent (ex post) performance. As a means of addressing the challenges of heterogeneity in propensity to innovate with ICT and the subsequent heterogeneity in the value that accrues thereof, we adopt a group-based trajectory modeling approach that is designed to take into account heterogeneities in the underlying traits of interest. We introduce this technique and then discuss the data and empirical specification in the next section.

3. Data and Measures

The data for our study comprise 7753 firms at the intersection of Compustat, Center for Research in Security Prices (CRSP), and the Google patent assignment database[3]. Our data span the years 1981–2010, and our unit of observation is the firm-year. Although the Google patents data begins in 1975, we only include data from 1981 to ensure the quality of R&D expenditure data. The accounting treatment of R&D expenses reporting was standardized in 1975 (Financial Accounting Standards Board Statement no. 2). Consistent with prior research (Cohen et al. 2013; Hirshleifer et al. 2013), we estimate R&D intensity beginning 1979 to allow for a full five-year period with reliable R&D expenditure data. The two-year patent application-grant lag renders 1981 our first year of estimation of innovative output. Therefore, our sample comprises the universe of all patents granted by the USPTO from 1981 to 2010. For all patents granted to the firms in our sample, we obtain information on citations, grant years, application years, and patent technology classes (IPC classes). We additionally obtain information on market performance, fundamentals, and other firm and industry characteristics of the sample firms as detailed below.

3.1. Patent Data

For each firm-year in our sample, we estimate the intensity of digital innovation using the raw proportion of ICT patents, proportion of ICT patents weighted by forward citations received as is standard in the literature, and average proportion of backward citations to ICT patents. We use the IPC classes identified in Corrocher et al. (2007) to classify the patents granted to our sample firms as ICT patents. Corrocher et al. (2007) use patent abstracts to detect important applications in the ICT field by selecting the most frequent sequential triples of words that identify technological applications in the field. Consequently, they identify a set of IPC classes related to these applications as identifiers of ICT patents. We consider a patent as an ICT patent when, at least, one of the ICL classes assigned to the focal patent identifies ICT patents as defined in Corrocher et al. (2007). We use the average proportion of backward citations to ICT patents

[3] Several new studies exploit the Google Patents database as we do in this paper. For example, see Mani and Nandkumar (2016), Kogan et al. (2015), Moser and Voena (2012) and Lampe and Moser (2011).

instead of the total proportion of backward citations to ICT patents since the latter may be an outcome of only a few technologies incorporating ICT and not completely reflective of the extent of digitization of R&D.

3.2. Stock Market Performance

3.2.1 Market Valuation

We use Compustat and CRSP data to estimate Tobin's Q as a measure of market performance of the sample firms. Following prior research (e.g. Kogan et al. 2015, Mani and Nandkumar 2016, Bharadwaj et al. 1999), we estimate Tobin's Q as the sum of the market value of common equity (using CRSP December market capitalization), the book value of debt, the book value of preferred stock, less the book value of inventories and deferred taxes, divided by gross property, plant and equipment.

3.2.2 Market Expectations

We estimate market expectations of growth for the sample firms through decomposition of their returns into tangible and intangible returns. Indeed, Daniel and Titman (2007) argue that market returns of a firm comprise two components: (a) tangible returns that are associated with past accounting performance and can be explained by accounting growth measures, and (b) intangible returns that are unrelated to fundamental performance measures. Intangible returns reflect in large part the market valuation of future growth versus past fundamentals and to that extent, represent market expectations of future growth versus profitability from the firm.

Following Daniel and Titman (2007), we create the following accounting ratios for each year of our sample time period: book-to-market equity (BM), sales-to-price (SP), cash flow-to-price (CP), and earnings-to-price (EP). We estimate these ratios at the end of June of year t using fiscal year-end data from year t – 1 and market capitalization as of the end of December of year t – 1. We set a ratio to missing if the relevant accounting measure for that year is negative. In year t, we include NYSE-, AMEX-, and Nasdaq-listed firms whose price as of the end of June is greater than USD 5 per share. Consistent with Daniel and Titman (2007), we define intangible returns as the residual from the following regression:

$$r_i(t-1,t) = \gamma_0 + \gamma_{BM} bm_{i,t-1} + \gamma_B r_i^B(t-1,t) + \epsilon_{i,t},$$

where $r_i(t-1,t)$ is the log of past one-year stock returns (measured from December of year t – 2 through December of year t – 1), $\mathrm{bm}_{\mathrm{i,t-1}}$ is the log of the firm's one-year lagged book-to-market ratio (from fiscal year ending in year t – 2), and $\mathrm{r_i^B(t-1,t)}$ is the log of past one-year book returns (using book value per share from fiscal years ending in year t – 2 and year t – 1). The fitted values from this model are the firms' tangible returns, that is, the part of stock returns predicted by past book equity-based performance. We similarly estimate intangible returns using other fundamental ratios, notably, SP, CP, and EP.

3.3 Fundamentals and other Firm-level Data

We use data from Compustat to estimate fundamentals of the sample firms as well as other firm characteristics. Specifically, we estimate sales efficiency as sales divided by number of employees; income efficiency as earnings before interest and taxes divided by number of employees; cash flow as income before extraordinary items less total accruals (that is, changes in current assets plus changes in short-term debt minus changes in cash, changes in current liabilities, and depreciation expenses) normalized by total assets; firm size as natural log of total assets. We control for industry affiliation using two-digit SIC codes.

Table 1 summarizes the above measures and provides descriptive statistics.

4. Methodology

Our analysis of the market valuation of the digitization of R&D proceeds in four stages. First, we discern market performance types in the data prior to 1997 using GBT models. GBT models are a specialized application of mixture models that use longitudinal data or firm-year observations to identify heterogeneous unobserved firm types. In brief, firm types are defined not just by the magnitude of the underlying variable of interest, as is the case with other data reduction techniques such as cluster analysis, but also by how this variable of interest evolves over time. Therefore, the estimation of GBT models involves the specification of two important parameters - the number of types and, for each type *j*, the relation between the variable of interest y_{it} and time *t*. For instance, when we use a quadratic specification for market performance types, we specify $y_{it}^{j} = \beta_0^j + \beta_1^j t + \beta_2^j t^2$, where β_0^j, β_1^j, and β_2^j are parameters that estimate how the Tobin's Q for every firm in that type evolves as a quadratic function of time.

We begin by using the quadratic specification outlined above for all market performance types and progressively increase the number of types until the Bayesian Information Criterion (BIC) score can no longer be improved[4]. After identifying the number of types, for each type, we sequentially try the linear, cubic, quartic, and quintic specifications until the BIC can no longer be improved. In this way, we identify the specification for each market performance type that best fits the data. Subsequently, we calculate BIC_{max}, which is the maximal BIC value that corresponds to different specifications and BIC_j, which is the BIC of the focal specification. These two measures are then used to estimate the probability of membership in market performance type j, defined as $p_j = \left(e^{BIC_j - BIC_{max}} / \sum_j e^{BIC_j - BIC_{max}}\right)$. The specification with the highest value of this probability of type membership is identified as the one that best fits the data. Similar to other empirical methods, we determine the accuracy of type membership using standard errors of the abovementioned probabilities of membership.

Subsequent to using GBT models to identify heterogeneous types or trajectories of market performance (Tobin's Q) prior to 1997, we try to gain more insights into the content of these trajectories. Specifically, assuming that each trajectory created by the GBT model embodies underlying market expectations and a strategic position that informs the firm's choice to digitize R&D and create digital technologies, we characterize each type based on firm attributes that estimate the content of these market expectations and strategic position.

[4] The BIC is estimated as 2 log(L) – k log(N), where L denotes the value of the maximized likelihood; N, the number of observations; and k, the number of parameters (Kass and Raftery, 1995; Schwarz 1978). The model with the highest BIC score is the one that best fits the data.

Third, within each trajectory, we classify firms as "*innovators*" and "*laggards*" in digital innovation. As mentioned earlier in this study, we measure the intensity of digital innovation using the raw proportion of ICT patents, proportion of ICT patents weighted by forward citations received, and average proportion of backward citations to ICT patents. For each of these variables, within each trajectory, we create a binary measure that classifies constituent firms into two groups: (1) "*innovators*," characterized by above-median intensity of digital innovation, and (2) "*laggards*," characterized by below-median intensity of digital innovation. We estimate a logit model that conditions the likelihood of being an innovator on market performance types and firm-level controls, thereby, controlling for the endogenous relationship between technological innovation and performance as well as providing insights into the factors that enable or constrain technological innovation and change.

Finally, in order to control for the impact of unobserved heterogeneity that simultaneously impacts intensity of digital innovation and subsequent performance, we match the *innovators* with a set of *laggards* that are in the same trajectory and display similar propensity to engage in digital innovation as of 1997. We use the variables that are significant in the logit model to create the matched sample using propensity score matching. This process yields a set of control firms that have the same performance trajectory as the sample firms as well as similar propensity to create digital technologies or innovations. We use this matched sample through the following analysis. For the time period 1998-2006, for each of the performance trajectories, we regress market performance on the intensity of digital innovation, firm-level controls, and industry and year fixed effects. The results inform us about the heterogeneous impacts of digital innovation.

5. Results

5.1. Identification of market performance types using GBT models

The first step in our analysis involves using GBT models to identify market performance types (trajectories) based on *Tobin's Q* for the period 1981 - 1996. We fit a censored normal specification of the GBT model and choose the specification with the maximum BIC value. The results of this analysis are presented in Figure 1 and Table 2. In Table 2, we present the results of two specifications. In specification 1, we estimate an unconditional GBT model that does not include any controls. In specification 2, we include industry- and firm-level controls, notably, the two-digit SIC code of the firm, sales efficiency, log total assets and cash flow. The results of specification 1 suggest that the standard errors associated with the probability of type membership are low and that the type membership probabilities for each market performance type are accurately estimated. Specification 2 suggests that the inclusion of industry and firm controls does not significantly alter our estimates.

Figure 1 points to three market performance types estimated by the GBT model: Type 1, Type 2, and Type 3, which constitute 60, 31 and 9 percent of the sample, respectively. We rely on the results of the fully specified model (specification 2) for further analysis.

In order to improve our theoretical understanding of these market performance types, we profile them in terms of market expectations, fundamentals and resources. The operationalization of these constructs is detailed in Table 1. Specifically, we explore how the sample mean firm size, tangible returns, intangible returns, R&D intensity, marketing intensity, sales growth, net income growth, and cash flow vary between the trajectory groups (other options: relative cost efficiency and breadth of product markets). Table 3 presents the sample means for these dimensions of market expectations and strategic position across the three performance types. In the following paragraphs, we use the results of specification 2 of Table 2 and Table 3 to define and interpret the three trajectories of market performance. In doing so, we include only those variables that exhibit differences in the mean estimates at the 10 percent level.

Type 1: High Relative Value of Profitability

Figure 1 and Table 2 show that a bulk of the sample, nearly sixty percent, has low market valuation. The firms in this performance type are characterized by the lowest levels of intangible returns and highest levels of tangible returns amongst the three performance types. Therefore, in contrast to firms with high relative value of growth, the intangible returns for these firms are negative, suggesting that their market valuation is almost exclusively driven by significant market expectations of current period accounting performance versus future growth. Indeed, current period fundamentals, including sales efficiency and cash flow for this class of firms, are the highest amongst the performance types. These firms are also relatively larger in size with highest mean levels of total assets. In brief, this performance type includes relatively larger firms that focus on improving current period accounting performance often at the cost of opportunities for long-term growth. Relatively low valuation by the stock market also constrains the capital available to these firms for growth.

Type 2: Moderate Relative Value of Growth

Figure 1 and Table 2 also suggest that about thirty one percent of the sample has moderate market valuations. Further, the results in Table 3 suggest that the valuation of these firms is driven by a combination of expectations of future growth and current period accounting performance. Indeed, firms in this performance type are characterized by equal magnitudes of tangible and intangible returns. They are moderately sized firms with intermediary values of total assets. The current period fundamentals of these firms, although better than firms with high relative value of growth, are inferior to firms with high relative value of profitability. In brief, this performance type includes moderately sized firms that pursue growth, but not aggressively at the cost of current period accounting performance. Moderate valuation of this strategic position provides capital for the strategic position of these firms.

Type 3: High Relative Value of Growth

Figure 1 and Table 2 together suggest that about nine percent of the sample is highly valued by the stock market. Further, the results in Table 3 suggest that the superior valuation of these firms is driven by significant market expectations of future growth versus current period accounting performance. Indeed, firms in this performance type are characterized by greater than mean levels of intangible returns and lower than mean levels of tangible returns. Tangible returns are negative suggesting that the valuation of these firms is almost completely driven by expectations of future period growth. Current period fundamentals, including sales efficiency and cash flow for this class of firms, are the lowest amongst the performance types. These firms are also relatively smaller in size with lowest mean levels of total assets. In brief, this performance type includes relatively smaller firms that pursue growth aggressively often at the cost of current period accounting performance. Relatively high valuation by the stock market, in addition to validating the strategic position of firms, also provides capital for their growth strategies.

5.2. Logit specification of likelihood of digital innovation

Using a logit specification, we explore how the probability of being an "innovator" (versus "laggard"), that is, engaging in above median intensity of digital innovation, varies by market performance type or group. As mentioned earlier, we include two dummy variables, namely, Type 2 and Type 3 that indicate affiliation with performance type 2 (moderate relative value of growth) and type 3 (high relative value of growth) respectively. The reference (or baseline) category is performance type 1 (Type 1). In addition to the performance type dummies, we also control for time effects using year dummies, the total assets of a firm, its cash flow and sales efficiency. To the extent that we have described the differences between these performance types in the earlier section, the performance type dummies fold the differences into a single variable.

The results of the logit regressions are shown in Table 4. Specification 1 of Table 4 includes time dummies alone. Specification 2 includes all the controls listed above. We use the latter specification to interpret the impact of market performance type on propensity to be innovators. Specification 2 suggests that relative to Type 1, both Type 2 and Type 3 firms are more likely to be innovators. While Type 2 firms have a 40 percent greater likelihood of being an innovator relative to Type 1, Type 2 firms have a 61 percent greater likelihood of being an innovator relative to Type 1. Moreover, the difference between the coefficients of

Type 2 and Type 3 are significant at five percent suggesting that Type 3 firms are also more likely to be innovators than Type 2 firms.

Since Type 3 firms are characterized by greater than mean levels of intangible returns and lower than mean levels of tangible returns and low current period fundamentals, our results suggest that relatively smaller firms that aggressively pursue growth and enjoy high market valuations for this reason are most likely to be innovators. Further, moderately sized firms whose market valuations are driven by a combination of expectations of future growth and current period accounting performance (Type 2) are more likely to be innovators relative to large firms whose valuations are largely driven by current period accounting performance (Type 1). Therefore, the results of the logit specification suggest that the propensity to be an innovator is conditioned by whether the market values firms for future growth or current period profitability.

5.3. Performance impacts of digital innovation

Table 5 presents the results for the impact of digital innovation on Tobin's Q using a matched sample of firms between 1997 and 2010. We find that the impact of digital innovation on market performance is significantly positive for Type 2 and Type 3 firms and significantly negative for Type 1 firms. In the context of the descriptives presented earlier for each type, these results emphasize the important role of financial markets in benefiting from innovation choices. In the case of the ex ante performance type Whereas, high digital innovators are rewarded with higher valuations in firms that are valued for growth, the opposite is true in the case of firms that are valued for their current profits.

6. Discussion and Conclusion

Emergent research documents a significant digitally biased shift in innovation over the past decade. However, significant questions still remain as to whether this shift in the content of innovation is valuable and if so, which firms benefit from this shift. Part of the challenge in responding to this question lies in the reciprocal relationship between innovation and performance, making it hard to disentangle the effects of one on the other. Further, prior research documents the moderating impact of a variety of factors internal to the firm, notably, management and organizational capabilities, on the relationship between ICT investments and performance (Saunders and Brynjolffson 2016). The role played by external factors, especially, financial markets, in shaping innovation choices and their performance consequences in firms is relatively unexamined. Finally, the moderating effects of financial markets on innovation choices of firms and their performance consequences may vary by unobserved firm types. In the absence of theoretical guidance on proxies for these heterogeneous types, regressions, while well suited to controlling for these types, are limited in informing theory about the moderating effects of these firm types. This study makes progress on all these fronts.

We apply GBT models to study how the moderating effect of market expectations on the relationship between digital innovation choices of firms and performance varies by market performance types that are *ex-ante* unobserved by the researcher. In doing so, we also address the endogenous relationship between innovation and performance. We find that higher market valuations and market expectations of growth versus profitability significantly increase the likelihood of digital innovation and performance gains from such innovation.

Our study illuminates the debate on the ability of market incumbents and leaders to respond to technological innovation and change. The rich body of empirical work in this area has been described as "notable for its inconclusiveness" (Cohen and Levin 1989) with limited generalizability of findings beyond specific industry sectors or product markets. The findings are mixed with one school of research (Athey and Schmutzler 1992; Cohen 2010) highlighting the superior ability of market incumbents and leaders to appropriate value from the innovation through greater scale economies, dedicated resources for change management, larger base of complementary assets to appropriate value, and risk bearing capacity; and another school of research (e.g. Christensen; Turshman and Anderson 1986; McElheran 2015) emphasizing how incumbents falter in the face of technological change because of internal and external adjustment costs. Our results reconcile these opposing views by suggesting that not all incumbents are created equal and that predicting the distribution of technological innovation as well as gains from such innovation requires an understanding of the distribution of heterogeneous, unobserved firm types with respect to internal capabilities and external interdependencies. Regression analyses used in prior research causally identify the mean impact of a variety of firm attributes on gains from technological change while controlling for unobserved firm types in the data.

In the absence of theoretical guidance on proxies for these heterogeneous firm types, we use GBT models to robustly identify the latter based on their market performance (as reflected in Tobin's Q) between the years 1981-1996. We find that firms with the highest Tobin's Q and highest underlying market expectations of growth versus current period performance are more likely to engage in digital innovation and benefit from it. Future research could identify firm types based on other measures of capabilities and performance to derive strategic positions that moderate the performance impact of technological change.

Our study also emphasizes the complex interplay between stock markets, technological change and performance. Prior research (Narayanan 1985; Stein 1988, 1989; Bresnahan et al. 1990) suggests that imperfect information, together with managerial emphasis on short-run valuations, leads to underinvestment in long-run projects, including technological innovation. In turn, some of these studies (e.g. Dechow and Sloan, 1991; Cheng, 2004) view innovative activity as a real earnings management tool. However, our results suggest that not all firms seeking equity financing or facing other valuation pressures underinvest in technological innovation and change. Only those firms facing high investor expectations of current period profitability versus future growth are likely to underinvest in innovation.

This finding that a firm's propensity to drive digital innovations is related to market expectations of growth versus profitability provides strong evidence for the agency model of corporate control in modern organizations and the role of financialization in strategic decision-making (Christensen 1997; Zajac and Westphal 1995, 2004; Graham et al. 2006). Indeed, our results reaffirm the assumptions of the agency model that investors are a key source of financial capital for the firm, and over time, incentives, compensation plans and decision-making structures within firms are honed to serve the investor community. Therefore, even in the face of significant increase in digital innovation and its demonstrated impact on a range of R&D outcomes (e.g. Bransetter et al. 2015; Mani et al. 2016), our findings show why firms find it difficult to move away from their existing sources of value to pursue these new digitally biased innovations. To the extent that innovators outperform (underperform) laggards in the group of firms with high (low) market expectations of growth, our results provide some evidence of the allocative efficiency of capital markets. However, future research could examine in more detail the efficiency of managerial focus on stock prices and the optimality of resultant outcomes.

Notwithstanding the allocative efficiency of capital markets, the implications for firms that are valued for growth is that managers in these firms must recognize the opportunity presented by the growing importance of digital innovation and create capabilities to exploit this opportunity. The higher financial valuation reflects incentives to invest in complementary capabilities that increase the marginal value of digital innovation to these firms. Conversely, there are risks to digital innovation for firms that are valued more current period fundamentals rather than for future growth prospects. In general, these firms are less likely to pursue strategies that increase the variance of cash flows and more likely to invest in 'quick profit' strategies that have quick payback but lower present value. In turn, financial markets will punish these firms for digital forays that are necessarily complex strategies whose benefits are realized over longer periods of time. Managers in these firms should therefore try to reset market expectations through proactive and carefully calibrated communications to investors before they pursue digital innovations. Alternatively, these firms should think of structures and arrangements (e.g. spin-offs) that are better aligned with the expectations of the financial markets to pursue digital innovations.

Most important, our study emphasizes the critical association between digital innovation and firm value. Although the concept of intangiblevalue has been around for a while (Miller and Modigliani 1961), there is still a lack of understanding of how the financial market assesses the growth prospects of a firm. Our results emphasize digital innovation as a key component of intangible value and future growth prospects of modern firms (Corrado and Hulten 2010; Saunders and Brynjolffson 2016).

This paper is subject to certain limitations. Our first set of limitations is imposed by the data. As is the practice in the literature, we measure the extent of digital innovation in a firm-year using the proportion of ICT patents held by the focal firm in the focal year. This measure only captures certain types of digital innovations. Given that our regressions that discern the effect of digital innovation on performance is a linear specification, our results are likely to be attenuated by selective inclusion of specific types of digital innovation, implying that the true effects might be larger. However, given that our intent is also to discern differences between unobserved firm types, whether these attenuation biases close the difference between types such that they are indistinguishable is an open question. Second, our study assumes that the digitization of a firm's R&D portfolio significantly increased after 1996. Our results are robust to the assumption that this remarkable increase in digitization of R&D commenced a year before or after 1996. However, it is plausible that digitization of a firm's R&D varies by firm or industry. We lack information on when or whether a given firm adopted digital innovation. Once again, whereas our average effects are likely to be similar, it is unclear how our plausibly erroneous measure of digitization might influence the demonstrated differences in propensity to digitize and its performance consequences across the three firm types. Finally, our within-type analysis, in conjunction with propensity score matching, assumes that the problem of estimating the treatment effect due to non-random assignment of firms to the treatment versus control category can be overcome by matching on observable firm characteristics and also by matching on ex-ante performance, which plausibly overcomes the issue that firms may also differ based on unobserved attributes. It is, however, plausible that certain unobservable firm characteristics are not reflected in its ex-ante performance. If that is the case, our estimates will likely from the selection problem. Once again, how such a problem will differentially affect the different firm types in our data is an open question. Despite these limitations, we hope our paper contributes to our understanding of how external factors, specifically, stock market expectations, influence the nature of technological innovation and its influence on subsequent performance.

Appendix: Figures and Tables

Figure 1: Trajectories of Tobin's Q, all firms

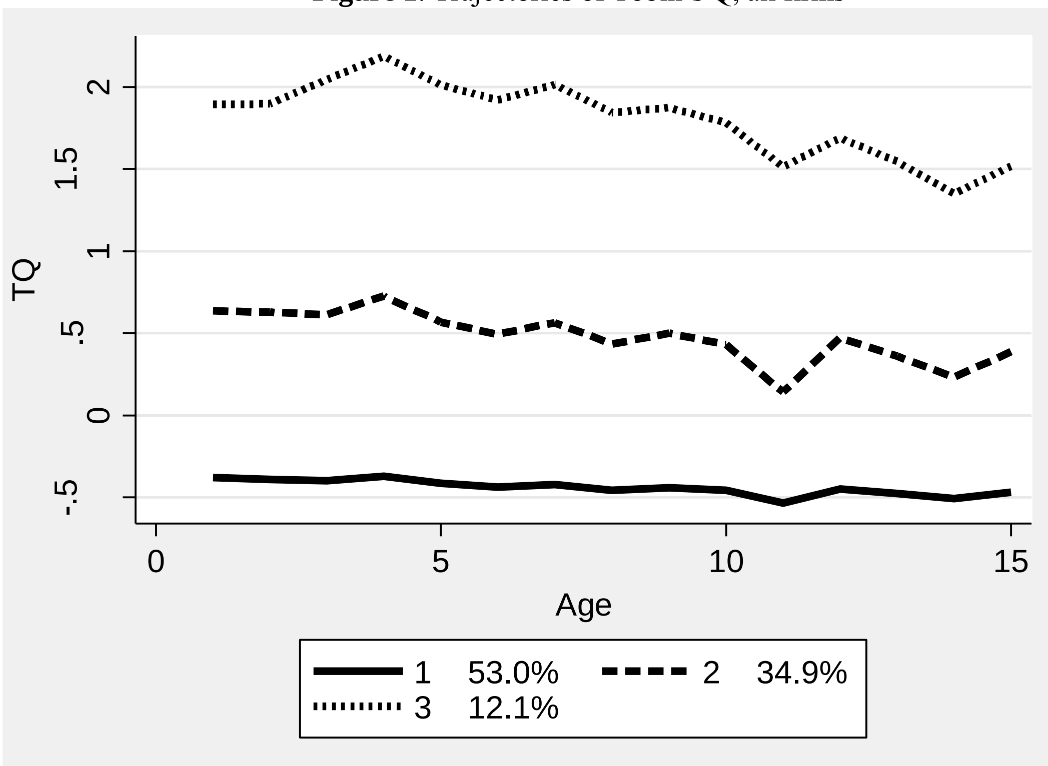


Table 1 Descriptive statistics

Variable	Description	Unit of variation	N	Mean	SD
Tobin's Q	The sum of the market value of common equity, the book value of debt, the book value of preferred stock, less the book value of inventories and deferred taxes, divided by gross property, plant and equipment in each year	Firm, year	66,216	1.75	2.90
Intangible returns	3-year stock return that are not explained by the past fundamental-growth measures of firm. This measure was calculated using the fitted values from equation (1)	Firm, year	66,216	0.00	0.43
Tangible returns	3-year stock return that are not explained by the past fundamental-growth measures of firm. This measure was calculated using the residual values from equation (1)	Firm, year	66,216	0.04	0.26
Sales	The revenues of a firm in each year in millions	Firm, year	66,216	2527.064	10963.63
Log total assets	The total book value of the assets held by a firm in each year	Firm, year	66,216	6303.06	53889.39
Cash flow	The cash flow of a firm	Firm, year	66,216	0.18	0.15
High adopt dummy	=1 if the total number of forward citation weighted patents exceed the yearly sample mean or zero otherwise	Firm, year	66,216	0.09	0.28
Sales efficiency	Sales of a firm divided by its total assets	Firm, year	66,216	360.89	2563.27
Income efficiency	Income of a firm divided by total assets	Firm, year	66,216	32.90	1070.15
Firm fixed effects	One per firm in the sample	Firm			
Year dummies	One for each calendar year. The left-out year is 2010	Year			
Industry dummies	64 dummies, one dummy per two digit SIC code with the left-out industry being SIC code 99	Firm			

Table 2. GBT estimates of Tobin's Q types

	Spec. 1 Unconditional	Spec. 2 With controls
Type 1	0.68***	0.60***
	(0.01)	(0.01)
Type 2	0.26***	0.31***
	(0.01)	(0.01)
Type 3	0.06***	0.09***
	(0.00)	(0.00)
σ	0.63***	0.63***
	(0.00)	(0.00)
LL	-70116.56	-50211.60
BIC	-70177.61	-50319.18
N	66,216	66,216

Notes: This table uses GBT models to classify firms into Tobin's Q types. The unit of observation is firm-year. Spec. 1 uses GBT without controls. Spec. 2 uses industry controls, sales efficiency, log total assets and cash flow as controls. Standard errors within parentheses. Number of firms is 7,753 and covers the period 1981-1996. The trajectories for these types are shown in Figure 1.

Table 3. Descriptive statistics based on GBTs

	Mean by type			Difference between types		
	1	2	3	(1) -(2)	(2) -(3)	(1) -(3)
Assets	2098.18	506.33	301.37	1591.85***	204.96**	1796.81***
	(196.69)	(92.63)	(51.76)	(217.41)	(106.11)	(203.39)
Intangible returns	-0.02	0.02	0.06	-0.04***	-0.04**	-0.08***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Tangible returns	0.10	0.02	-0.04	0.08***	0.06***	0.14***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.01)
Sales efficiency	418.67	267.56	164.87	151.11*	102.69	253.80***
	(45.20)	(71.85)	(19.33)	(84.89)	(74.41)	(49.16)
Cash flow	0.00	-0.11	-0.20	0.11***	0.09***	0.20***
	(0.00)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)

Notes: This table provides descriptive statistics for each of the Tobin's Q types estimated through GBT as per spec. 2 of Table 2. These statistics help us understand differences between the types. The unit of observation is firm. Standard errors within parentheses. Number of firms are 7,753 which comprise of 4,651, 2,403 and 698 firms in types 1, 2 and 3 respectively.

Table 4. Logit regressions of ICT adoption, DV=1 if a firm's proportion of weighted ICT patents are higher than the yearly sample mean proportion of weighted ICT proportion of patents (unmatched sample)

	Spec.1	Spec. 2
Type 2 dummy	0.22***	0.34***
	(0.04)	(0.04)
Type 3 dummy	0.40***	0.48***
	(0.06)	(0.06)
Log total assets		0.42***
		(0.01)
Sales efficiency		-0.33***
		(0.07)
Cash flow		-0.03
		(0.03)
Constant	-3.62	-6.87***
	(0.19)	(0.23)
N	66,216	66,216
LL	-12316.04	-10593.98
Number of firms	1069	721

Notes: This table reports logit estimates of regressions of ICT adoption to understand how adoption of firms varies by Tobin's Q types. All specifications include 13 time dummies one each for years 1997-2009 and 64 2-digit SIC code dummies. The sample covers the period 1997-2010. ***Significant at 1%; **significant at 5%; *significant at 10%.

Table 5. OLS regressions of performance by Tobin's Q type conditional on ICT adoption using a matched sample. DV, Tobin's Q standardized (by year)

	Type 1	Type 2	Type 3
High adopter dummy	-0.04***	0.08***	0.32***
	(0.01)	(0.02)	(0.08)
Log total assets	-0.00	-0.04***	-0.20***
	(0.01)	(0.01)	(0.02)
Sales efficiency	-0.00	0.01	0.39***
	(0.00)	(0.01)	(0.09)
Cash flow	-0.01	-0.00	0.44***
	(0.01	(0.01)	(0.04)
Constant	-0.04	0.27***	1.39***
	(0.03)	(0.08)	(0.45)
N	7,456	5,163	1,967
R-squared	0.06	0.09	0.68
Number of firms	1069	721	272

Notes: This table reports OLS estimates of regressions of TQ to understand how the performance of firms varies by ICT adoption using a matched sample of firms from 1997-2010. The regression for type 1 uses 64 industry dummies. Types 2 and 3 use 57 and 44 industry dummies respectively. Standard errors within parentheses. Given that we have standardized Tobin's Q by year we do not include year dummies in these regressions. ***Significant at 1%; **significant at 5%; *significant at 10%.

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