The (de)Concentration of Sources of Inventive Ideas:

Evidence from ICT Equipment

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July 10, 2013

(Preliminary Draft)

Abstract

What does statistical evidence from patent activity suggest about change to the concentration of sources of inventive ideas in Information and Communications (ICT) Equipment? This article characterizes levels, and changes in those levels, in the concentration of sources of invention from 1976 to 2010. The analysis finds pervasive long run deconcentration across a wide set of areas. It also finds that the deconcentration happens despite the role lateral entry by existing firms play in driving concentration levels up. Although we find evidence that new firm entry drives part of this deconcentration, the evidence also suggests that the deconcentration trend cannot be attributed to a single supply factor in the market for ideas, such as the breakup of AT&T during the deregulation of the telecommunications industry. Finally, the evidence also shows that mergers and acquisitions activity results in the transfer of approximately 11% of patents in the ICT equipment industry, but this transfer does not make up for the declines in concentration. That conclusion holds for high-quality patents, and, to a weaker extent, when examining the entire US patent database.

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1. Introduction

It is not an exaggeration to say that the market structure for the Information and Communications Technology (ICT) equipment industry has undergone enormous changes in the last three decades. Thirty years ago most innovation took place in established firms, in particular large, centrally controlled laboratories such as Bell Labs and IBM Labs. Decades ago such labs began to lose their prominence to widespread, decentralized, and small-scale innovators (Rosenbloom and Spencer, 1996). The trend goes by many names in many models. In this study we use the label "divided technical leadership" (Bresnahan and Greenstein, 1999), or DTL for short. DTL plays a key role in models of open innovation (Chesbrough, 2003) and in models of open and proprietary platforms (Greenstein, 2010). It also plays a key role in models of the externalization of R&D by large firms, who use acquisitions of smaller firms for many of these innovative activities (Gans, Hsu, and Stern, 2002). Firms such as Cisco, IBM, and Apple participate in such activities, each having made more than 100 acquisitions over the last two decades. In all such models, DTL corresponds with a market structure in which the origin of innovative ideas arises from a dispersed set of market participants.

While the presence of DTL has received notice, examination of its causes has not moved beyond casual empirism and anecdote. In part this is due to the slow pace of change in market structure. Large scale DTL does not arise instantaneously; rather, it has gradually altered the landscape of different parts of ICT markets, and only over long time spans – several decades – would we expect stark differences to become apparent. Against such challenges in observation, this study offers the first statistical information and econometric analysis of the long run causes behind DTL. Accordingly, the research goals are both descriptive and causal, and measurement challenges determine the lengths we can pursue in both.

We first establish some facts. Does statistical evidence of long-term changes show a deconcentration of sources of inventive ideas, as held by conventional models of DTL? To address this question, the article characterizes the levels and changes in those levels in the concentration of origins of innovation in the ICT equipment industry, employing a broad definition of ICT. Finding long term trends consistent with the increasing importance of DTL, the study turns to a second question: what are the determinants of deconcentration, factors related to the supply of inventive ideas, or factors related to the demand for inventive ideas? This part of the study uses variance between different technology segments within ICT equipment to identify determinants of changes in concentration. The statistical exercise tests several key hypotheses, measuring the contribution of economies of scope, product market leadership, entry by domestic and foreign firms, and changes in demand for ideas from 1976 to 2010.

To construct measures of the origins of innovation, the study examines the concentration in granted patents in ICT equipment in the period from 1976 to 2010, roughly 14% of all US patents. The study utilizes a data set constructed from xml and text files of patents granted by the United States Patent and Trademark Office (USPTO) between 1976 and 2010. The data covers four more recent years than NBER patent data files, the standard data source for many studies on patents.[1] The length of time covered is novel, and essential to realizing the research goals, as we expect increasing presence of DTL to manifest slowly, if at all, and at different paces in different segments. In addition, the timing allows the analysis to be robust to the consequences of a unique event, the dot-com boom, which is coincident with acceleration in patenting in the late 1990s. In addition, the new data contains standardized patent assignee names that enable linking patent data to other data files, which we used to link patent data to data about mergers and acquisitions (M&A) activity. That permits an examination of mergers of both publicly traded and private firms.

The findings first cover long-term trends. The study reveals a large grain of truth to the prevailing view about DTL. We find a deconcentration trend both in the ownership of new patent applications, and also in the cumulative ownership of active patents. The analysis documents considerable variation in the size and scope of the changes, with some segments of ICT equipment undergoing dramatic changes in concentration. For example, while on average the top 25 firms accounted for 72% of new patents in 1976 and 59% of the patent stock in 1986, the top 25 firms accounted for only 55% of new patents and 50% of the patent stock by the end of the sample. Furthermore, the deconcentration trend is even starker when we restrict the sample to high-quality patents based on the citations received by each patent, with a decline in top 25 firms' ownership from 86% to 62% in new patents and 65% to 51% in the patent stock over the same period.

Why does this deconcentration arise? On the supply side, one hypothesis stresses that large firms may utilize economies of scope by entering other technologies, which may appear as increased or decreased concentration depending on the size of the entry. We use such lateral entry as a proxy for economies of scope, and find evidence that ownership concentration *increases* with lateral entry, i.e., that economies of scope is not a cause of deconcentration. Next we provide evidence that *de novo* firm entry, which may be used as a proxy for the hypothesis that reduced transaction cost of entry facilitated more of it. We find mixed evidence. There is little evidence that non-US firm entry caused the change, which is another common hypothesis (reflecting a larger fraction of imports and exports in the US economy over

[1] For details on the NBER patent data files, see Hall, Jaffe, and Trajtenberg (2001).

this period).[2] Rather, established changes in concentration may come from two distinct areas of the ownership distribution: 1) declines in the leading, large firms, and 2) an increase of innovation in the small, "tail" firms within the US. These entry results are consistent with the growth of small firms as a source of ideas, perhaps as part of redistribution from other domestic large firms. Of course, this finding then begs another question: what are the driving forces behind firm entry in the ICTE innovation market?

We further explore a hypothesis about large firms, that the decline in the importance of the very largest firms in inventive activity merely reflects a decline in their importance in downstream markets. We provide evidence that decreases in product market leadership explain the deconcentration in some instances, but the preponderance of evidence suggests this is not the single most important factor explaining variance across segments. More specifically, we find that long-term trends in deconcentration cannot be fully accounted for by the divestiture of AT&T, or the loss in commercial leadership at IBM, Motorola, or any other large firm in the industry, which is the way this hypothesis is most commonly stated. We can reject the most sweeping version of the hypothesis that points to one antitrust case, one company's strategic error, or the break-up of one large, leading innovator of yesteryear as the cause for this change in structure.

Finally, the study looks at the demand for inventive ideas by examining the merger market. As noted by many observers, there has been a secular change in the demand for patented inventive ideas due to a reduction in transactions costs of absorbing technology from small firms. That is, rather than own all the inputs into creating ideas that lead to patents, many large firms increasingly let others focus on that activity and make the purchase after the patent is granted. Accordingly, we perform a (first-ever) census of such merger activity for ICT equipment, involving extensive data-matching (described below). The study finds that M&As result in the transfer of approximately 11% of the entire patent stock, and 12% of the high quality patent stock in the ICT equipment industry. Though the intensity of patent transfer through M&As is associated with a slight decrease in concentration for high-quality patents, the size of this transfer is not enough to revert the composition of ownership to its pre-deconcentration levels in any segment. In the regression analysis merge activity and intensity cannot explain variance in concentration between segments. We conclude that the trend towards deconcentration has not been due to, or reversed by, leading firm strategies to externalize R&D activity.

[2] As with the rest of the literature, we are somewhat cautious in our interpretation of foreign firms. A patent owned by Sony, for example, will appear as a US patent due to the location of its US-based subsidiary. As with the prior literature (e.g., Hall, 2005), we focus on changes due to US patents with US assignees and non-US assignees, and examine whether the surge in patenting with Asian and European assignees accounts for change.

Relation to Prior Research

Our study relates to the research streams in two main channels. First, the deconcentration of ownership relates to the literature on DTL, as noted, and, more broadly, debates about the causes of market leadership and incentives in innovative activities. Following this literature about innovation in computing and communications (reviewed in Greenstein, 2010), we generally distinguish between product market leadership and technological leadership, and focus on the latter, where a strand of the literature argues that the dispersion of capabilities over frontier technology shapes firm behavior. Second, the impact of M&A activity on the technological leadership relates to the literature on R&D incentives in an M&A context on one hand, and the start-up commercialization framework of Gans, Hsu, and Stern (2002) on the other. We differ from prior literature with our focus on understanding the causes behind changes in technical leadership in the more recent decades, an unexamined question in prior work. Finally, this is the first study to put these together. That is, we investigate the extent of, and causes behind, deconcentration in innovation in the ICT equipment industry specifically, and the potentially countervailing M&A mechanism. We now establish this novelty with a more detailed comparison and contrast with prior research.

We build on prior research into patenting, which touches on related themes. The dramatic increase in US patenting activity since the 1970s has attracted attention of scholars: Kortum and Lerner (1999) investigated the US patenting activity and found that changes in US patent policy, more specifically the establishment of the US Court of Appeals to hear patent cases, did not have a verifiable impact on the increased patenting activity. Instead, the study associated the increase in patenting to an increase in US innovation and to changes in the management of R&D, which may have included actions such as reallocating efforts to more applied problems with higher patent yields. Kim and Marschke (2004) analyzed the same issue and concluded that the increased patenting activity was due to increases in R&D in some sectors and increases in the patent yield in the computing, electronics, and auto sectors. Hall (2005) found that growth occurred in complex product industries such as telecommunications, in which products are based not only on a single patent but on a set of patents. She further concluded that increased patenting activity by firms in complex product industries spilled over to those firms' patenting behavior in other industries, resulting in an overall increase in patenting activity across all technology classes.

These studies mostly focused on activity at the technology class level as described in NBER patent data files. In this study we focus on the distribution of the increase in patenting between firms within each technology class; in other words, we differ in that we look at the technical leadership of firms in addition to the main trends in the technology class level. Furthermore, our up-to-date data on patents allow us to answer the open questions suggested by the earlier studies, including, "What happened during the 1990s? Did the positive premium for entry with patents continue during the rapid growth of the computing and electronics sector in the late 1990s? Has the growth in patenting continued to be due almost entirely to U.S. firms in computing and electronics?" (Hall, 2005).

This study supports the view that the changes in ownership concentration are consistent with a secular trend towards divided technical leadership, namely, more widespread access to the fundamental knowledge and building blocks for innovative activity in this sector of the economy. This is the framework put forward in Bresnahan and Greenstein (1999), which suggests that high rates of firm entry and exit may occur without changing the concentration at the platform level. This study contributes to two aspects of the literature. First, this study finds considerable evidence consistent with the central premise—that DTL has increased over time in inventive ideas upstream to computing and related sectors, such as Internet equipment. We find evidence for this effect in the period analyzed by Bresnahan and Greenstein and for periods thereafter. Second, this study finds that our demand side measure—mergers—alone did not reverse that trend, which is again consistent with the speculation that supply-side factors played an important role in producing DTL.

The deconcentration results of our study also relate to the research stream on how incentives change with competition. If incentives to innovate are monotonic in increasing competition, then DTL is indicative of high incentives, hence increased innovation. If, on the other hand, incentives are not monotonic, e.g. Aghion et. al. (2005), then DTL could be indicative of intensive competition that potentially could be decreasing innovation. In this study we provide evidence about the increased competitive condition in the ideas market through firm entry and the deconcentration of ownership of innovation. Note that our conceptualization of an upstream ideas market as distinct from the downstream product market is different than the framework of Aghion. et. al. (2005), where vertical integration is used. That underlies our search for evidence of increased competition in the upstream ideas market.

Furthermore, our results of deconcentration can be interpreted as a switch from a Chandlerian to a Schumpeterian market in terms of market leadership in innovative activities in ICT equipment (Malerba and Orsenigo, 1996). The Chandlerian view of market leadership focuses on the accumulative nature of leadership, and asserts that market leadership persists for a long time, embedded within the organizational form of leading firms. The Schumpeterian "creative destruction" view states that market leadership is transient and subject to frequent threats of replacement.[3] Malerba and Orsenigo address this debate by identifying two classes of sectors. The first class of sectors, the Schumpeter Mark II (Chandlerian) sectors, has high concentration of innovative activities, big innovator size, high rank stability among innovators, and low entry levels. These sectors include chemicals and electronics firms. The second class of sectors, the Schumpeter Mark I (Schumpeterian) sectors, has the opposite characteristics, and includes mechanical technologies and traditional sectors. In this study, we show that the ownership of innovative activities were highly concentrated in the early periods of our data, which is consistent with Malerba and Orsenigo's (1996) classification of electronics as a Schumpeter Mark II industry. In addition, we further show that this high concentration of ownership has seen a dramatic change over the last four decades, and, using their framework, may be interpreted as a switch from a Chandlerian to a Schumpeterian market structure.

The discussion of the M&A activity of the established firms in our study relate to the start-up commercialization framework of Arora, Fosfuri, and Gambardella (2001); Gans, Hsu, and Stern (2002); and Gans and Stern (2003), which posit that a startup innovator with a successfully developed, commercializable technology faces a choice between competing with incumbent firms in the market, and cooperating through selling or licensing the technology to the incumbent firm. This study also proceeds from the same premise as the prior work—the market for inventive ideas operates in a realm related to, but distinct from, the market for final output. We provide a census of a cooperation-through-acquisitions mechanism in the ICT equipment industry. In other words, we focus on measuring the demand for inventive technology created by startup firms, which, in turn, may entice incumbents' acquisition of startups.

The transfer of patents is another venue our study contributes to: Serrano (2010) finds that recently traded patents have a higher probability of being traded compared to other patents of similar characteristics, and explains this empirical finding with "a theory of technology transfer where the arrival of opportunities for surplus-enhancing transfer is a significant element." Our findings suggest an alternative explanation to why recently traded patents have a higher probability of re-trade: if acquirers in M&A deals resell part of the target firms' patent portfolio, then this would generate the empirical pattern Serrano finds. This effect may be generated especially by M&As in which the target possesses many patents. In our sample, the average number of patents that change hands in an M&A deal is 17, though the distribution is quite skewed, with the top 95 deals (3.3%) accounting for 77% of the patents

[3] For a detailed discussion of Schumpeterian and Chandlerian views of market leadership, and a benchmark for the *transient* and *long time* periods, see Sutton (2007).

transferred. In the top 95 deals where each target firm has at least 50 patents, it is highly unlikely that the entire patent portfolio of the target plays an important role in the acquisition decision, and potential resale of such unrelated patents is plausible, which would also generate the empirical patterns Serrano observes in the patent transfers data. A matching of the patent transfer data to the M&A data is required to distinguish between these alternative mechanisms, which is beyond the scope of our study.

Finally, most of the prior literature on the interaction of M&A activity with innovation comes from analyses of public firms, as data on private firms is scarce. Yet private firms constitute an important part of the US economy: Asker et al. (2012) estimates that private US firms account for 67.1% of private sector employment, 57.6% of sales, and 20.6% of aggregate pre-tax profits. As a result, analyses of M&A activity that filter out the deals of private firms yield biased results (see Netter et al., 2011, for a detailed discussion of the impact of M&A filtering criteria on the results). We expect this bias to be exacerbated in the study of innovation through acquisition of startup firms, as startup firms are likely to be underrepresented in deals of only public firms. Linking the USPTO patent data to the M&A data enables us to work around this issue and to provide new insights on the behavior of this nontrivial yet underexplored part of the US economy.

The rest of the paper is organized as follows: Section 2 provides background on the ICT equipment industry, which motivates a framework for analysis. Section 3 describes the data construction, sample selection, and variable construction. Section 4 presents the empirical methodology and deconcentration of patent ownership results for both new patents and cumulative patent stock in ICT equipment, and Section 5 concludes. We present details of data construction, data linking methodology, and results using alternative concentration measures in the Appendices.

2. ICT Equipment Industry Concentration

How should we think about deconcentration of innovation activity in the ICT equipment industry after the late 1970s to the present? ICT equipment is responsible for electronics, computing, and infrastructure of radio, television, voice, and broadband communication services. It would take several books to describe the changes in market structure during this time, and this section cannot hope to review all the details. The purpose here is only to refresh the reader's memories about what the literature takes for granted about major changes in the concentration of origins of inventive ideas in a wide set of related industries. This will provide just enough of a brief overview to guide the development of a framework for the statistical exercise.

2.1 Historical Overview

Prior to the 1980s the ICT equipment industry consisted of various segments, depending on whether it was oriented towards computing, as it was then understood, or communications, namely, voice or data. Both of these segments were highly concentrated in final goods markets. At the end of the 1970s IBM dominated the computing segment with its mainframe systems and components built around those systems. It also dominated the personal computer system market for a short time, growing a small systems division that in 1984 would have been the third largest computer company on the planet (behind Digital Equipment Corporation and IBM itself).

Starting in the mid-1980s and accelerating thereafter, IBM lost market share in personal computers and in many of the peripheral markets. After the introduction of the IBM PC in 1981 a wide range of firms entered into printers, software, component production, local area networks, and more. In the 1990s Microsoft and Intel began to assert control over an increasing fraction of valuable components within the PC market; nonetheless, a large number of firms played a role in many of its segments.

Before the 1980s AT&T was the dominant provider of networking equipment in the voice segment, largely due to its regulated monopoly position in telecommunication services: approximately 90% of AT&T's equipment purchases were supplied from its equipment subsidiary, Western Electric. The voice segment was based on circuit-switching technology and provided the infrastructure mainly for local and long-distance telephone companies. Furthermore, AT&T fought regulations that ended its requirement that any equipment attached to its network had to be supplied by AT&T, even on the end-user site. The purchase behavior and network attachment requirement of AT&T restricted entry into the telecommunications equipment markets, thus carrying AT&T's dominant position in telecom services into the telecom equipment sector.

Those fights yielded change, but slowly. In 1968 AT&T lost an antitrust suit against Carterfone Company, and was forced to permit private interconnection equipment on the AT&T network. In 1975 the Federal Communications Commission (FCC) extended the Carterfone decision to all private subscriber equipment that is registered to and certified by the FCC. These decisions enabled entry into the telecommunications equipment industry; however, as long as AT&T remained the dominant purchaser of equipment, entry was limited. The market structure changed further with the 1974 US Department of Justice antitrust suit against AT&T. The case was settled in 1982, with AT&T divesting its local telephone service into seven independent, regional holding companies, breaking up equipment purchasing decision. As a result the telephone markets underwent considerable changes in the early to mid-1990s.[4]

The data segment was based on packet-switching technology and supplied the communication equipment required in the computing industry, including modems and local area networks. Until the emergence of the Ethernet standard, this segment was characterized by proprietary protocols. Only with widespread use of the Ethernet standard in the late 1980s and the Internet IP stack in the early 1990s did non-proprietary standards begin to shape industry structure.

The networking and Internet revolution of the 1990s blurred the distinction between different segments of ICT equipment. This process sometimes receives the label "convergence," which means that previously independent product market segments increasingly become substitutes or complements in demand. On the computing side, systems of PCs and workstations were initially hooked together with a local area network (LAN). Over time client-server systems within large enterprises and across ownership boundaries were established. Novell, 3Com, Oracle, and Cisco were among the firms with dominant positions in this era.[5] With widespread Internet use the scope of ambitions became quite large, touching on virtually every economic activity in which transmission of information played an important role. This period was marked by economic experiments across a wide range of activities that overlapped with applications of computing and communications, as well as any related upstream or downstream activity. It was marked by optimism and labeled "the dot-com bubble" in recognition of the many startups that ended with the top-level domain name "com."[6]

In contrast, by the beginning of the millennium many layers of the industry underwent upheaval. Some of this was associated with large, painful adjustments due to a decline in demand that was linked to the implementation of the 1996 Telecommunications Act and resulting growth and Telecom Meltdown. Some of it was due to the bursting of the dot-com bubble. Eventually the equipment market stabilized, leaving Cisco in the dominant position in enterprise computing to serve data communications. Yet other firms who grew spectacularly during the 1990s, such as JDS Uniphase, Corning, Lucent, Nortel, and 3Com, did not fare as well.

This brief review suggests several of the core questions that motivate our statistical work. First, is the evidence consistent with the common presumption that there has been a deconcentration in the ownership of innovative ideas? Second, can this deconcentration be explained by something

[4] See, e.g., Crandall and Waverman (1995) for a detailed discussion.
[5] See, e.g., Bresnahan and Greenstein (1999).
[6] For a review of the extensive literature on trends and causes, see Greenstein (2010).

straightforward, such as the divestiture of AT&T, the loss of commercial leadership at IBM or Motorola, or any other large industry firm? Third, what role do other factors play, such as firm entry, particularly non-US-firm entry, which has accelerated over this period? Fourth, has the externalization of R&D by established firms merely changed the structure of the origins of innovation, but not its concentration as it relates to final output markets?

2.2 Theoretical Framework

This section provides a brief overview of our framework. It fixes a few key ideas, and provides a roadmap for later developments.

Following prior literature (Arora and Gambardella, 2001, Gans, Hsu and Stern, 2002), we divide the industry into an upstream sector that supplies invention and a downstream sector that supplies products. The downstream sector employs inventions from the upstream sector in production.

The literature on the rise of DTL focuses on the increasing infrequency of situations where one firm has a monopoly over an idea. In practice, these ideas come from very specific classes of technologies and map into very specific product markets. The literature stresses that such monopolies are less likely to arise where many technical substitutes can emerge. Substitutes are more likely to emerge in settings where many potential inventors generate similar ideas, and where entry into production of ideas is less costly.

We considered a wide range of alternatives ways of measuring settings where many potential inventors generate similar ideas. For reasons explained below, we settled on a top-25 concentration ratio over the ownership of inventive ideas, which we label as C25, in technological class, indexed as i. Illustrating the concept, a technological class i is said to be more concentrated if the largest 25 firms owns 80% of the inventive ideas instead of, say, 50% of the ideas in that technology class.

The literature discussed many related measures of concentration for a sector, and these are book-ended by two concepts, one related to the *flow of new ideas,* another related to the *stock of ideas in use*. The existing literature on DTL suggests the flow of ideas is relevant for fostering entry into product markets, for example, while the stock of ideas is relevant for new combinations of technologies fostering entry or industrial change. Hence, we consider both.

Flow and stock of ideas in technology class i will be related to one another. The stock in sector i in time t is:

$$Stock_{i,t} = Flow_{i,t} + (1 - \delta) * Stock_{i,t-1},$$

where δ is a discount rate for old inventive ideas, and flow is the total available new ideas in sector i in a given year. Some of the writing on DTL suggests that many patents are not relevant for entry, but only high quality patents facilitate entry. The above definition can be modified to focus on the stock and flow of only high quality ideas.

The first key question concerns changes in concentration of ownership over time. Is evidence consistent with decreasing concentration over time? That focused on the question for each i, namely,

$$(C25_{flow\ or\ stock})_{it} - \left(C25_{flow\ or\ stock}\right)_{it-1} < 0\,.$$

Generally, we will find that a wide range of technology classes did become more deconcentrated. That motivates the second question, concerning the causes of changes in concentration over time. In general, our approach will identify causes of the variance in changes of concentration between different technology classes. That is, we posit:

$$(C25_{flow\ or\ stock})_{it} - \left(C25_{flow\ or\ stock}\right)_{it-1} = f(Supply\ in\ i, demand\ in\ i).$$

The literature on DTL frames the open question: what factors caused changes in concentration? As our review of the history suggests, important supply-side factors include the decline of dominant firms, increasing economies of scope across technology sectors, the entry of foreign firms, and the entry of small firms. Important demand-side factors include the increasing use of merger by leading firms to obtain invention from external sources, increasing acceptance of technical products from unbranded firms by users, and the increasing use of open standards that permit customers to buy interoperable products from more than one supplier. As will turn out, we will construct measures for all three supply factors, while the latter two demand factors will be absorbed into time trends, so we will be able to measure only the demand for merger.

3 Data

Patents are one of the most utilized sources of information in the innovation literature. The use of patent data as a proxy for economic activity dates back to Schmookler (1951) and Griliches (1990), and since then an extensive literature on using patents as indicators of innovative activity has developed.[7] Here we follow this literature and focus on patents granted in the ICT equipment industry as a proxy for the origins of innovative activity. Since pursuing questions related to DTL led us to modify the practices underlying existing patent datasets widely in use, we first devote space to explaining our overlap and departures from the existing literature. We then establish changes in the level of ownership composition of new and cumulative innovative activity, and then link these changes to underlying supply- and demand-side factors. Supply-side factors include new entry, lateral entry (a firm's economies of scope), and growth; the demand-side factor we utilize is the M&A activity of established firms.

The standard source for patent data in the innovation literature has been the NBER patent data file. However, we use raw USPTO files to construct an updated patent data file, and to enable linking the patent data to the M&A data. Appendix A describes the construction of patent data from 1976 to 2010, and the data linking procedure.

3.1 Patent Sample Selection

The ICT equipment industry is a knowledge-intensive market that corresponds to hundreds of billions of dollars in investments by end users in the downstream, and roughly 14% of US patent stock in the upstream. We identify ICT equipment industry in the patent data by extracting 44 patent technology classes from the newly constructed USPTO patent data: 14 technology classes identified as communications by Hall, Jaffe, and Trajtenberg (2001); 22 technology classes in the 700 ranges; and 8 classes identified as relevant to telecommunications in the USPTO communications report. We then drop 14 classes due to sparse patenting activity.[8] The classification variable is taken from the December 2010 version of the US Patent Grant Master Classification File (MCF) published by the USPTO.

While our patent data includes granted patents between 1976 and 2010, we encounter truncation created by the application-grant lag in the patent system. Accordingly, we restrict our sample to patents applied for between 1976 and 2007. The final dataset has 550,884 patents with primary technology classes in the 30 ICT equipment classes, assigned to 38,359 unique assignees.

The 550,000 patents granted in the ICT equipment industry during our sample period correspond to roughly 14% of all patenting activity in the United States. Figure 1 provides a breakdown of granted patents over the years. As observed, the number of patents granted in ICT equipment follows a trend

[7] See, e.g., Griliches (1990) and Nagaoka et al. (2010).

[8] Appendix C contains lists of all considered classes. The dropped classes correspond to roughly 10% of the entire patenting in ICTE.

akin to the total number of utility patents granted by USPTO: the number of patents granted increases starting in the 1980s, followed by a sharp decline in the 2000s due to the patent grant delay, the time between the patent application by inventors and their receipt of a grant from the USPTO. The figure also provides the relative magnitude of unassigned patents, roughly 30,000, which we drop from our sample as we are interested in analyzing the assigned patents. Given the small magnitude, it is unlikely that any of our results are driven by the unassigned patents.[9]

The patent literature firmly establishes that patent values are highly skewed, with studies noting that the most valuable 10% of patents account for as much as 80% of total value of patents.[10] Below we provide results for patents that receive the bulk of citations, which are presumed to be of higher quality.[11] We define high-quality patents as the top quartile within their technology class-year group cells in terms of citations received. We have also examined the entire sample of patents, and the top decile of patents, without any large change in inference. These results are reported and discussed in Appendix D.

3.2 M&A Sample Selection

We use M&A activity as a measure of the demand for patented technology from other firms because of our focus on the concentration of ownership over the source of inventive ideas, and mergers provide a closer understanding of ownership. We identify acquisitions in the ICT equipment industry using the Securities Data Company's M&A data module, which includes SEC filings, firms' press releases, news articles, and a variety of other public sources. The data covers all US corporate transactions, public and private, since 1979. An M&A deal is included in the sample if it involves at least 5% of the ownership of the target company, and for the pre-1992 period if the deal valuation is at least $1 million (all deal

[9] In addition to assigning technology classes, the USPTO assigns technology subclasses to each patent. To remedy the concern that some technology subclasses may dominate the entire technology class, in unreported analyses we have shown that the patents are highly distributed across subclasses within each technology class: on average the top three subclasses contain 15% of all patents in the parent technology class. As a result, it is not possible to dominate the entire technology class by simply dominating a single subclass. This result holds for patent flow and patent stock analyses, and also holds after we control for patent quality. Therefore, the broad unit of analyses used in this study reflects general trends within a technology class, and not any trends driven by an outlier subclass.

[10] See, e.g., Scherer and Harhoff (2000). Other studies stressing the skewed distribution of patent values include Harhoff et al. (1999) and Pakes and Schankerman (1984).

[11] An interpretation of this approach is through the Schumpeterian framework. Schumpeter (1934) distinguishes between inventions and innovations: an invention is a potential innovation, and becomes an innovation only when it is commercialized. One could argue that the count of all patents is a better proxy for inventions and the count of high-quality patents is a better proxy for innovations (West and Bogers, 2011). Caballero and Jaffe (1993) offer another alternative interpretation: "We assume that patents are proportional to ideas, and that citations are proportional to ideas used." Harhoff et al. (1999) and Hall et al. (2005), among others, show a significant relation between the value of patents and the number of citations they receive.

values are included for the post-1992 period). The data also includes deals in which the deal value is undisclosed. Reported items include the identities of acquiring and target companies, their industry codes, and deal-specific information including the deal value whenever available.

We identify M&A deals in which either the target, the acquirer, or both firms have at least one patent in the ICT equipment industry between 1979 and 2010. After identifying the ICT equipment-related deals, we eliminate deals that are not of interest, including incomplete deals, rumors, and repurchases. In this way we keep completed M&A deals that have one of the following forms: merger, acquisition, acquisition of majority interest, acquisition of assets, and acquisition of certain assets.[12] We also drop deals in which the target or the acquirer is in the financial industry (SIC codes 6000 to 6999) or is a utility firm (SIC codes 4900 to 4999). In addition, we drop deals in which the target is a subsidiary. Finally, we manually examine the remaining deals and drop repurchases, or self-acquisitions of a subsidiary that are not already identified by the variables in the SDC data. The final sample has 19,878 M&A deals from 1976 to 2010.

We are concerned that M&A is not the only channel for transferring ownership of patents between firms. Licensing of patents and outright sale of patents are two other channels, and both provide additional information about the market demand for ideas.[13] However, comparison with Serrano (2010) leads us to believe that merger is a very good proxy for demand. Serrano records that 13.5% of all granted patents are traded over their life-cycle; We obtain a similar scale of transfer (11%) through M&A activity, which suggests that over 80% (11/13.5 > .8) of the transfers in ownership of patents measured by Serrano occur due to M&As.

3.3 Concentration and Other Measures

In this section we describe the market structure, technology supply, and technology demand proxies we use in our empirical framework. Table 3 provides a summary of these variables.

Our main variable is the patent ownership concentration in a technology class. We capture the ownership concentration of granted patents in each technology class-year group as the share of top firms in the ICT equipment industry. More specifically we create variables $C1_{flow}$, $C2_{flow}$, …, $C25_{flow}$, where CX_{flow} is the share of patents applied by the top X firms within the technology class-year group. In each year group we reselect the top firms; in other words, even though the number of firms used to

[12] In our sample, this step is equivalent to keeping deals that have either disclosed or undisclosed dollar value and dropping deals that are Stake Purchases, Repurchases, Self Tenders, and Recaps.
[13] See Arora and Gambardella (2010) and Serrano (2010).

calculate CX is kept constant at X, the set of firms may be different from period to period. We stop at $C25_{flow}$ because in many of the technology class-year groups the top 25 firms reach 100% ownership in the early years of our sample. Table 3 reports that on average the top 25 firms in a technology class-year group own 68% of high quality patents. Though, as we discuss in the next section, there is considerable variation in this concentration over time.

In this context, more general measures of concentration, including Gini coefficients and HHIs for each patent class-year group, could be constructed. In Appendix D we discuss our choice of C25 further, and repeat our analyses using these alternative measures of concentration, and find qualitatively similar results.

There are various theories on why the changes in concentration have come about. We divide these theories into two distinct groups: those concerning the demand of technology, and those concerning the supply of technology. In acquisition of innovation, patent applications reflect only the innovations created by the patent applicant and do not take into account the alternative mechanisms of obtaining patents, including acquisition of patents or acquisition of other patent assignees. We consider the acquisition of patents through acquisition of other patent assignees as a source of demand for innovation, and construct a measure of *Merger Intensity* to account for this phenomenon. The merger intensity in a technology class in a year is the ratio of total patent stock transferred through assignee acquisitions to the total stock of patents in that year.[14] In our theoretical setting, a higher *Merger Intensity* implies a lower transaction cost of absorbing ideas from small firms. On average, each year around 1.1% of existing high quality patent stock has been transferred through M&A activity (Table 7), with considerable variation across different technology sectors. Though this may seem small, when we construct the stock of transferred patents over the years we see that around 12% of high quality patents change hands through the merger and acquisition of patent assignees.

Firm entry into innovative activities provides one theory on deconcentration (Hall, 2005, and Kortum and Lerner, 1999, among others). In an effort to capture the impact of firm entry, we have three classes of entry variables. In the first class, patent-weighted entry level, we construct two measures of entry based on the previous patenting activity of the firm: *new entry* and *lateral entry*. Firm *i* is considered a new entrant to technology class *j* in period *t* if the firm does not have any patents in any of the ICT equipment classes prior to period *t*, and has at least one patent in technology class *j* in period *t*. When such an entry occurs, we consider all patents of firm *i* in period *t* in technology class *j* to be patents by a

[14] Details of how patent stocks are calculated are discussed in Section 4.3.

new entrant, and calculate the new entry share by dividing the total number of new entry patents by the total number of patents in technology class *j* in period *t*. The new entry variable then captures the level of transaction costs of entry into the market for ideas. When we restrict the variable to account for only foreign entry, we then capture the transaction costs of entry by non-US firms. Table 3 suggests that firms that had no prior ICT equipment innovation activity produce, on average, 19% of patents in a technology class.[15]

In addition to firms entering into the ICT equipment industry from outside, firms may also be active in one ICT equipment class and later move to a new ICT equipment class. We consider such firms as lateral entrants. More specifically, we consider firm *i* a lateral entrant to technology class *j* in period *t* if the firm did not have any patents in technology class *j* prior to period *t*, had at least one patent in another ICT equipment technology class prior to period *t*, and has at least one patent in class *j* in period *t*. We then calculate the *lateral entry share* as the ratio of patents by lateral entrants in period *t* in class *j* to the total patent count in period *t* in class *j*. We theorize that a higher lateral entry level implies higher economies of scope across different technology classes. From the summary statistics in Table 3, we see that on average 15% of high quality patents come from lateral entrants.

The two entry variables, *new entry share* and *lateral entry share,* proxy for patent-count weighted entry into a technology. We should note that when combined, these two variables capture the inverse of the serial dependence of patenting by firms already in a technology class. In other words, considering the 19% new entry and 15% lateral entry averages, we deduce that on average 66% (100-19-15) of patents come from firms that already had patents in a technology class in prior periods. As a result, when we include both entry variables in the model, we also account for the serial dependence.

The second class of entry variables is the growth in the number of firms active in a technology class. Using simple firm counts, we calculate the growth in the number of firms over time. We see that on average the number of firms has increased by 15% every two years, with firms located outside the United States having a relatively higher growth rate of 22%.[16] As an overwhelming majority of the firms

[15] Note that in this setting the sample is restricted to high-quality patents, hence the entry variables capture entry into the high-quality patent pool rather than entry into the entire patent pool. In other words, a firm with many low-quality patents and no high-quality patent in prior periods would be considered an entrant in the first period it produces a high-quality patent.

[16] One should take the statements about foreign firms with a grain of salt for the following reason. The *foreign* indicator in the patent data captures the location of a firm, but not its origin or ultimate ownership. For example, even though practitioners would consider Sony Electronics Inc. a non-US firm, in the patent data it is located at Park Ridge, NJ, and therefore is considered to be a US firm (e.g., USPTO patent 5,828,956).

in the sample are US-based, the total growth in the number of firms is very close to the growth in US-firms, which is around 14%.

The growth in the number of patents constitutes our third class of independent variables. We see that on average the patent count has grown by 20% every two years (19% in domestic and 230 in foreign firms). When we take into account the 15% average increase in the number of firms over two-year periods, which is considerably less than the 20% growth in patent count, we deduce that patent growth is coming from both entrants and incumbents.

The final class of control variables in our model consists of proxies for increase or decrease in product market leadership: dummies for the presence of a big firm. Conventional wisdom that the breakdown of AT&T caused the deconcentration in patent ownership calls for these controls. In an attempt to discern whether the existence of big firms, namely AT&T, Motorola, and IBM, have an impact on the concentration, we include lagged indicators for their existence among the top five patent applicants. We see that the presence of AT&T is somewhat dwarfed by the strong presence of IBM: IBM is among the top five patent applicants in 47% of technology class-year group cells, whereas AT&T and Motorola are in the top five patent applicants in only 41% and 25% of the cells, respectively.[17]

4 Deconcentration of Patent Ownership

4.1 Composition of Ownership in New Patents: Historical Trends

We begin by describing long-term trends, which characterizes our endogenous variable. We construct a measure of concentration, and then analyze the new patent creation across the 30 ICT equipment technology classes. To capture the dynamics of new patent creation, we calculate the *patent flow* variable—the number of new patents a firm has applied for in a given year and was granted at a later date.[18]

To ensure that we have enough observation in each patent class each period in our analyses of patent flow, we use two-year intervals as the measure of time instead of individual years. Therefore, the observation level throughout the patent flow analyses is a technology class-year group.

[17] These cells correspond to two-year periods as opposed to one year. This construct is explained in Section 4.1.

[18] The patent grants may come many years after a patent is applied for, and this delay is coined as the patent application-grant delay. The convention in the literature on patents is to use the patent application year as the year of the innovation/invention because the application year is closed to the actual creation of the idea; whereas the delay, hence the grant year, is a function of other factors including the workload and staffing issues at the USPTO. In this study, we follow this convention, and use the patents applied for and granted between 1976 and 2010.

We use $C25_{flow}$, the share of top 25 firms in new patents, as our measure of concentration. In calculating the $C25_{flow}$ measure, we reselect the top firms in each period; hence, the measure is based on 25 firms in each period, yet there may be changes in the identities of these firms from period to period based on their respective rankings within each period. We choose $C25_{flow}$ as opposed to other CX_{flow} values because in many cells $C25_{flow}$ reaches to 100% for the early periods of our sample. We discuss the choice of the concentration measure further in Section 3.3.

Figure 2 illustrates the CX_{flow} values for technology class 385 (Optical Waveguides). The top line in Figure 2 represents the share of top 25 firms in the class ($C25_{flow}$), and the bottom line represents the share of the top firm only ($C1_{flow}$). The share of the top 25 firms has seen a decline from around 70% in 1976-77 to around 41% in 2006-07. In fact, we observe a similar trend in 26 of the 30 classes in our sample. In only four classes the values of $C25_{flow}$ fluctuates. All these trends suggest a deconcentration of ownership in new patents in our sample period.

We now turn to Table 1 to observe this deconcentration trend across all technology classes. Table 1 shows the distribution of $C25_{flow}$ values across all technology classes for all high quality patents in the ICT equipment sample. The mean value of the top 25 firms' new patent share across technology classes follows a gradual decline over the years from 86% in the 1976-77 period to 62% in 2006-07.

Figure 3 is simply an alternative way of observing this trend of deconcentration: in 1976-77 ten classes possess more than 90% of the new patents, whereas in 2006-07 there is only one class that shows such concentrated ownership at the top.[19]

We now investigate potential causes of this deconcentration across technology classes. Industry insiders attribute this deconcentration to the breakdown of AT&T in 1982 during the deregulation of the telecommunications industry. To see if this claim holds in a first pass through the data, we calculate a simple statistic, the number of firms that contribute 90% or more of the changes in $C25_{flow}$, the share of top 25 firms, over our sample period. The results are presented in Table 2 reports the changes for high quality ICT equipment patents. We see that of the 26 classes with deconcentration, in only three classes are three or fewer firms responsible for 90% or more of the reduction in $C25_{flow}$. In the remaining 24 classes there is an industry-wide deconcentration trend, which suggests that the breakdown of AT&T, or another leading firm, cannot be the sole reason for the established

[19] Similar results hold for the entire patent sample, and also for the top 10% of the patents, with five and 24 classes in 1976-77 and zero and six classes in 2006-2007, respectively.

deconcentration. The qualitative observations remain the same when we remove the restriction on the high quality patents, and consider the entire patent sample..

4.2 Composition of Ownership in New Patents: The Model

In Section 4.1 we presented historical trends and provided evidence for a deconcentration trend in the ownership of new patents in the ICT equipment industry. In this section we combine these historical trends in a single fixed effects model to provide a coherent framework on the potential causes of the established deconcentration. In this analysis, $C25_{flow}$, the share of top 25 firms is our dependent variable. The basic model is as follows:

$$(C25_{flow})_{jt} = \beta_1 * (\text{New Entry})_{jt} + \beta_2 * (\text{Lateral Entry})_{jt} + \beta_3 * (\text{Growth})_{jt}$$

$$+ \beta_4 * \delta_{j,t-1,AT\&T} + \beta_5 * \delta_{j,t-1,,Motorola} + \beta_6 * \delta_{j,t-1,IBM} + \gamma_j + \theta_t + \varepsilon_{jt},$$

where j is the technology class indicator and t is the time indicator. The list of regressors include new entry and lateral entry into technology classes, growth measures, and indicator variables for the presence of big firms, namely AT&T, Motorola, and IBM.[20] We use two sets of growth measures, one for growth in the number of firms and a second for growth in the number of patents. We further divide these growth variables into two components: growth in US-based firms and patents, and their foreign counterparts. The growth measures are highly correlated (the Pearson correlation between total firm growth and total patent growth is 0.87), therefore, we use either the firm-based or the patent-based measure in a single model.

We present the results of the fixed effects models in Table 4. The dependent variable in the model is $C25_{flow}$, the share of the top 25 firms in new patents. All models include class fixed effects; models 1-4 include a linear and a quadratic time trend, whereas models 5-8 include time fixed effects. The standard errors are clustered by technology-class. The columns differ in the inclusion of different patent growth and number of firm growth variables.

The main qualitative results seem to hold across all models, and here we provide illustrations using the results from column 1. Growth in the number of firms is one of the main drivers of deconcentration, with a 1% growth in the number of firms resulting in a decrease of 7.8% in the ownership share of top 25 firms; a technology class at the average firm growth rate of 15% every two years faces a reduction of approximately 1.2% (=7.8% * 0.15) in the share of top 25 firms in two years, even after controlling for

[20] The construction and summary statistics of these variables are provided in Section 3.6 and Table 3.

individual class effects and time trend.[21] When we break the growth variable into US-based growth and foreign growth, we observe that contrary to conventional wisdom, only the US-based growth is a driving force of deconcentration, and the foreign growth does not have a statistically or economically significant impact on our concentration measures. We observe the same qualitative result in the growth of the number of patents: a technology class at the average firm growth rate of 20% every two years faces a reduction of approximately 0.6% (=3.22% * 0.20).

However, new entry does not seem to have a statistically significant impact, though the sign of the estimates are in the negative direction, as expected. The lateral entry is associated with an increase in the ownership of top firms, and the impact is both statistically and economically significant: a technology class experiencing the average level lateral entry, 15% per period, faces a 2.8% (=18.93% * 0.15) increase in $C25_{flow}$. This result may be driven by the fact that firms conducting lateral entry operate in multiple segments of the industry, and hence are expected to have a bigger operation than others. Note that lateral entry in this context means having a high-quality patent in one ICT equipment class, and producing a new high-quality patent in another ICT equipment class in which the firm did not have high-quality patents previously; having low-quality patents in either industry has no effect on the entry measure among high-quality patents.

Finally, the models suggest that the existence of AT&T as one of the top five patent owners in the prior period does not have a statistically significant impact on the concentration of the patent class, which is consistent with our earlier trend analyses. The coefficient of the IBM indicator is also not significant. The presence of Motorola as a prior top-five patent applier, however, is associated with an approximately 1.8% increase in the ownership concentration of the patent class over two years, but this is borderline statistically significant only in model 1. Furthermore, a detailed look at Motorola's activity reveals that it focuses on five technology classes in which the deconcentration is less than the average across all technology classes. We cannot say whether the increased concentration is driven by the presence of Motorola or whether it is simply an artifact of selection on technology classes.

The main results across all models show that growth in the number of firms is an important driver of deconcentration, suggesting that a smaller transaction cost for entry results in lower ownership concentration. Lateral entry works in the opposite direction of entry by increasing the concentration of patent ownership. When we turn our attention to the entire sample of patents, we obtain similar results

[21] This result is consistent with the fertile technology hypotheses of Kortum and Lerner (1999).

for the growth in the number of firms; and, the impact of lateral entry is both higher, and is statistically significant in all models.[22]

These findings also raise an interesting open question. Looking at how the new entry and lateral entry vary over time (averaged across technology classes), we observe a declining trend in both. The new entry share starts around 23% in 1978-79 and gradually drops to 10% in 2006-07. The lateral entry share follows a similar declining trend, with 32% in 1978-79, and 48% in 2006-07. It is possible that the factors of lateral entry and new entry only reflected a one-time change that has largely played itself out. If both have declined permanently, then neither factor can play as a large a role in driving change going forward.

4.3 Patent Ownership Variables: Patent Flow and Patent Stock

In earlier sections we presented historical trends of ownership composition of innovation in the ICT equipment industry, using the flow of granted patents of a firm as a measure of its innovative activity in a given year. However, firms accumulate patents over the active lifetime of patents. We now turn our attention to this historical stock of patents and calculate a proxy for all the patents the firm has created that are still active—the discounted sum of patent flow over the firm's history, less the expired (old) patents, called *the patent stock*. For the purposes of calculating the patent stock, we consider a patent active for 20 years starting with the patent filing year, or for 17 years starting from the patent grant year, whichever comes later.[23] Based on the set of active patents in a given year, we then calculate the patent stock by discounting the patents from prior years using the declining balance formula. More specifically, we calculate the cumulative patent stock of firm *i* in period *t* by the following formula:

$$Stock_{i,t} = Flow_{i,t} + (1 - \delta) * Stock_{i,t-1},$$

where we use the depreciation rate, δ, of 15%.[24] This depreciation accounts for two main mechanisms: the obsolescence of patents over time as the technology becomes older and irrelevant, and the shorter

[22] In unreported results, these changes are even more pronounced when we restrict the patents to the top 10%: lateral entry is no longer statistically significant in any of the models, though the total growth in the number of firms is still of the same magnitude and is statistically significant. The results also hold qualitatively.

[23] The patent term for applications before June 8, 1995, expire at the later of (i) 17 years from the issue date, or (ii) 20 years from the application date. For applications on or after June 18, 1995, the patent term is 20 years from the filing date, which is equivalent to the older definition for our sample period ending in 2010.

[24] The returns to patents are estimated to decline by 10% to 20% per year (Schankerman and Pakes, 1986). In calculating the patent stock, use of the declining balance formula with 15% depreciation rate is prevalent in the literature (e.g., Griliches, 1989; Hall, Jaffe, and Trajtenberg, 2005; and Hall and MacGarvie, 2010).

remaining active time of older patents that reduces the protection of the patent into the future. Both of these mechanisms imply a lower value for the patents.

The stock variable depends on the history of patenting activity; therefore, we allow for the variable to accumulate for the first 10 years of our sample period, and start our analyses of the patent stock in 1986. In other words, our sample for the patent stock section reduces to the 1986-2007 period.

A second difference between the patent flow and patent stocks is the leadership dynamics: an entrant may obtain a leadership position in patent flow relatively quickly by producing more than its competitors in a given period, as there is no dependence on past activity. However, assuming a leadership position in patent stocks may take longer due to the accumulated patent stock of incumbents over prior decades.

4.4 Composition of Ownership in Cumulative Patent Stock

In this section we turn our focus from new patent applications to the entire stock of patents in the ICT equipment industry, i.e., patents that have been granted since 1976 absent expired patents. Thus we repeat the analyses of patent flow from Section 4.1 on the cumulative patent stock. This switch also enables us to include the merger intensity measures in our analyses as merger intensity is a measure of stock. The switch to the patent stock is interesting mainly because in new patent applications entrants may surpass industry incumbents in a relatively short period, but this may not be the case for the cumulative patent stock. Leading industry incumbents, even if they lose their edge in new patents, will enjoy the benefits of their prior patents for a while. Microsoft illustrates this lag well. It appears as one of the top five patent applicants in a technology class for the first time in 1992. However, it appears as one of the top five holders of cumulative patent stock in a technology class only three years later, in 1995.

The measure of concentration in this section is the ownership share of top 25 companies in the entire patent stock, $C25_{stock}$. As opposed to using two-year periods as the unit of time, in the stock analyses we use each year as a separate period, because in stock variables we do not have the scarcity issue of the flow variables. Figure 4 replicates Figure 2 using the patent stock, and plots the CX_{stock} variables over our sample period for the technology class 385, Optical Waveguides. We observe that the share of top 25 firms, the top line in the figure, decreases from 78% in 1986 to 39% in 2007.

The deconcentration trend in patent stock prevails across technology classes in ICT equipment. Table 5 reports the annual averages of $C25_{stock}$ values across the technology classes in our sample. The average share of top 25 firms in the stock follows a trend downward, from 65% in 1986 to 51% in 2004, and plateaus thereafter. This deconcentration trend also holds for the entire sample of patents, with a reduction from 59% in 1986 to 50% in 2007 (see Table D.5). As in the patent flow case, we see no clear relationship between the presence of large leading firm and this deconcentration trend. Table 6 reports the number of firms responsible for 90% or more of the reduction between 1986 and 2007, and in only nine technology classes do three or fewer firms account for this change. In the remaining classes the reduction comes from a group of companies, providing evidence that the divestiture of AT&T, or the activities of Motorola or IBM, cannot account singlehandedly for this trend. We observe a similar trend in the entire sample of patents, as reported in Table D.6..

4.5 Role of Acquisitions

We have shown that the top 25 firms in the ICT equipment industry hold a smaller share of the patent flow and stock than they did three decades ago. However, these analyses consider only the in-house production of patents and do not take into account the patents acquired through alternative mechanisms, including acquisition of innovative firms. However, we see tremendous numbers of acquisitions taking place in the ICT equipment industry, and the impact of the transfer of patents through acquisitions on concentration depends on the status of the target and the acquirer. In cases where the buyer is simply supplementing its existing portfolio of patents by acquiring a target active in the same technology class, then ownership becomes more concentrated. However, if the acquirer is simply entering a new technology class by acquiring a target active in that technology class, then the ownership concentration does not change in that technology class.

We resort to the M&A data to proxy for the demand for innovation and to see the magnitude of patent transfers through M&As in the ICT equipment industry. Table 9 reports the M&A deal counts based on the ICT equipment patent ownership status of acquirers and targets. In 1,881 of these M&A deals (9%) both the acquirer and the target firm have at least one ICT equipment patent, and in 1,127 deals (6%) only the target has ICT equipment patents. Please note that transfers of patents take place in approximately 1 out of 7 (3,008 out of 19,878) M&A deals involving ICT equipment patent holders.

The sheer ratio of M&A deals with patent transfers may not translate into a large number of patents if the target firms possess only a few patents. To assess the share of patents transferred through M&As, we report the patent stock for the ICT equipment industry, and also for the firms that were targeted in an M&A deal, in Table 10. We calculate the patent stock using the declining balance formula as described in Section 4.3. The total stock of acquirers includes patents by the acquirers independent of the year they make acquisitions. As an example, the patents of a firm that makes an acquisition in 1997 are accounted for in the patent stock before, during, and after 1997. For the purposes of Table 10 we similarly calculate the patent stock of target firms. Note that unlike earlier sections, which considered the patents of only top 25 firms, Table 10 reports patents acquired by all firms.

In Table 10 we observe that the stock of patents that changed hands through M&A transactions increase over time in nominal terms, though with some fluctuations in the 1980s. Yet the share of patents transferred with respect to the entire stock of ICT equipment patents gradually decreases from approximately 20% in the early 1980s to 12% in 2007. When we remove the restriction to high-quality patents (Table D.10) we observe similar trends, though the share of patents transferred slightly decreases across the board by around 2%.

The ratio of transfers increases dramatically when we change the denominator from the entire ICT equipment patents to patents of firms that conduct an acquisition. In the early years of our sample, the size of transferred patents corresponds to more than 30% of the acquirer patent stock, which decreases to 19% in 2007. We see a similar trend with slightly lower transfer ratio in the entire patent sample.

The transfer of 12% of an industry's patents through M&A activity is a significant source of ownership change. However, we can compare the 14% approximate decrease in the ownership share of the top 25 firms in cumulative patent stock to the 12% of patents being transferred through acquisitions. A back-of-the-envelope calculation using the fact that not all the transferred patents go to the top 25 firms, the magnitude of transferred patents is not big enough to revert the deconcentration trend we established in Section 4.1. The following section puts the various, competing explanations of deconcentration in patent stock ownership into a single framework.

4.6 Composition of Ownership in Patent Stock: The Model

Having established historical trends of patent stock ownership in Section 4.5, we now turn our attention to combining demand-side and supply-side explanations in a fixed effects model. Table 7 presents the summary statistics used in the patent stock model. These variables are constructed in the same way as described Section 3.3, with the difference that we now use the depreciated stock of active patents instead of the flow of new patents. Keep in mind that the period for these patent stock analyses is a single year, as opposed to the two-year period in the flow section above. In light of this information, we see that the number of firms grows at a pace of 9% each year and the number of patents grows at 10%.

As expected, recycling patents over their lifetime results in a lower new entry and lateral entry share: each year 3.7% of the patents in a technology class belongs to new entrants, and another 2.7% belongs to lateral entrants. This implies that each year roughly 94% of the depreciated high quality patents stock belongs to firms that were active in the technology class in a prior year. The positions of AT&T, IBM, and Motorola appear slightly stronger in the patent stock than in the patent flow due to the cumulative impact of their prior patents.

We now combine the various factors in the following fixed effects model:

$$(C25_{stock})_{jt} = \beta_0 * (\text{M\&}A\ Intensity)_{jt} + \beta_1 * (\text{New Entry})_{jt} + \beta_2 * (\text{Lateral Entry})_{jt} + \beta_3 * (\text{Growth})_{jt}$$

$$+ \beta_4 * \delta_{j,t-1,AT\&T} + \beta_5 * \delta_{j,t-1,,Motorola} + \beta_6 * \delta_{j,t-1,IBM} + \gamma_j + \theta_t + \varepsilon_{jt},$$

where *j* is the technology class indicator and *t* is the time indicator. The independent variables include the same variables as in Section 4.2, except that they are now constructed on stocks of patents instead of flows. The use of patent stock enables us to include M&A intensity, i.e., the measure of transferred patents through M&A activity in a technology class, in our analyses as an additional variable.[25]

We present the fixed effects model of patent stocks in Table 8. The dependent variable in the model is $C25_{stock}$, the share of top 25 firms in cumulative patent stock up to the period. All models include class fixed effects; models 1-4 include a linear and quadratic time trend, and models 5-8 include time fixed effects. We clustered the standard errors by technology class. The columns differ in the inclusion of different patent and number of firm growth variables.

The results somewhat mimic our observations on patent flow. The existence of individual firms does not appear to have a big toll on concentration changes, none of the coefficients on firm growth is statistically significant.

M&A intensity does not have a statistically significant impact on market concentration. This is true for both the entire sample and the high-quality patents, implying that demand for ideas does not have a big impact on the concentration of ownership.[26]

The results on new entry, which is a proxy for the patent-weighted entry of firms that were not active in ICT equipment previously, are mixed. In the entire sample of patents the new entry has a statistically

[25] The construction and summary statistics of these variables are provided in Section 3.6 and Table 7.

[26] In unreported results we found that by restricting the sample to the 10% highest-quality patents, M&A intensity has a marginally significant negative impact on concentration, but even this impact is economically small.

and economically significant impact on the concentration: a yearly 2% entry (the average level) results in a 0.8% (=0.02 * 39.67%) yearly decline in concentration. But when we restrict the sample to high-quality patents, new entry share loses its statistical significance.

As in the flow analyses, our main result comes from the increase in the number of firms.A class that experiences the mean level of firm growth (9%) in the number of firms that produce high-quality patents faces a 4.6% (=0.09 * 51.22%) reduction in $C25_{stock}$. This result is robust to various samples we considered, including the analyses on the entire sample of patents, the highest quality (top quintile) of patents, and on using the Gini coefficients or the HHIs as the dependent variable.

Based on these results, one may ask what causes entry into new innovative areas by firms who previously has little inventive experience. The changes in entry levels may be due to various factors, including increased technological opportunities or product market demands, easier access to external funding sources such as Venture Capital funding, and demand from firms with established product market presence for external innovation. This question constitutes the next step in analyzing the innovation markets, and is left for future work.

5 Conclusion

In this article we characterize long-term trends related to the concentration of the origins of inventive ideas in the ICT equipment industry. Analyzing the concentration in granted patents in this industry from 1976 to 2010, we compare measured changes against popular assumptions about the size and scale of changes in innovation.

Overall we show a substantial decline in concentration. The data show that the deconcentration trend is present both in the ownership of new patent applications and in the cumulative ownership of active patents. We also show that the size and scope of the changes vary considerably, with some segments of ICT equipment undergoing much more dramatic changes in concentration.

We also provide evidence about the causes of this change. The statistical evidence is consistent with explanations that stress the role of supply-side changes more than demand-side changes. We present evidence that firm entry accounts for part of this deconcentration. Importantly, we reject the notion that non-US-firm entry caused the change. We also reject the notion that one antitrust case, one company’s strategic error, or the break-up of one large leading innovator of yesteryear accounts for this change in structure.

Furthermore, we show that the deconcentration results, as well as the results on the drivers of deconcentration, hold in the entire patent sample and in the high quality patent sample, across a variety of concentration measures.

The deconcentration of ownership results we obtain relate to the literature on Divided Technical Leadership (DTL), and, more broadly, debates about the causes of market leadership and incentives in innovative activities. By distinguishing between product market leadership and technological leadership, and focusing on the latter, we provide evidence of increased competition in the ideas market. This increased competition may be indicative of higher incentives to innovate, hence higher levels of innovation under a model of monotonic innovation in increasing competition. Alternatively, under an inverted-U relationship, this may be evidence of decreasing innovation under increasing competition.

Finally, this is the first study to investigate the extent of the potentially countervailing M&A mechanism using a census of the M&A activity in ICTE Industry. First, we showed that there is a considerable transfer of patents through M&As, which relate to the literature on R&D incentives in an M&A context on one hand, and the start-up commercialization framework of Gans, Hsu, and Stern (2002) on the other. We then showed that the size of the patent transfer through M&As is not enough to revert the composition of ownership to its pre-deconcentration levels. We conclude that leading firms' strategies to externalize R&D activity has not reversed the trend towards deconcentration. Furthermore, M&A intensity does not have a statistically significant impact on the ownership concentration of ideas.

The study has several inherent limitations. The USPTO classification system we used constitutes a limitation. Though no single technology class dominates our data, the definition of these classes may depend on industry developments, which may have ramifications for our analyses. In addition, our data includes patents granted in 1976. This restriction does not impact our patent flow variables as they are based on the patent applications within each year; however, it truncates the patent stock variable for early years of our sample, as we do not have information on active patents before 1976.

References

Arora, Ashish, Andrea Fosfuri, and Alfonso Gambardella. 2001. *Markets for Technology: The Economics of Innovation and Corporate Strategy*. Cambridge, MA: MIT Press.

Arora, Ashish, and Alfonso Gambardella. 2010. "The Market for Technology." In *Handbook of the Economics of Innovation,* vol. 1*,* ed. Bronwyn H. Hall and Nathan Rosenberg, 641-678. Amsterdam: Elsevier/North Holland.

Asker, J., J. Farre-Mensa, and A. Ljungqvist. 2012. Comparing the Investment Behavior of Public and Private Firms. Working paper, New York University.

Bound, J., C. Cummins, Z. Griliches, B. H. Hall, and A. Jaffe. 1984. "Who Does R&D and Who Patents." In *R&D, Patents, and Productivity*, ed. Z. Griliches, 21–54. Chicago: University of Chicago Press.

Bresnahan, T. F, and Shane Greenstein. 1999. Technological Competition and the Structure of the Computer Industry. *The Journal of Industrial Economics*. 47 (1): 1–40.

Caballero, R., and A. Jaffe. 1993. "How High Are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth." In *National Bureau of Economic Research Macroeconomics Annual*, vol. 8, ed. O. Blanchard and S. Fischer. Cambridge, MA: MIT Press.

Chesbrough, Hank. 2003. *Open Innovation: The New Imperative for Creating and Profiting From Technology.* Boston: HBS Press.

Crandall, Robert W., and Leonard Waverman. 1995. *Talk Is Cheap.* The Brookings Institute.

Gans, J., D. Hsu, and S. Stern. 2002. When Does Start-Up Innovation Spur the Gale of Creative Destruction? *Rand Journal of Economics*. 33(4): 571–586.

Gans, Joshua, and Scott Stern. 2003. The Product Market and the Market for Ideas: Commercialization Strategies for Technology Entrepreneurs. *Research Policy.* 32(2): 333-350.

Greenstein, Shane. 2010*.* "Innovative Conduct in U.S. Commercial Computing and Internet Markets." In *Handbook on the Economics of Innovation*, ed. Bronwyn Hall and Nathan Rosenberg, 477-538. Burlington, MA: Academic Press.

Griliches, Z. 1989. "Patents: Recent Trends and Puzzles," Brookings Pap. Econ. Act., Microeconomics, 291-330.

Griliches, Z. 1990. Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature.* 28: 1661–1707.

Hall, B. H. 2005. Exploring the Patent Explosion. *Journal of Technology Transfer*. 30: 35–48.

Hall, B. H., and Megan MacGarvie. 2010. The Private Value of Software Patents. *Research Policy*. 39 (7): 994–1009.

Hall, B., A. Jaffe, and M. Trajtenberg. 2001. "The NBER Patent Citations Data File: Lessons, Insights and Methodological Tools." NBER Working Paper No. 8498.

Hall, B. H., A. Jaffe, and M. Trajtenberg. 2005. Market Value and Patent Citations. *Rand Journal of Economics*. 36: 16–38.

Harhoff, D., F. Narin, F. M. Scherer, and K. Vopel. 1999. Citation Frequency and the Value of Patented Inventions. *Review of Economics and Statistics*. 81: 511-515.

Jacquemin, A., and A. M. Kumps. 1971. Changes in the Size Structure of the Largest European Firms: An Entropy Measure. *Journal of Industrial Economics*. November: 59-68.

Kerr, W., and S. Fu. 2008. The Survey of Industrial R&D-patent Database Link Project. *Journal of Technology Transfer*. 33: 173-186.

Kim, J., and G. Marschke. 2004. Accounting for the Recent Surge in U.S. Patenting: Changes in R&D Expenditures, Patent Yields, and the High Tech Sector. *Economics of Innovation and New Technology*. 13(6): 543-558.

Kortum, S., and J. Lerner. 1999. What Is Behind the Recent Surge in Patenting? *Research Policy*. 28:1-22.

Malerba, F., and L. Orsenigo. 1996. Schumpeterian Patterns of Innovation Are Technology-specific. *Research Policy*. 25: 451–478.

Nagaoka, S., K. Motohashi, and A. Goto. 2010. "Patent Statistics as an Innovation Indicator." In *Handbook of the Economics of Innovation*, ed. B. H. Hall and N. Rosenberg. Amsterdam: Elsevier.

Netter, J., M. Stegemoller, and M. B. Wintoki. 2011. Implications of Data Screens on Merger and Acquisition Analysis: A Large Sample Study of Mergers and Acquisitions from 1992 to 2009. *Review of Financial Studies.* 24: 2316–2357.

Ouimet, P., and R. Zarutskie. 2010. Mergers and Employee Wages. Working paper, University of North Carolina, Chapel Hill.

Pakes, Ariel, and Mark Schankerman. 1984. "The Rate of Obsolescence of Patents, Research Gestation Lags, and the Private Rate of Return to Research Resources." In *R&D, Patents, and Productivity,* ed. Z. Griliches. Chicago: University of Chicago Press.

Rosenbloom, R. S., and W. J. Spencer, eds. 1996. *Engines of Innovation: U.S. Industrial Research at the End of an Era*. Boston: Harvard Business School Press.

Schankerman, M., and A. Pakes. 1986. Estimates of the Value of Patent Rights in European Countries during the Post-1950 Period. *The Economic Journal*. 96: 1052-1076.

Scherer, F. M., and D. Harhoff. 2000. Technology Policy for a World of Skew-distributed Outcomes. *Research Policy*. 29(4–5): 559–566.

Schmookler, Jacob. 1951. Invention and Economic Development. Unpublished Ph.D. Dissertation, University of Pennsylvania.

Schumpeter, J. A. 1934. *The Theory of Economic Development*. Cambridge, MA: Harvard University Press.

Serrano, C. J. 2010. The Dynamics of the Transfer and Renewal of Patents. *RAND Journal of Economics*. 41: 686-708.

Sutton, J. 2007. Market Share Dynamics and the "Persistence of Leadership" Debate. *American Economic Review*. 97: 222–241.

West, Joel, and Marcel Bogers. 2011. Profiting from External Innovation: A Review of Research on Open Innovation Available at SSRN: http://ssrn.com/abstract=1949520 or http://dx.doi.org/10.2139/ssrn.1949520.

Table 1: Distribution of $C25_{flow}$ Values

Year Group	Mean (%)	St. Dev. (%)	10%	25%	50%	75%	90%
76-77	86	15	66	77	88	100	100
78-79	83	16	65	72	80	100	100
80-81	81	16	63	71	80	100	100
82-83	80	17	59	68	75	100	100
84-85	77	19	51	67	72	100	100
86-87	73	18	49	63	71	84	100
88-89	71	16	51	60	68	81	100
90-91	70	15	52	61	68	77	91
92-93	67	13	49	60	66	74	82
94-95	62	11	43	60	65	70	73
96-97	60	12	43	53	60	69	74
98-99	58	11	38	53	61	66	71
00-01	56	12	35	50	57	62	72
02-03	55	13	36	48	56	60	72
04-05	59	13	41	53	59	66	77
06-07	62	14	46%	53%	60%	73%	82%

Notes: Evolution of the patent application *flow* share for top 25 firms that are ultimately granted on or before 2010. Each row corresponds to a two-year time period. The sample includes patent applications from 30 patent technology classes in the ICT equipment industry, and the highest quartile of patents, where quality is measured by citations received.

Table 2: No. of Companies Accounting for 90% of Change in $C25_{flow}$

No. of Companies	No. of Classes
1-3	3
4-19	13
20-24	11
Total	27

Notes: The number of ICT equipment industry patent technology classes that went through a deconcentration of patent *flow* ownership from 1976 to 2007, grouped by the number of companies that account for the 90% of the deconcentration. The sample includes the highest quartile of patents, where quality is measured by citations received.

Table 3: Summary Statistics of Key Patent Flow Variables

Variable		Mean (%)	Std. Dev. (%)
$C25_{flow}$		68	17
Gini		42	15
HHI		49000	48900
New Entry Share		19	12
Lateral Entry Share		15	11
Growth in No of Firms			
	Total	15	31
	US only	14	32
	Foreign only	22	54
Growth in No of Patents			
	Total	20	38
	US only	19	39
	Foreign only	30	68
Firm in Top 5 in Previous Period			
	AT&T	41	49
	Motorola	25	43
	IBM	47	50

Notes: The sample includes the highest quartile of patent applications in the period 1976 to 2007 that are ultimately granted by USPTO on or before 2010. The averages are across the 30 ICT equipment industry patent technology classes, and two-year time period cells. $\mathrm{C25_{flow}}$ is the patent application share of top 25 companies within a cell. Gini refers to the Gini index calculated within each cell. HHI refers to the Herfindahl–Hirschman Index calculated within each cell. New Entry Share is the share of patents in a technology class in a period that are held by assignees that did not have any patents in any ICT equipment industry patent technology classes in prior periods. Lateral Entry Share is the share of patents in a technology class in a period that are held by assignees that had patents in other ICT equipment industry patent technology classes in prior periods, but did not have any patents in the current technology class in an earlier period. Growth is measured within each technology class across two consecutive two-year periods. The firm dummies indicate the presence of the firm among the top 5 patent *flow* holders in the previous two-year period.

Table 4: OLS Analysis of Patent *Flow* Ownership Concentration

Dependent Variable: $C25_{flow}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New Entry Share	-1.45	0.89	-9.09	-7.59	-1.63	1.65	-8.62	-5.95
	(12.51)	(12.87)	(13.4)	(13.62)	(11.72)	(12.2)	(12.27)	(12.71)
Lateral Entry Share	18.93	20.28	13.66	15.45	22.74	24.94	17.65	20.32
	(9.77)*	(9.30)**	(9.74)	(9.3)	(9.95)**	(9.30)**	(9.77)*	(9.19)**
Total Growth in No. of Firms	-7.82				-6.43			
	(1.76)***				(1.95)***			
US only		-6.98				-5.96		
		(1.15)***				(1.21)***		
Foreign only		-2.29				-2.01		
		(0.61)***				(0.66)***		
Total Growth in No. of Patents			-3.22				-1.34	
			(1.22)**				-1.33	
US only				-2.62				-1.12
				(1.19)**				-1.27
Foreign only				-1.57				-1.24
				(0.50)***				(0.52)**
Lagged Dummies if Firm Is in Top 5								
AT&T	0.27	0.16	0.32	0.16	-1.09	-1.35	-0.87	-1.16
	(1.08)	(1.21)	(1.11)	(1.25)	(1.29)	(1.55)	(1.35)	(1.62)
Motorola	1.76	1.36	1.48	1.24	1.26	0.9	1.12	0.87
	(0.88)*	(0.85)	(0.93)	(0.9)	(1.02)	(1)	(1.11)	(1.06)
IBM	-1.5	-1.69	-1.38	-1.51	-1.12	-1.27	-1.07	-1.13
	(1.55)	(1.54)	(1.58)	(1.58)	(1.5)	(1.49)	(1.53)	(1.5)
Time Trend	-3	-2.58	-3.43	-3.06				
	(0.81)***	(0.77)***	(0.77)***	(0.72)***				
Time Trend Sq.	0.07	0.05	0.09	0.07				
	(0.04)*	-0.04	(0.04)**	(0.04)*				
Intercept	84.52	82.7	87.74	86.1	77.56	75.5	80.18	78.01
	(5.10)***	(4.93)***	(4.84)***	(4.59)***	(4.98)***	(4.81)***	(4.81)***	(4.58)***
Class Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	-	-	-	-	Yes	Yes	Yes	Yes
R-Squared	60%	59%	58%	57%	63%	63%	62%	61%

Notes: Regressions are ordinary least squares, with S.E. in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. Standard errors are clustered by class. An observation is a patent technology class and a two-year time period. N is 450 in odd numbered models, and 443 in even numbered models. Each model includes technology class fixed effects. Models 1-4 include a linear and a quadratic time trend; models 5-8 include time fixed effects. The sample includes the highest quartile of patents in the period 1976 to 2007 that are ultimately granted by USPTO on or before 2010, where quality is measured by citations received.

Table 5: Distribution of $C25_{stock}$ Values

Year Group	Mean (%)	St. Dev. (%)	10%	25%	50%	75%	90%
1986	65	17	43	56	63	75	89
1987	63	16	42	56	59	75	87
1988	61	15	41	53	60	72	84
1989	60	14	41	53	59	69	82
1990	59	14	41	54	58	67	78
1991	59	13	39	53	59	70	78
1992	58	12	38	52	58	67	72
1993	58	13	36	52	57	67	72
1994	57	12	36	51	57	66	70
1995	56	12	35	51	57	63	69
1996	55	12	34	51	57	60	70
1997	54	12	34	50	56	60	69
1998	54	11	34	50	55	59	67
1999	53	11	32	48	54	59	66
2000	52	11	31	47	54	58	65
2001	51	11	31	46	53	57	64
2002	50	11	32	44	52	56	64
2003	50	11	32	44	52	56	63
2004	50	12	32	44	52	55	64
2005	51	12	33	45	52	56	65
2006	51	12	34	45	52	56	65
2007	51	11	34	44	52	56	65

Notes: Evolution of the patent application *stock* share for top 25 firms. Each row corresponds to a calendar year. The sample includes the highest quartile patents in the 30 patent technology classes in the ICT equipment industry, where quality is measured by citations received. The patent *stock* of a firm is the discounted sum of its unexpired patents that are applied for between 1976 and 2007 and are ultimately granted on or before 2010.

Table 6: No. of Companies Accounting for 90% of Change in $C25_{stock}$

No. of Companies	No. of Classes
1-3	9
4-19	13
20-24	8
Total	30

Notes: The number of ICT equipment industry patent technology classes that went through a deconcentration of patent *stock* ownership from 1986 to 2007, grouped by the number of companies that account for the 90% of the deconcentration. The sample includes the highest quartile of patents, where quality is measured by citations received.

Table 7: Summary Statistics of Key Patent *Stock* Variable

Variable	Mean (%)	Std. Dev. (%)
C25_stock	55	13
Gini	67	10
HHI	30000	21400
Merger Intensity	1.1	1.6
New Entry Share	3.7	3.0
Lateral Entry Share	2.7	2.1
Growth in No of Firms		
Total	9	6
US only	9	7
Foreign only	9	8
Growth in No of Patents		
Total	10	10
US only	10	11
Foreign only	12	14
Firm in Top 5 in Previous Period		
AT&T	43	50
Motorola	33	47
IBM	55	50

Notes: The sample includes patent stock values from 1986 to 2007, calculated from patent applications in top quartile quality level in the period 1976 to 2007 that are ultimately granted by USPTO on or before 2010. The averages are across the 30 ICT equipment industry patent technology classes and years. $C25_{stock}$ is the patent *stock* share of top 25 companies within a cell. Gini refers to the Gini index calculated within each cell. HHI refers to the Herfindahl–Hirschman Index calculated within each cell. New Entry Share is the share of patents in a technology class in a period that are held by assignees that did not have any patents in any ICT equipment industry patent technology classes in prior periods. Lateral Entry Share is the share of patents in a technology class in a period that are held by assignees that had patents in other ICT equipment industry patent technology classes in prior periods, but did not have any patents in the current technology class in an earlier period. Growth is measured within each technology class across two consecutive calendar years. The firm dummies indicate the presence of the firm among the top 5 patent *stock* holders in the previous period.

Table 8: OLS Analysis of Patent *Stock* Ownership Concentration

Dependent Variable: $C25_{stock}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M&A Intensity (No of patents transferred in M&A / All Telecom)	-2.33	-1.47	-5.26	-4.68	-13.77	-11.56	-13.38	-12.79
	(9.44)	(9.49)	(10.32)	(10.32)	(12.56)	(12.05)	(14.83)	(14.48)
New Entry Share	59.49	51.41	-3.68	-3.65	60.40	51.98	-0.74	-1.07
	(26.93)**	(26.05)*	(30.38)	(29.30)	(26.81)**	(26.02)*	(31.09)	(29.87)
Lateral Entry Share	105.67	107.05	62.05	65.02	107.44	107.89	63.61	66.24
	(40.24)**	(42.60)**	(46.25)	(48.22)	(41.82)**	(44.47)**	(47.39)	(49.33)
Total Growth in No of Firms	-51.22				-55.09			
	(9.54)***				(10.65)***			
US only		-30.68				-34.01		
		(6.94)***				(7.75)***		
Foreign only		-18.14				-18.04		
		(4.08)***				(4.53)***		
Total Growth in No of Patents			-5.53				-7.54	
			(6.65)				(7.69)	
US only				-3.11				-4.96
				(3.69)				(4.20)
Foreign only				-2.88				-2.96
				(3.32)				(3.50)
Lagged Dummies if Firm is in Top 5								
AT&T	-0.66	-0.73	-0.66	-0.63	-0.88	-0.94	-0.94	-0.91
	(1.19)	(1.15)	(1.29)	(1.28)	(1.20)	(1.17)	(1.34)	(1.33)
Motorola	-1.06	-1.05	-0.45	-0.46	-0.86	-0.83	-0.22	-0.23
	(0.92)	(0.93)	(0.96)	(0.96)	(0.88)	(0.89)	(0.95)	(0.96)
IBM	-2.68	-2.63	-2.87	-2.82	-2.83	-2.77	-2.99	-2.97
	(2.01)	(1.95)	(2.36)	(2.32)	(1.97)	(1.93)	(2.30)	(2.27)
Time Trend	-1.33	-1.35	-1.60	-1.58				
	(0.55)**	(0.54)**	(0.58)**	(0.60)**				
Time Trend Sq	0.02	0.02	0.02	0.02				
	(0.01)	(0.01)	(0.01)*	(0.01)				
Intercept	77.19	77.42	78.67	78.46	67.59	67.36	66.29	66.22
	(5.90)***	(5.82)***	(6.38)***	(6.43)***	(2.89)***	(2.75)***	(2.64)***	(2.62)***
Class Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Number of Classes	30	30	30	30	30	30	30	30
R-Squared	0.56	0.57	0.52	0.52	0.57	0.58	0.53	0.53

***, **, * indicate significance at the 1%, 5%, and 10% levels respectively.

Notes: Regressions are ordinary least squares, with S.E. in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. Standard errors are clustered by class. An observation is a patent technology class and a calendar year. N is 660. Each model includes technology class fixed effects. Models 1-4 include a linear and a quadratic time trend; models 5-8 include time fixed effects. . The sample includes patent stock values from 1986 to 2007, calculated from the highest quartile of patents in the period 1976 to 2007 that are ultimately granted by USPTO on or before 2010, where quality is measured by citations received.

Table 9: M&A Deals by ICT Equipment Patent Ownership

		Target has ICT equipment patent		
		Yes	No	Total
Acquirer has ICT equipment patent	Yes	1,881 (9%)	9,667 (49%)	11,548 (58%)
	No	1,127 (6%)	7,203 (36%)	8,330 (42%)
	Total	3,008 (15%)	16,870 (85%)	19,878 (100%)

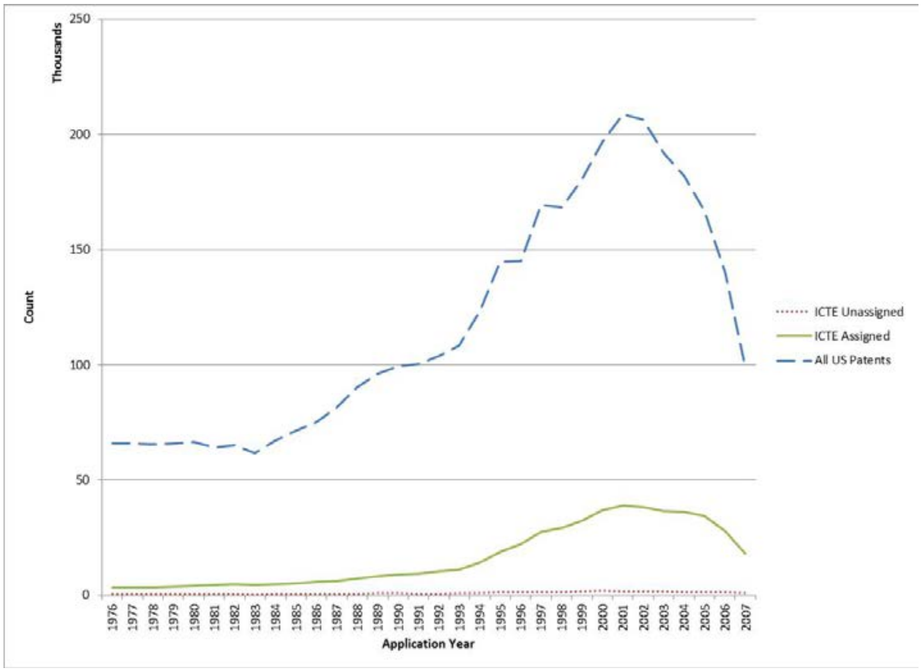
Notes: Breakdown of M&A deal counts based on acquirer and target ICT equipment industry patent ownership status. The sample includes M&A deals from SDC's M&A module between 1979 and 2010, in which either the acquirer or the target has at least one ICT equipment industry patent between 1976 and 2007. The sample includes only the following transaction forms: merger, acquisition, acquisition of majority interest, acquisition of assets, and acquisition of certain assets. Deals that include a firm from the financial industry or a utility firm on either side, or a subsidiary as a target, are dropped from the sample.

Table 10: Cumulative ICT Equipment Patent Stock

Year	Patent Stock			Share Transferred	
	All ICTE	Acquirer	Target	Target/ All ICTE (%)	Target/ Acquirer (%)
1979	2,741	30	2	22	38
1980	3,383	36	3	20	36
1981	3,945	268	39	20	35
1982	4,498	1,062	87	20	33
1983	4,956	1,289	82	19	32
1984	5,402	1,841	90	19	32
1985	5,897	2,108	116	19	33
1986	6,409	2,486	318	19	32
1987	7,009	2,896	357	18	30
1988	7,773	3,497	321	18	30
1989	8,709	4,169	299	18	29
1990	9,619	5,100	272	18	30
1991	10,506	5,650	302	19	31
1992	11,490	6,236	300	18	30
1993	12,534	6,950	279	18	29
1994	14,207	7,948	289	19	29
1995	16,744	9,612	310	19	30
1996	19,762	11,615	385	20	31
1997	23,611	13,809	614	19	30
1998	27,351	15,959	1,024	19	30
1999	31,306	19,989	1,348	19	28
2000	35,736	23,123	1,792	18	27
2001	40,028	25,696	1,771	17	26
2002	43,444	27,572	1,925	16	25
2003	45,960	29,317	1,860	15	24
2004	48,074	30,675	2,909	14	22
2005	49,390	31,624	2,687	13	21
2006	48,904	31,294	3,494	12	20
2007	45,944	29,316	3,412	12	19

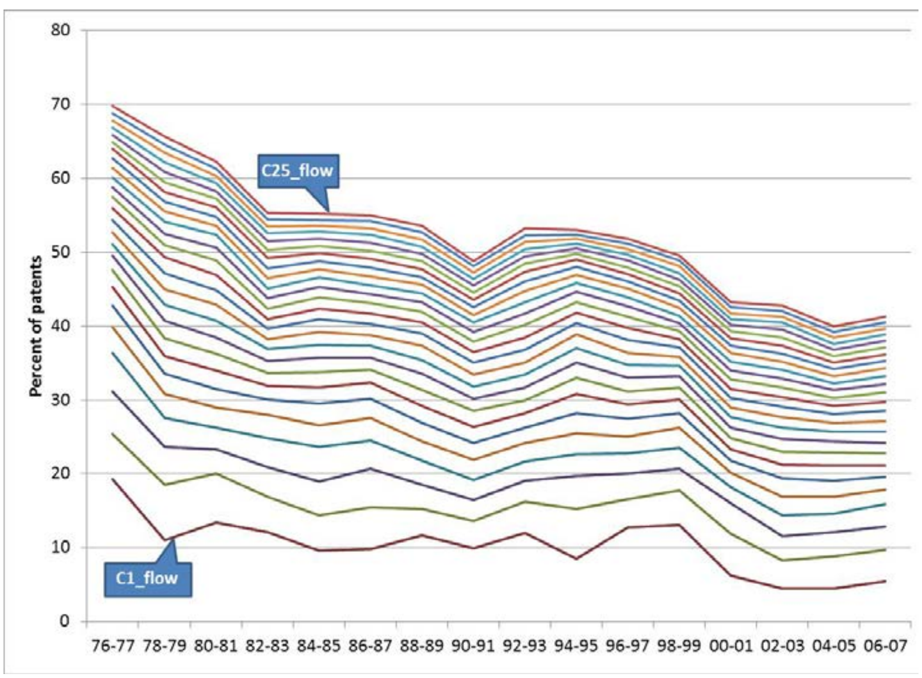
Notes: Cumulative ICT equipment industry patent *stock* transfers through mergers against the entire ICT equipment industry patent *stock* from 1979 to 2007, at the highest quartile patent quality level, where quality is measured by citations received. The patent *stock* is the discounted sum of unexpired patent holdings in the sample. The M&A activity includes deals from SDC's M&A module between 1979 and 2010, in which the target has at least one ICT equipment industry patent between 1976 and 2007. The sample includes only the following transaction forms: merger, acquisition, acquisition of majority interest, acquisition of assets, and acquisition of certain assets. Deals that include a firm from the financial industry or a utility firm on either side, or a subsidiary as a target, are dropped from the sample.

Figure 1: Granted Patents by Application Year



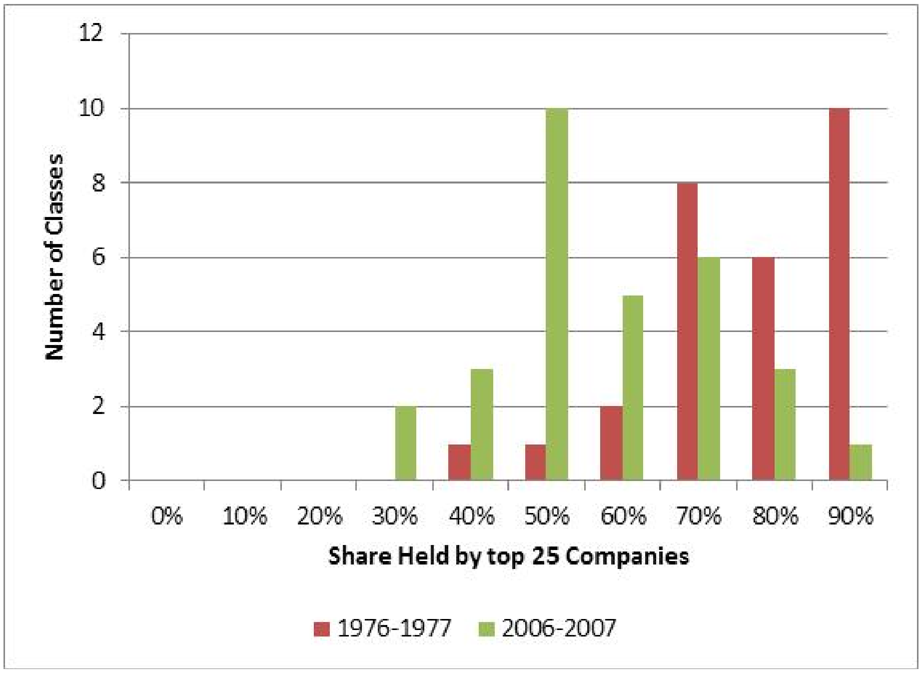
Notes: The sample includes patent applications from 30 patent technology classes in the ICT equipment industry from 1976 to 2007 that are ultimately granted on or before 2010, at all levels of patent quality.

Figure 2: Patent Flow Concentration Levels (Technology Class 385, Optical Waveguides)



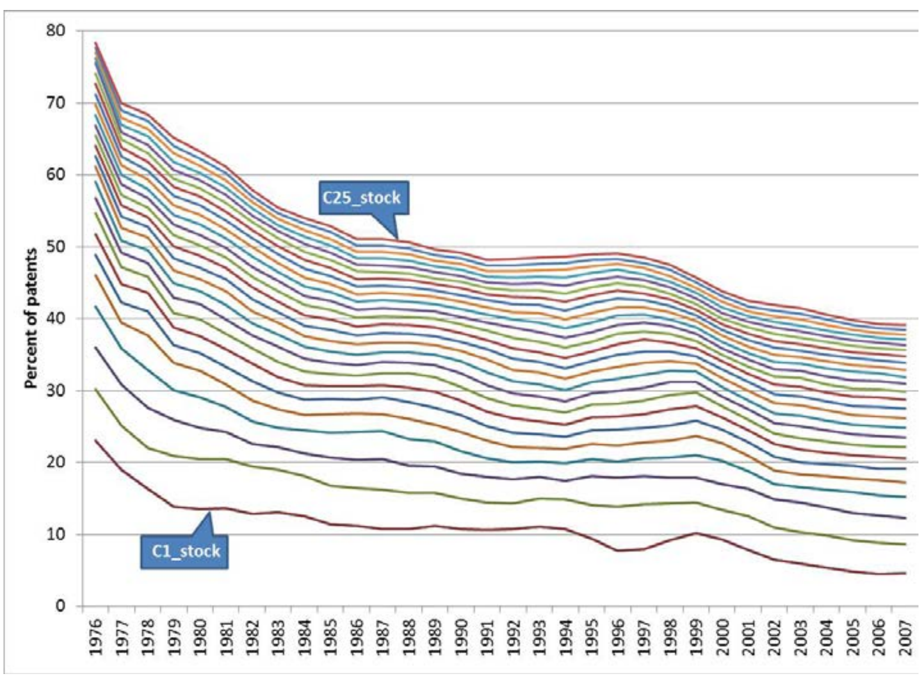
Notes: The sample includes patent applications from the Optical Waveguides technology class (class 385) from 1976 to 2007 that are ultimately granted on or before 2010, at all levels of patent quality. The years are grouped into two year cells. The concentration is measured by the share of top *i* firms in terms of patent applications within each two-year cell, where *i* ranges from 1 to 25.

Figure 3: Change in $C25_{flow}$ distribution from 1976-77 to 2006-07



Notes: The sample includes patent applications from the 30 ICT equipment industry patent technology classes from 1976 to 2007 that are ultimately granted on or before 2010, at top 25% of patent quality. The concentration is measured by the share of top 25 firms in terms of patent applications within each two-year cell.

Figure 4: Patent Stock Concentration Levels (Technology Class 385, Optical Waveguides)



Notes: The sample includes patent applications from the Optical Waveguides technology class (class 385) from 1976 to 2007 that are ultimately granted on or before 2010, at all levels of patent quality. The concentration is measured by the share of top *i* firms in terms of patent *stock* within each year, where *i* ranges from 1 to 25. The patent *stock* is the discounted sum of unexpired patents.

Appendix A. Construction of Patent Data

In this study we use patent data constructed from raw USPTO text files for the period from 1976 to 2010 for a variety of reasons. First, coverage of the NBER data files end in 1999 for the inventor variables, and in 2006 for the remainder of the data; our newly constructed data set goes to 2010. In addition, the NBER data does not include the original names of patent assignees; instead it provides assignee names that have gone through a series of standardizations. We use the original names from the newly constructed data in the process of linking the patent data to the M&A data as described below.

Each week the USPTO makes available a new XML file, which can be accessed on its FTP site, containing bibliographic information for the patents granted within the prior week. In addition, the USPTO makes historical files available through the Google Patents Bulk Downloads site. In this study we supplement the NBER patent data period with the XML files that go back to 2001, and the yearly hierarchical text files that cover the 1976-2001 period, resulting in the utilization of 474 weekly XML files and 26 yearly text files.[27] The newly organized data includes information on granted utility patents applied for and granted between 1976 and 2010, including the application year, grant year, patent technology class, patent assignee name, location, and type.

In order to verify the data quality, we conduct extensive comparison of the newly compiled data against NBER patent data files for the overlapping period. In addition, we compare various aggregate statistics against the USPTO aggregate patent statistics. Table A1 presents patent counts by grant year from our data and the USPTO aggregate statistics page. As observed in the table, the two datasets follow each other very closely. Comparisons on other patent properties follow similar close trends.

In addition to the main bibliographic items, the USPTO assigns a primary technology class and a number of secondary technology classes to each patent at the time of grant. The classification system may be modified over time due to advances in technologies or other reasons. The USPTO updates the technology classes of all patents granted since 1790 and publishes them in the US Patent Grant Master Classification File (MCF) once every two months. Our data includes classifications from the December 2010 version of this product.

As in prior work, we take advantage of citations. The patent data contains the citations made by the granted patents between 1976 and 2010 to other granted patents in earlier periods. This information is

[27] Between 1976 and 2010 the data format changed dramatically, once in 2002 and again in 2005. Some minor changes were also made in 2006. The corresponding variables from various years were matched using the relevant version of the Redbook documentation from the USPTO website.

used in controlling for the heterogeneity in patent value, which has a highly skewed distribution.[28] Prior studies have documented a strong, positive correlation between the value of a patent and the number of citations it receives.[29] In keeping with this literature we control for the quality of patents and repeat the analyses on the sample of highly cited patents, in addition to conducting our analyses on the entire sample of granted patents.

The main pillar of our study is the patent ownership composition, which is constructed using the share of granted patents to each unique assignee. However, the newly compiled USPTO patent data does not contain a unique assignee identifier (akin to NBER's pdpass variable) that is consistent across different patents and across time. The main assignee identifier is the firm name, which is a long string and is susceptible to errors in links due to potential misspellings, different spelling of foreign firms, and differences in abbreviations. To address the lack of unique firm identifiers, we developed a methodology to link different name strings representing the same entity to each other. We discuss the details of this algorithm and a comparison to NBER's unique identifiers in Appendix B.

[28] Harhoff et al. (1999), Pakes and Schankerman (1984).
[29] See, e.g. Harhoff et al. (1999).

Table A1: Granted Utility Patents

Grant Year	USPTO	XML Compilation	Difference
2010	219,614	219,909	295
2009	167,349	167,553	204
2008	157,772	157,894	122
2007	157,282	157,502	220
2006	173,772	173,922	150
2005	143,806	143,927	121
2004	164,290	164,413	123
2003	169,023	169,104	81
2002	167,330	167,424	94
2001	166,035	166,158	123
2000	157,494	157,595	101
1999	153,485	153,592	107
1998	147,517	147,576	59
1997	111,984	112,019	35
1996	109,645	109,653	8
1995	101,419	101,431	12
1994	101,676	101,696	20
1993	98,342	98,384	42
1992	97,444	97,473	29
1991	96,511	96,557	46
1990	90,365	90,421	56
1989	95,537	95,566	29
1988	77,924	77,937	13
1987	82,952	82,967	15
1986	70,860	70,865	5
1985	71,661	71,669	8
1984	67,200	67,215	15
1983	56,860	56,860	0
1982	57,888	57,878	10
1981	65,771	65,766	5
1980	61,819	61,812	7
1979	48,854	48,839	15
1978	66,102	66,084	18
1977	65,269	65,200	69
1976	70,226	70,190	36
Total	3,911,078	3,913,051	2,293

Notes: Patent counts by grant year from USPTO aggregate patent statistics and our newly constructed sample from USPTO XML and text files. Source: U.S. Patent Statistics Chart, Patent Technology Monitoring Team (PTMT), USPTO. Last accessed:2.22.2012. http://www.uspto.gov/web/offices/ac/ido/oeip/taf/us_stat.htm.

Appendix B: Firm Name Linking Algorithm

The newly compiled USPTO patent data does not contain a unique assignee identifier that is consistent across time. The main assignee identifier is the firm name, which is a long string and is susceptible to errors in links due to potential misspellings, different spelling of foreign firms, and differences in abbreviations (such as "corporation," "co." and "co"). To address the lack of unique firm identifiers, we developed a methodology to link different name strings representing the same entity to each other.[30]

We use the same methodology in linking the patent data to the M&A data. Even though the M&A data has better firm identifiers (such as CUSIP numbers), there is no common variable in both the M&A and patent data that can be used to link them, other than the firm name strings. As the process of linking the firm name strings is not trivial, prior merger studies usually use a small sample and link different sources manually.[31] Using the firm names from both datasets and the algorithm discussed below, we are able to identify M&A deals in which either the acquirer or the target firm has at least one patent in the ICT equipment industry.

The linking algorithm consists of two stages: an automated stage and a human intelligence stage. In the automated stage, a computer program standardizes the firm names using common abbreviations and misspellings identified from the data, such as corp, corporation, corpooration, etc. The program then conducts a linking based on common words in company names. Although this program captures a significant portion of actual matches across datasets, it also produces false positives. An example of a false positive would be flagging "ABC Business Solutions" and "XYZ Business Solutions" as the same company due to the common "Business Solutions" phrase. To work around this problem we conduct a human intelligence stage. In this stage the matches identified by the computer program are fed into a crowd-sourcing website, Amazon's Mechanical Turk, for manual human verification that will un-flag the false positives, and leave only the actual matches for use in the data linking.[32]

As a quality check of this process we compare the results to the NBER patent data files, which address the same issue only within the patent data, and mapped 322,783 names into 243,800 unique entities. A

[30] This new variable will assume the role of the NBER patent data's pdpass variable in our dataset.
[31] Ouimet, Zarutskie (2010) uses only the mergers in which the target is a public company; Kerr and Fu (2008) focuses on firms that are in the National Science Foundation's Industry R&D Survey.
[32] Crowdsourcing sites enable the outsourcing of simple tasks to a large group of workers on demand. In our case, workers see a pair of company names matched by the computer program, and are asked to simply choose "yes" or "no" to indicate whether the two companies are the same companies, or not. Outsourcing the linking process to a large workforce and using standard quality control techniques facilitate the timely completion of the task at a reasonable cost.

comparison of the results from our algorithm on a sample of 70,000 firm names to the NBER patent data file suggests that our results are as good as the NBER matches, if not better.

Differences exist between the two algorithms, partly due to random errors and partly due to the difference in what is considered a unique entity. Table B1 provides an illustration through a subset of names for the Sony Corporation. In this list, each line represents a different entity (different pdpass) in the NBER data, whereas all are considered part of the same entity in our data. The three versions of "Sony Electronics Inc" being assigned to different entities in the NBER data give an example of random errors in the matching process.[33] However, designating "Sony Corp of America" and "Sony Electronics Inc" as different entities highlights differences in what we consider a firm. In this assignment we believe that firms create different subsidiaries for a variety of reasons, including tax blueprint, legacy, and other managerial or strategic issues. However, we conjecture that two such firms would go through patent infringement issues only under very extreme, unlikely conditions; therefore we consider them the same entity.

Table B1: Assignee Names for SONY Corp.

NBER pdpass	NBER Assignee Name
11297047	SONY AUSTRALIA PTY LTD
11277610	SONY BROADCAST & COMMUNICATION
11958546	SONY CHEM CORP
13040458	SONY CHEM CORP NEAGARI PLANT
12059716	SONY CINEMA PROD CORP
12104210	SONY COMPUTER ENTERTAIMENT INC
12805945	SONY COMPUTER ENTERTAINMENT AM
13147302	SONY CORP ENTERTAINMENT AMERIC
11205194	SONY CORP OF AMERICA
13171917	SONY CORPORATIOM
21878152	SONY ELECTONICS INC
21589106	SONY ELECTRONIC INC
11399266	SONY ELECTRONICS INC

[33] Similar cases where a match missed by our algorithm is captured by the NBER also exist in the data. Table B1 does not indicate superiority of our algorithm over NBER's.

Appendix C: ICT Equipment Patent Technology Classes Considered

Class	Description
178	Telegraphy
330	Amplifiers
331	Oscillators
332	Modulators
333	Wave transmission lines and networks
334	Tuners
340	Communications: electrical
342	Communications: directive radio wave systems and devices (e.g., radar, radio navigation)
343	Communications: radio wave antennas
348	Television
358	Facsimile and static presentation processing
367	Communications, electrical: acoustic wave systems and devices
370	Multiplex communications
371	Error Detection/Correction and Fault Detection/Recovery
375	Pulse or digital communications
379	Telephonic communications
380	Cryptography, subclasses 255 through 276 for a communication system using cryptography
381	Electrical Audio Signal Processing Systems and Devices, subclasses 1+ for broadcast or multiplex stereo
385	Optical waveguides
398	Optical communications
455	Telecommunications
700	Data processing: generic control systems or specific applications
701	Data processing: vehicles, navigation, and relative location
702	Data processing: measuring, calibrating, or testing
703	Data processing: structural design, modeling, simulation, and emulation
704	Data processing: speech signal processing, linguistics, language translation, and audio compression/decompression
705	Data processing: financial, business practice, management, or cost/price determination
706	Data processing: artificial intelligence
707	Data processing: database and file management or data structures
708	Electrical computers: arithmetic processing and calculating
709	Electrical computers and digital processing systems: multicomputer data transferring
710	Electrical computers and digital data processing systems: input/output
711	Electrical computers and digital processing systems: memory
712	Electrical computers and digital processing systems: processing architectures and instruction processing (e.g., processors)
713	Electrical computers and digital processing systems: support
714	Error detection/correction and fault detection/recovery
715	Data processing: presentation processing of document, operator interface processing, and screen saver display processing
716	Data processing: design and analysis of circuit or semiconductor mask
717	Data processing: software development, installation, and management
718	Electrical computers and digital processing systems: virtual machine task or process management or task management/control
719	Electrical computers and digital processing systems: interprogram communication or interprocess communication (ipc)
720	Dynamic optical information storage or retrieval
725	Interactive video distribution systems
726	Information security

Appendix D: Sensitivity to Patent Quality Levels and Concentration Measures

In the body of the study we use the sample of the highest quartile of patents in terms of quality, present evidence for a deconcentration of patent ownership, and find de novo entry to be one of the main drivers of this deconcentration. In this appendix we show that these results are robust to using alternative quality levels (entire sample and the highest quintile) and alternative measures of concentration (Gini coefficients and HHIs).

The patent literature firmly establishes that patent values are highly skewed, with studies noting that the most valuable 10% of patents account for as much as 80% of total value of patents.[34] An interpretation of this approach is through the Schumpeterian framework. Schumpeter (1934) distinguishes between inventions and innovations: an invention is a potential innovation, and becomes an innovation only when it is commercialized. One could argue that the count of all patents is a better proxy for inventions and the count of high-quality patents is a better proxy for innovations (West and Bogers, 2011). Caballero and Jaffe (1993) offer an alternative interpretation: “We assume that patents are proportional to ideas, and that citations are proportional to ideas used.” Harhoff et al. (1999) and Hall et al. (2005), among others, show a significant relation between the value of patents and the number of citations they receive.

In this study we define high-quality patents as the top quartile within their technology class-year group cells in terms of citations received, and provide results from the sample of high quality patents. However, our main results are robust to inclusion of the entire sample of patents, as well as the highest 10% of the patent pool in terms of quality. Table D1 presents a similar deconcentration result to the result from Table 1, but this time for the entire sample of patents. In comparison to the deconcentration from 86% to 62% in the average flow of high quartile patents, we observe a more modest but persistent deconcentration in the average flow of entire sample of patents from 72% to 55%. Similarly, Table D5 reports a deconcentration from 59% in 1986 to 50% in 2007 in the stock of the entire sample of patents, compared to the reduction from 65% in 1986 to 51% in 2007 in the top quartile of patents.

Table D3 mimics Table 3, and provides the summary statistics of the flow variables from the entire sample of patents, and Table D4 presents the fixed effects regression results. Again, we observe that de novo firm entry is one of the main drivers of deconcentration. Growth in the number of patents also has the same sign as in the high quality patent analyses, but in the entire sample of patents this result is not

[34] See, e.g., Scherer and Harhoff (2000). Other studies stressing the skewed distribution of patent values include Harhoff et al. (1999) and Pakes and Schankerman (1984).

statistically significant. Tables D7 and D8 provide similar results for the patent stock in the entire patent sample, also yielding qualitatively same results.

A similar yet stronger deconcentration and the same qualitative results from the regressions are also observed in the top quintile of patents; though we do not report these results for brevity.

Having established the existence of a deconcentration trend at different levels of patent quality, we now turn our attention the alternative measures of concentration. The share of top 25 firms, C25, is a direct measure of concentration and is easy to interpret in our setting. However, more general measures of concentration may be constructed from the underlying ownership data, including Gini coefficients and HHIs. In our data the correlation among HHIs, Gini coefficients, and C25 within each technology class across years exceeds 0.75 on average, and this also holds after controlling for patent quality. As a result, not surprisingly, we observe a deconcentration trend in average HHIs and average Gini coefficients across technology classes over time (Figures D.5 and D.6), and this result is robust at various levels of patent quality.[35]

In choosing among these alternative measures of concentration, prior literature is inconclusive at best, and the choice is usually arbitrary (see, e.g., Jacquemin and Kumps, 1971). In our sample, the patenting behavior of firms is heterogeneous and the ownership is highly skewed, with few firms owning a majority of the patents, and a majority of the firms owning only few patents. Both HHI and Gini coefficient measures are susceptible to the presence of many small patent owners in the data. In fact, Malerba and Orsenigo (1996) use HHI to proxy for the asymmetry in the data (and C4 as the concentration measure). Furthermore, the literature suggests a sharp contrast in the patenting behavior of large and small firms, with large firms having a higher patents-per-R&D-dollar than smaller firms (Bound et al. 1984). To mitigate the effects of the skewed distribution and the different patenting behavior, we adopt the share-based measure of concentration, C25.

In addition to observing similar historical trends of deconcentration in C25, HHI and Gini coefficients, the regression models that use C25, HHIs and Gini coefficients also produce qualitatively same results, a summary of which is presented in Table D11. Panel A in Table D11 presents the coefficients for the total firm growth and the total patent growth from the first column of Table 4, Table D4, and their counterpart models using Gini coefficients and HHIs as the dependent variable. Panel B presents the same model estimates from the patent stock models. As noted earlier, the results suggest that growth in the number of firms results in reduced ownership concentration in both patent flow and patent stock,

[35] Note that by construction C25 and HHI both increase with concentration, whereas Gini coefficient decreases.

across all dependent variables, and across all levels of patent quality (indicated by a negative coefficient estimates when the dependent variable is C25 or HHI, and by a positive coefficient estimate when the dependent variable is the Gini coefficient). Similarly, the estimates for the growth in the number of patents also suggest a deconcentration in the C25 and Gini coefficient models. The positive estimates in the HHIs are not statistically significant, hence do not contradict the evidence presented in the C25 and Gini models. The similarity of the results across the board suggest that the results presented in the body of the paper using top quartile of patents on the share of top 25 firms are not artifacts of our choice of quality level or measure of concentration, but are representative of the underlying phenomena.

Table D1: Distribution of $C25_{flow}$ Values

Year Group	Mean (%)	St. Dev. (%)	10%	25%	50%	75%	90%
76-77	72	17	53	62	70	86	100
78-79	72	17	52	62	67	85	98
80-81	72	16	53	63	72	82	90
82-83	69	16	51	61	68	76	94
84-85	64	14	48	56	62	72	83
86-87	62	13	45	55	63	70	80
88-89	60	13	45	53	63	68	76
90-91	61	12	46	53	62	69	76
92-93	60	12	40	54	61	68	74
94-95	58	12	35	54	61	66	71
96-97	58	12	36	53	60	65	71
98-99	56	12	36	50	58	62	71
00-01	53	12	35	45	55	59	66
02-03	53	12	37	46	55	59	65
04-05	54	13	38	49	53	61	73
06-07	55	13	37	49	55	63	71

Notes: Evolution of the patent application *flow* share for top 25 firms that are ultimately granted on or before 2010. Each row corresponds to a two-year time period. The sample includes patent applications from 30 patent technology classes in the ICT equipment industry, at all levels of patent quality.

Table D3: Summary Statistics of Key Patent *Flow* Variables

Variable	Mean (%)	Std. Dev.(%)
C25_flow	60	14
Gini	57	13
HHI	34100	26200
New Entry Share	12	8
Lateral Entry Share	11	7
Growth in No of Firms		
Total	13	25
US only	13	27
Foreign only	17	54
Growth in No of Patents		
Total	19	35
US only	18	37
Foreign only	26	81
Firm in Top 5 in Previous Period		
AT&T	37	48
Motorola	25	43
IBM	41	49

Notes: The sample includes patent applications from all levels of quality in the period 1976 to 2007 that are ultimately granted by USPTO on or before 2010. The averages are across the 30 ICT equipment industry patent technology classes, and two-year time period cells. $\mathrm{C25_{flow}}$ is the patent application share of top 25 companies within a cell. Gini refers to the Gini index calculated within each cell. HHI refers to the Herfindahl–Hirschman Index calculated within each cell. New Entry Share is the share of patents in a technology class in a period that are held by assignees that did not have any patents in any ICT equipment industry patent technology classes in prior periods. Lateral Entry Share is the share of patents in a technology class in a period that are held by assignees that had patents in other ICT equipment industry patent technology classes in prior periods, but did not have any patents in the current technology class in an earlier period. Growth is measured within each technology class across two consecutive two-year periods. The firm dummies indicate the presence of the firm among the top 5 patent *flow* holders in the previous two-year period.

Table D4: OLS Analysis of Patent *Flow* Ownership Concentration

Dependent Variable: $C25_{flow}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New Entry Share	-28.29	-29.66	-34.76	-34.95	-20.74	-22.59	-29.23	-29.58
	(34.95)	(35.41)	(34.88)	(35.01)	(35.74)	(36.32)	(35.90)	(36.11)
Lateral Entry Share	30.37	29.52	25.41	24.83	35.71	34.9	29.46	29.22
	(12.03)**	(12.52)**	(12.74)*	(13.13)*	(12.69)***	(13.45)**	(13.51)**	(14.26)**
Total Growth in No. of Firms	-5.87				-7.87			
	(1.95)***				(2.37)***			
US only		-4.57				-5.98		
		(1.57)***				(1.86)***		
Foreign only		-0.16				-0.34		
		(0.32)				(0.36)		
Total Growth in No. of Patents			-0.69				-1.39	
			(1.12)				(1.44)	
US only				-0.28				-0.97
				(0.83)				(1.04)
Foreign only				0.02				-0.03
				(0.2)				(0.26)
Lagged Dummies if Firm Is in Top 5								
AT&T	-1.43	-1.26	-1.06	-1.01	-1.83	-1.63	-1.31	-1.28
	(0.95)	(0.96)	(0.95)	(0.94)	(0.97)*	(0.97)	(0.94)	(0.94)
Motorola	1.55	1.52	1.52	1.5	0.74	0.75	0.9	0.9
	(0.83)*	(0.84)*	(0.83)*	(0.83)*	(0.74)	(0.77)	(0.75)	(0.76)
IBM	-0.02	-0.16	-0.28	-0.34	-0.17	-0.31	-0.32	-0.37
	(1.15)	(1.14)	(1.06)	(1.07)	(1.31)	(1.3)	(1.2)	(1.2)
Time Trend	-1.76	-1.82	-2.27	-2.33				
	(0.60)***	(0.60)***	(0.66)***	(0.68)***				
Time Trend Sq.	0.03	0.03	0.06	0.06				
	(0.03)	(0.03)	(0.03)*	(0.03)*				
Intercept	73.17	73.38	75.19	75.32	68.18	68.39	70.36	70.39
	(6.82)***	(6.84)***	(6.56)***	(6.64)***	(7.90)***	(8.02)***	(7.68)***	(7.78)***
Time Fixed Effects	-	-	-	-	Yes	Yes	Yes	Yes
R-Squared	57%	56%	55%	55%	59%	58%	56%	56%

Notes: Regressions are ordinary least squares, with S.E. in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. Standard errors are clustered by class. An observation is a patent technology class and a two-year time period. N is 450. Each model includes technology class fixed effects. Models 1-4 include a linear and a quadratic time trend; models 5-8 include time fixed effects. The sample includes patent applications from all levels of quality in the period 1976 to 2007 that are ultimately granted by USPTO on or before 2010.

Table D5: Distribution of $C25_{stock}$ Values

Year Group	Mean (%)	St. Dev. (%)	10%	25%	50%	75%	90%
1986	59	12	44	53	60	66	73
1987	58	12	43	51	59	64	72
1988	57	12	42	51	59	63	71
1989	56	11	42	50	57	62	71
1990	56	12	43	50	57	63	71
1991	56	12	43	49	57	63	72
1992	56	12	42	50	56	64	71
1993	56	12	41	49	56	64	71
1994	56	12	38	49	57	64	71
1995	55	12	36	49	57	63	70
1996	55	12	35	49	56	62	70
1997	55	12	35	49	57	62	69
1998	54	12	35	48	56	61	69
1999	53	12	34	46	55	61	69
2000	53	12	33	46	55	59	68
2001	52	12	33	44	54	59	66
2002	51	12	34	42	53	58	64
2003	51	12	33	43	52	57	63
2004	50	12	33	43	52	56	64
2005	50	12	34	43	51	56	65
2006	50	12	34	43	51	56	65
2007	50	12	33	43	51	56	64

Notes: Evolution of the patent application *stock* share for top 25 firms. Each row corresponds to a calendar year. The sample includes patent applications from 30 patent technology classes in the ICT equipment industry, at all levels of patent quality. The patent *stock* of a firm is the discounted sum of its unexpired patents that are applied for between 1976 and 2007 and are ultimately granted on or before 2010.

Table D7: Summary Statistics of Key Patent *Stock* Variable

Variable		Mean (%)	Std. Dev.(%)
C25_stock		54	12
Gini		77	8
HHI		25900	16200
Merger Intensity		0.9	1.5
New Entry Share		2.3	1.9
Lateral Entry Share		1.8	1.2
Growth in No of Firms			
	Total	9	6
	US only	9	6
	Foreign only	9	5
Growth in No of Patents			
	Total	10	10
	US only	10	11
	Foreign only	11	10
Firm in Top 5 in Previous Period			
	AT&T	42	49
	Motorola	32	46
	IBM	43	50

Notes: The sample includes patent stock values from 1986 to 2007, calculated from patent applications from all levels of quality in the period 1976 to 2007 that are ultimately granted by USPTO on or before 2010. The averages are across the 30 ICT equipment industry patent technology classes and years. $\mathrm{C25}_{\mathrm{stock}}$ is the patent *stock* share of top 25 companies within a cell. Gini refers to the Gini index calculated within each cell. HHI refers to the Herfindahl–Hirschman Index calculated within each cell. New Entry Share is the share of patents in a technology class in a period that are held by assignees that did not have any patents in any ICT equipment industry patent technology classes in prior periods. Lateral Entry Share is the share of patents in a technology class in a period that are held by assignees that had patents in other ICT equipment industry patent technology classes in prior periods, but did not have any patents in the current technology class in an earlier period. Growth is measured within each technology class across two consecutive calendar years. The firm dummies indicate the presence of the firm among the top 5 patent *stock* holders in the previous period.

Table D8: OLS Analysis of Patent *Stock* Ownership Concentration

Dependent Variable: $C25_{stock}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M&A Intensity (No of pats transferred in M&A / All Tekecom)	0.58	0.53	0.67	0.58	-12.02	-12.10	-11.37	-11.18
	(6.60)	(6.57)	(6.63)	(6.68)	(8.82)	(8.56)	(9.06)	(9.01)
New Entry Share	-39.67	-40.56	-47.88	-47.89	-39.09	-39.74	-47.57	-46.61
	(19.05)**	(19.01)**	(20.85)**	(20.10)**	(20.33)*	(20.26)*	(22.26)**	(21.52)**
Lateral Entry Share	3.92	3.84	-1.64	-2.55	4.63	4.60	2.40	1.85
	(38.40)	(38.56)	(42.53)	(42.98)	(39.73)	(39.94)	(43.98)	(44.24)
Total Growth in No of Firms	-3.43				-6.61			
	(6.33)				(6.81)			
US only		-1.48				-4.05		
		(5.33)				(5.55)		
Foreign only		-1.88				-2.52		
		(4.77)				(4.81)		
Total Growth in No of Patents			0.64				-1.55	
			(5.15)				(5.90)	
US only				0.04				-2.19
				(2.84)				(3.30)
Foreign only				0.85				0.80
				(4.43)				(4.89)
Lagged Dummies if Firm is in Top 5								
AT&T	-1.64	-1.65	-1.56	-1.56	-1.85	-1.84	-1.77	-1.78
	(0.87)*	(0.86)*	(0.92)	(0.92)*	(0.89)**	(0.88)**	(0.94)*	(0.93)*
Motorola	0.56	0.56	0.58	0.58	0.36	0.36	0.41	0.41
	(0.57)	(0.57)	(0.56)	(0.57)	(0.61)	(0.61)	(0.60)	(0.61)
IBM	-0.35	-0.36	-0.41	-0.43	-0.55	-0.55	-0.54	-0.57
	(0.87)	(0.88)	(0.80)	(0.80)	(0.91)	(0.91)	(0.84)	(0.85)
Time Trend	-0.11	-0.12	-0.17	-0.17				
	(0.36)	(0.36)	(0.32)	(0.34)				
Time Trend Sq	-0.01	-0.01	-0.01	-0.01				
	(0.01)	(0.01)	(0.01)	(0.01)				
Intercept	62.40	62.43	62.70	62.69	62.30	62.32	61.87	61.78
	(4.11)***	(4.09)***	(3.61)***	(3.78)***	(1.81)***	(1.73)***	(1.63)***	(1.66)***
Class Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Number of Classes	30	30	30	30	30	30	30	30
R-Squared	0.48	0.48	0.48	0.48	0.50	0.50	0.50	0.50

***, **, * indicate significance at the 1%, 5%, and 10% levels respectively.

Notes: Regressions are ordinary least squares, with S.E. in parentheses. ***, **, * indicate significance at the 1%, 5%, and 10% levels respectively. Standard errors are clustered by class. An observation is a patent technology class and a calendar year. N is 660. Each model includes technology class fixed effects. Models 1-4 include a linear and a quadratic time trend; models 5-8 include time fixed effects. The sample includes patent stock values from 1986 to 2007, calculated from patent applications from all levels of quality in the period 1976 to 2007 that are ultimately granted by USPTO on or before 2010.

Table 11D: Fixed effects regression estimates

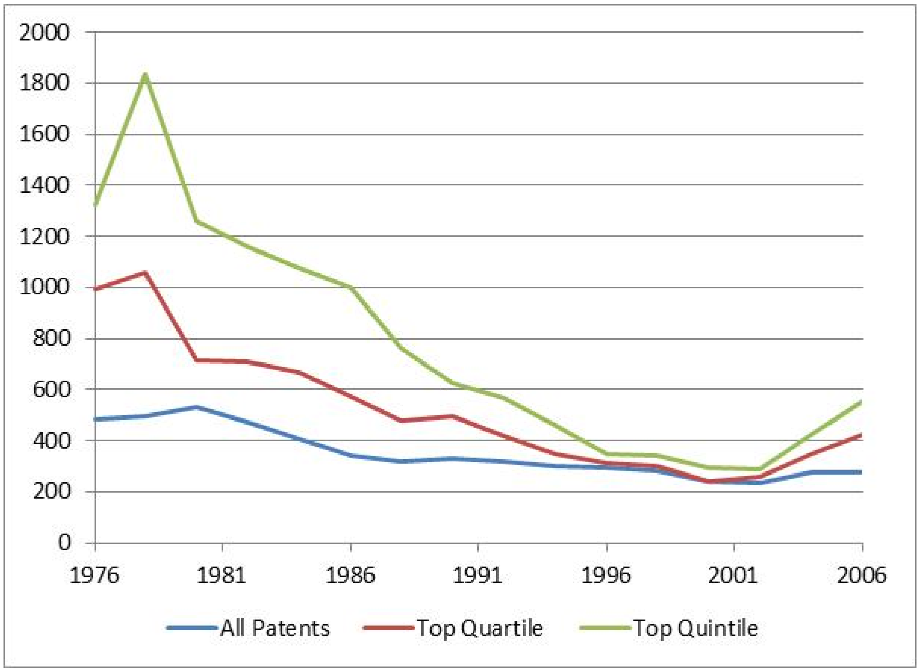
Panel A: Patent Flow

	Independent Variable					
	Total Growth in No of Firms			Total Growth in No of Patents		
Dependent Variable	All Patents	Top 25%	Top 10%	All Patents	Top 25%	Top 10%
C25	-5.87 (1.95)***	-7.82 (1.76)***	-6.41 (1.97)***	-0.69 (1.12)	-3.22 (1.22)**	-4.66 (1.60)***
Gini	8.72 (1.98)***	5.94 (1.54)***	1.53 (1.16)	8.65 (0.93)***	7.82 (1.28)***	6.22 (1.36)***
HHI	-120 (29)***	-350 (131)**	-259 (118)**	73 (83)	-25 (132)	35 (163)

Panel B: Patent Stock

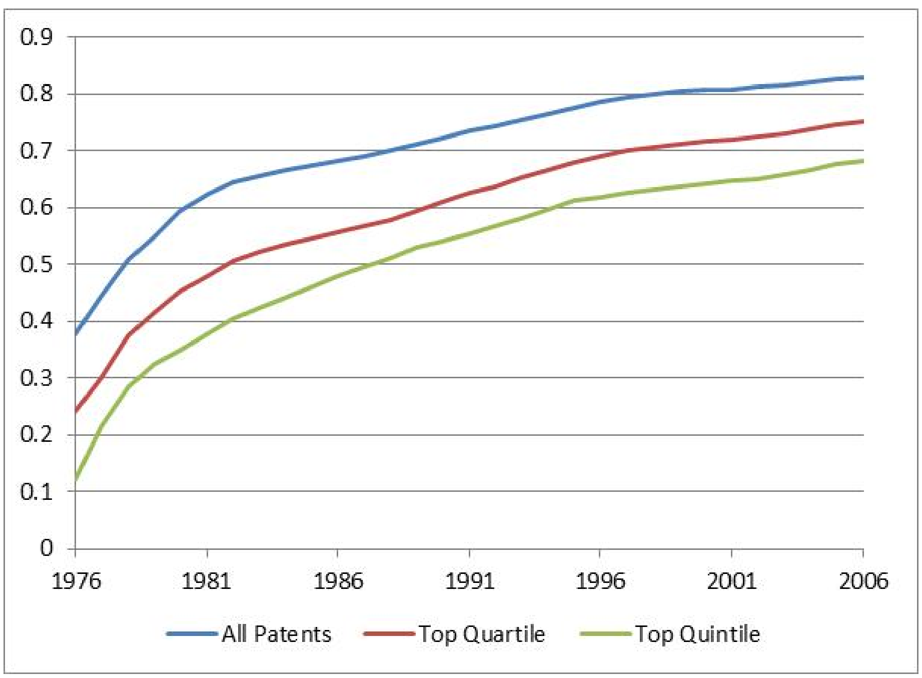
	Independent Variable					
	Total Growth in No of Firms			Total Growth in No of Patents		
Dependent Variable	All Patents	Top 25%	Top 10%	All Patents	Top 25%	Top 10%
C25	-3.43 (6.33)	-51.22 (9.54)***	-90.27 (26.58)***	0.64 (5.15)	-5.53 (6.65)	-7.30 (7.30)
Gini	37.27 (4.51)***	23.52 (5.59)***	3.76 (5.95)	12.20 (1.98)***	13.36 (3.10)***	6.44 (3.04)**
HHI	-244 (215)	-726 (222)***	-1129 (326)***	44 (100)	82 (121)	84 (138)

Figure D5: Average Patent Ownership HHIs across ICT Equipment Technology Classes



Notes: The sample includes patent applications from the 30 ICT equipment industry patent technology classes from 1976 to 2007 that are ultimately granted on or before 2010. The concentration is measured by the Herfindahl–Hirschman Index (HHI) within each technology class and two year cell. The patent quality is measured by citations received.

Figure D6: Average Gini Coefficients for Patent Ownership across ICT Equipment Technology Classes



Notes: The sample includes patent applications from the 30 ICT equipment industry patent technology classes from 1976 to 2007 that are ultimately granted on or before 2010. The concentration is measured by the Gini Coefficient within each technology class and year. The patent quality is measured by citations received.