Technological Leadership (de)Concentration: Causes in ICTE

June, 2016

Appendices

Appendix A: Data

Appendix A1: 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 ends 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 twenty-six yearly text files.[1] 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

[1] 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.

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 used in controlling for the heterogeneity in patent value, which has a highly skewed distribution.[2] Prior studies have documented a strong, positive correlation between the value of a patent and the number of citations it receives.[3] 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 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 A2.

[2] Harhoff et al. (1999), Pakes and Schankerman (1984).
[3] 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 A2: 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.[4]

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.[5] 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.[6]

[4] This new variable will assume the role of the NBER patent data’s pdpass variable in our dataset.
[5] 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.
[6] 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

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 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 A2 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." assigned to different entities in the NBER data give an example of random errors in the matching process.[7] 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 speculate that two such firms would go through patent infringement issues only under very extreme, unlikely conditions; therefore we consider them the same entity.

large workforce and using standard quality control techniques facilitate the timely completion of the task at a reasonable cost.

[7] Similar cases where a match missed by our algorithm is captured by the NBER also exist in the data. Table A2 does not indicate superiority of our algorithm over NBER's.

Table A2: 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

Appendix A3: 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 percent of US patent stock in the upstream. We identify the ICT equipment industry in the patent data by extracting forty-four patent technology classes from the USPTO patent data: fourteen technology classes identified as communications by Hall, Jaffe, and Trajtenberg (2001); twenty-two technology classes in the seven-hundred ranges; and eight classes identified as relevant to telecommunications in the USPTO communications report. We then drop fourteen 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 thirty 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 percent of all patenting activity in the United States. Figure A1 provides a breakdown of granted patents over the years. As observed, the number of patents granted in ICT equipment follows a trend similar 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]

[8] Appendix A5 contains lists of all considered classes. The dropped classes correspond to roughly 10% of the entire patenting in ICT.

[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

The patent literature firmly establishes that patent values are highly skewed, with studies noting that the most valuable 10 percent of patents account for as much as 80 percent of the 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 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 A4.

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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.

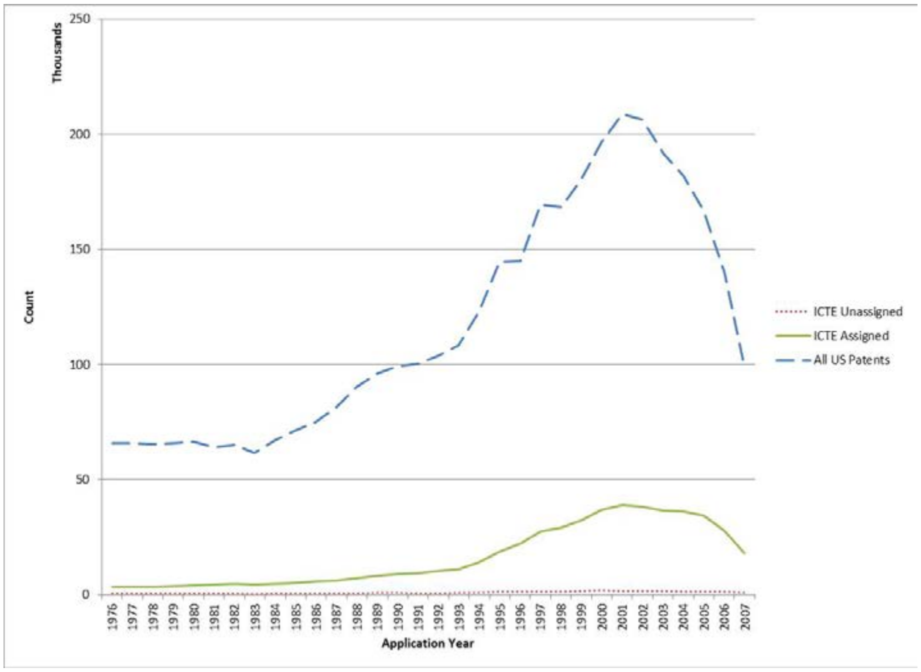

Figure A1: Granted patents by application year

Notes: The sample includes patent applications from thirty 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.

Appendix A4: 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. 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 percent of the ownership of the target company and, for the pre-1992 period, if the deal valuation is at least $1 million (all deal 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 and outright sale of patents are two other channels, both of which provide additional information about the market demand for ideas.[13] However, comparison with Serrano (2010) leads us to believe that a merger is a very good proxy for demand. Serrano records that 13.5 percent of all granted patents are traded over their life-cycle; we obtain a

[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).

similar scale of transfer (11%) through M&A activity, which suggests that over 80 percent (11/13.5 > .8) of the transfers in ownership of patents measured by Serrano occur due to M&A.

Table A3: 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.

Appendix A5: 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
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
720	Dynamic optical information storage or retrieval
725	Interactive video distribution systems
726	Information security

Appendix B: Composition of Ownership in New Patents: The Model

In this section we combine the historical trends we have established 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 twenty-five firms, is our dependent variable. The basic model is as follows:

$$(C25_{flow})_{jt} = \beta_1 * (\text{Top 10 MSA Share})_{jt} + \beta_2 * (\text{New Entry})_{jt} + \beta_3 * (\text{Lateral Entry})_{jt}$$

$$+ \beta_4 * (\text{Growth})_{jt} + \beta_5 * \delta_{j,t-1,AT\&T} + \beta_6 * \delta_{j,t-1,Motorola} + \beta_7 * \delta_{j,t-1,IBM}$$

$$+ \gamma_j + \theta_t + \varepsilon_{jt},$$

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.[14] We use two sets of entry measures, defined on one-year and four-year time windows. Similarly, 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 B2. The dependent variable in the model is $C25_{flow}$, the share of new patents held by the top twenty-five firms. All models include class and time fixed effects.[15] The standard errors are clustered by technology-class.[16] The columns differ in the inclusion of different patent growth and number of firm growth variables. With time fixed effects and class fixed effects, identification comes from changes within class.

Figure B1 reports the coefficient estimates of the time fixed effects from the model, which indicates a secular deconcentration over the years. On average, the concentration of a

[14] The construction of these variables are provided in the Data Section, and Table B1 provides summary statistics.

[15] In unreported results we use a linear and a quadratic time trend instead of time fixed effects. The qualitative results remain the same in these alternative specifications.

[16] Two-way clustering of the standard errors by class and time does not change our statistical inferences.

technology-class in a year-group is 16.7 percent (=-0.025-0.14) lower in the 2004 to 2005 period than in the 1978 to 1979 period. Considering the 24 percent overall decrease between these periods (Table 1), the secular time trend constitutes an important component. In discussing the impact of other covariates below, we will occasionally compare the impact induced to this time impact of 16.7 percent to gauge a relative sense.

The main qualitative results seem to hold across all models. 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 percent growth in the number of firms resulting in a decrease of 7.2 percent in the ownership share of top twenty-five firms; a technology class at the average firm growth rate of 15 percent every two years faces a reduction of approximately 1.1 percent (=0.071 * 0.15) in the share of top twenty-five firms in two years, even after controlling for individual class and time effects.[17] Assuming the average growth rate over the 1978 to 2004 period, this corresponds to 91 percent (=14 periods * (0.011 / 0.16)) of the change induced by time fixed effects over the same period. When we break the growth variable into US-based growth and foreign growth, we observe that, contrary to conventional wisdom, the US-based growth is a bigger driving force of deconcentration than the foreign growth. Furthermore, in the entire sample of patents, the foreign growth coefficient loses its statistical significance. 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 percent every two years faces a reduction of approximately 0.4 percent (=0.018 * 0.20).[18]

However, new entry does not seem to have a statistically significant impact. 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 of lateral entry, 15 percent per period, faces a 3.5 percent (=0.23 * 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, hence they 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

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

[18] Intriguingly, foreign growth is the driving force for top quality patents. We do not know what accounts for this difference between the full sample and high quality sample. We speculate that foreign firms are few in numbers and hold disproportionately more high quality patents, but it is not clear why that should be the case.

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. The effect of lateral entry loses its statistical significance when the variable is defined based on the previous four years, though the signs of the estimates are in the same (positive) direction as the one-year construct.

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 2.7 percent increase in the ownership concentration of the patent class over two years. 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 caused* by the presence of Motorola in these technology areas or whether Motorola *selected to invent in areas* with this feature.

As in the stock analyses, the main results from the flow analyses 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* and *Top 10 MSA Share* work 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 for the growth in the number of firms; the impact of lateral entry and top ten MSA share increases, but the patent growth loses both economic and statistical significance.[19]

These findings also raise an interesting open question. Looking at how 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 percent in 1978 to 1979 and gradually drops to 10 percent in 2006 to 2007. The lateral entry share follows a similar declining trend, with 32 percent in 1978 to 1979, and 8 percent in 2006 to 2007. It is possible that the factors of lateral entry and

[19] 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 statistically significant at half the magnitude, whereas growth in the number of patents increases. The results also hold qualitatively.

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 large a role in the future.

Table B1: Summary statistics of key patent flow variables

Variable	Mean (%)	Std. Dev. (%)
C5_flow	34	15
C25_flow	68	17
HHI	49,000	48,900
Patent Share by Entrants		
New Entrants - 1 year	19	12
New Entrants - 4 years	30	23
Lateral Entrants - 1 year	15	11
Lateral Entrants - 4 years	16	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
Geography		
Top 10 MSA share	51	14
Top 10 County share	16	11
Firm in Top 5 in Previous Period		
AT&T	42	49
Motorola	29	45
IBM	49	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 thirty ICT equipment industry patent technology classes, and two-year time period cells. $C25_{flow}$ is the patent application share of top twenty-five companies within a 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 five patent *flow* holders in the previous two-year period.

Table B2: OLS analysis of patent *flow* ownership concentration

Dependent Variable: $C25_{flow}$		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Location Top 10 MSAs		18.43	18.59	17.14	17.70	16.61	16.52	16.09	16.56
		(6.13)***	(5.90)***	(5.66)***	(5.50)***	(5.59)***	(5.27)***	(5.30)***	(5.09)***
New Entry Share	(1 year)	5.19	8.22	-2.65	-0.07				
		(10.03)	(10.79)	(11.10)	(11.64)				
	(4 years)					-2.91	0.51	-8.89	-6.09
						(8.72)	(9.61)	(8.58)	(9.77)
Lateral Entry Share	(1 year)	23.26	25.29	17.67	20.27				
		(9.66)**	(8.82)***	(9.30)*	(8.69)**				
	(4 years)					9.29	11.76	5.58	8.18
						(12.06)	(13.83)	(11.50)	(14.16)
Total Growth in No of Firms		-7.19				-5.23			
		(1.71)***				(1.36)***			
	US only		-6.33				-5.54		
			(1.24)***				(1.10)***		
	Foreign only		-2.16				-1.52		
			(0.66)***				(0.80)*		
Total Growth in No of Patents				-1.81				-0.70	
				(1.07)*				(1.03)	
	US only				-1.11				-0.57
					(1.15)				(1.04)
	Foreign only				-1.36				-1.14
					(0.51)**				(0.64)*
Lagged Dummies if Firm is in Top 5									
	AT&T	-1.28	-1.69	-0.98	-1.40	-1.08	-1.53	-0.86	-1.26
		(1.29)	(1.54)	(1.32)	(1.60)	(1.44)	(1.63)	(1.49)	(1.72)
	Motorola	2.73	2.53	2.69	2.55	3.23	3.16	3.12	3.06
		(1.09)**	(1.09)**	(1.12)**	(1.10)**	(1.32)**	(1.36)**	(1.34)**	(1.42)**
	IBM	-0.59	-0.78	-0.42	-0.51	-0.44	-0.56	-0.24	-0.27
		(1.61)	(1.57)	(1.63)	(1.56)	(1.72)	(1.70)	(1.74)	(1.69)
Intercept		50.81	49.94	53.64	52.72	53.88	52.67	56.23	55.01
		(3.28)***	(3.16)***	(3.04)***	(2.87)***	(3.45)***	(3.38)***	(3.12)***	(3.02)***
N		450	443	450	443	450	443	450	443
Number of Classes		30	30	30	30	30	30	30	30
R-Squared		0.65	0.65	0.64	0.63	0.64	0.63	0.63	0.62

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 from 1976 to 2007 that are ultimately granted by USPTO on or before 2010, where quality is measured by citations received.

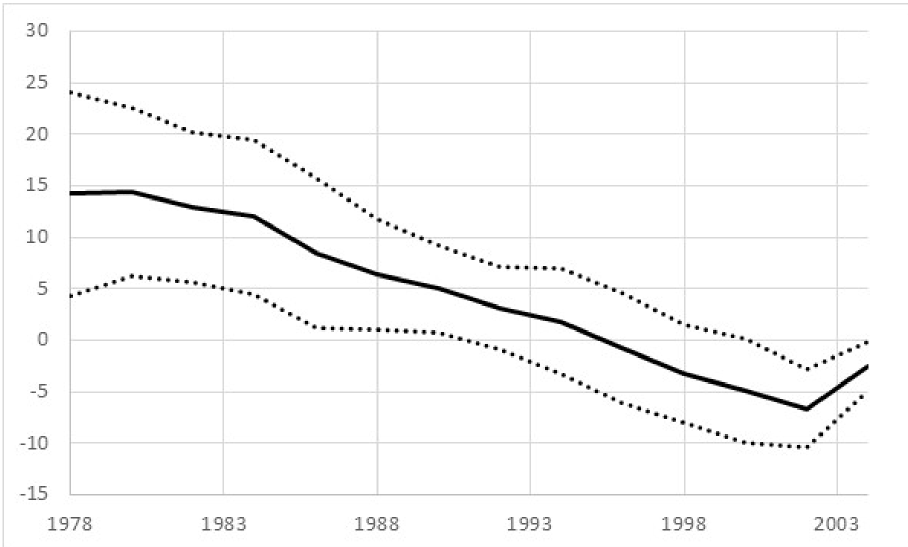

Figure B1: Patent flow – time fixed effects coefficient estimates

Notes: Coefficient estimates of time fixed effects from Model 1 in Table B2. Regressions are ordinary least squares, the solid line represents the coefficient estimates, and the dashed lines indicate the 95% confidence intervals obtained from standard errors clustered by class. An observation is a patent technology class and a two-year time period. N is 450. Each model includes technology class and 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.

Appendix C: 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 decile) and alternative measures of concentration (HHIs).

The patent literature firmly establishes that patent values are highly skewed, with studies noting that the most valuable 10 percent of patents account for as much as 80 percent of total value of patents.[20] 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 the inclusion of the entire sample of patents, as well as the highest 10 percent of the patent pool in terms of quality. Table C1 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 percent to 62 percent 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 percent to 55 percent. Similarly, Table C4 reports a deconcentration from 59 percent in 1986 to 50 percent in 2007 in the stock of the entire sample of patents, compared to the reduction from 65 percent in 1986 to 51 percent in 2007 in the top quartile of patents.

[20] 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).

Table C2 mimics Table B1 and provides the summary statistics of the flow variables from the entire sample of patents; Table C3 presents the fixed effects regression results. Again, we observe that growth in the number of firms is one of the main drivers of deconcentration at all quality levels. Growth in the number of patents is borderline statistically significant for C25 in the high quality samples and is insignificant everywhere else.

Having established the existence of a deconcentration trend at different levels of patent quality, we now turn our attention to the alternative measures of concentration. The share of top twenty-five 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 and C25s 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 across technology classes over time (Figure C1), and this result is robust at various levels of patent quality. The Gini coefficient, on the other hand, is highly sensitive to the presence of many small firms by construction, and hence is not a good proxy for the underlying phenomenon at the focus of this paper. In fact, average Gini values increase over the years (Figure C2), which is the opposite trend of our C25 and HHI measures.

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 a 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 and HHI, the regression models that use C25 and HHIs also produce qualitatively the same results, a summary of which is presented in Table C7. Panel A in Table C7 presents the coefficients for the total firm growth and the total patent growth from the first column of Table B2, Table C3, and their counterpart models using 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, 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). Similarly, the estimates for the growth in the number of patents is only borderline statistically significant for two of the samples in C25 and is insignificant everywhere else. The positive estimates in the HHIs are not statistically significant, hence do not contradict the evidence presented in the C25 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 twenty-five firms are not artifacts of our choice of quality level or measure of concentration, but are representative of the underlying phenomena.

Table C1: 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 twenty-five firms that are ultimately granted on or before 2010. Each row corresponds to a two-year time period. The sample includes patent applications from thirty patent technology classes in the ICT equipment industry, at all levels of patent quality.

Table C2: Summary statistics of key patent *flow* variables

Variable	Mean (%)	Std. Dev. (%)
C5_flow	30	11
C25_flow	60	14
HHI	34,100	26,200
Patent Share by Entrants		
New Entrants - 1 year	12	8
New Entrants - 4 years	22	23
Lateral Entrants - 1 year	11	7
Lateral Entrants - 4 years	12	8
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
Geography		
Top 10 MSA share	52	14
Top 10 County share	16	9
Firm in Top 5 in Previous Period		
AT&T	37	48
Motorola	26	44
IBM	42	49

Notes: The sample includes patent applications from all levels of quality in the period from 1976 to 2007 that are ultimately granted by USPTO on or before 2010. The averages are across the thirty ICT equipment industry patent technology classes, and two-year time period cells. $\mathrm{C25}_{\mathrm{flow}}$ is the patent application share of top twenty-five companies within a 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 five patent *flow* holders in the previous two-year period.

Table C3: OLS analysis of patent *flow* ownership concentration

Dependent Variable: $C25_{flow}$		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Location Top 10 MSAs		-1.64	-1.53	-2.33	-2.57	-0.09	0.23	-0.43	-0.49
		(15.04)	(15.02)	(15.39)	(15.39)	(13.29)	(13.33)	(13.37)	(13.37)
New Entry Share	(1 year)	-21.42	-23.23	-29.82	-30.14				
		(36.62)	(37.17)	(36.76)	(36.86)				
	(4 years)					-30.27	-30.90	-34.74	-34.75
						(26.19)	(26.39)	(25.60)	(25.58)
Lateral Entry Share	(1 year)	35.88	35.09	29.46	29.21				
		(12.74)***	(13.37)**	(13.81)**	(14.42)*				
	(4 years)					6.31	3.20	-0.52	-2.58
						(11.83)	(11.54)	(11.56)	(12.58)
Total Growth in No of Firms		-7.76				-5.80			
		(2.43)***				(1.19)***			
	US only		-5.89				-4.29		
			(1.96)***				(1.28)***		
	Foreign only		-0.33				0.11		
			(0.35)				(0.47)		
Total Growth in No of Patents				-1.21				0.05	
				(1.54)				(0.98)	
	US only				-0.84				0.33
					(1.22)				(0.97)
	Foreign only				-0.02				0.32
					(0.27)				(0.49)
Lagged Dummies if Firm is in Top 5									
	AT&T	-1.62	-1.40	-1.03	-0.99	-1.80	-1.55	-1.23	-1.11
		(0.80)*	(0.80)*	(0.80)	(0.82)	(1.00)*	(1.00)	(0.97)	(0.99)
	Motorola	0.67	0.64	0.90	0.90	0.97	0.90	1.13	1.08
		(0.67)	(0.71)	(0.74)	(0.76)	(0.68)	(0.66)	(0.70)	(0.71)
	IBM	-0.64	-0.80	-0.81	-0.86	-0.50	-0.59	-0.58	-0.62
		(1.01)	(1.00)	(0.92)	(0.91)	(0.94)	(0.94)	(0.86)	(0.86)
Intercept		54.18	53.93	55.95	56.22	57.23	57.03	58.85	59.24
		(8.35)***	(8.29)***	(8.38)***	(8.38)***	(7.45)***	(7.25)***	(7.19)***	(7.09)***
N		450	450	450	450	450	450	450	450
Number of Classes		30	30	30	30	30	30	30	30
R-Squared		0.59	0.58	0.57	0.56	0.57	0.57	0.56	0.56

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 from 1976 to 2007 that are ultimately granted by USPTO on or before 2010.

Table C4: 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 twenty-five firms. Each row corresponds to a calendar year. The sample includes patent applications from thirty 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 C5: Summary statistics of key patent *stock* variable

Variable	Mean (%)	Std. Dev. (%)
C5_stock	26	9
C25_stock	54	12
HHI	25,900	16,200
Merger Intensity	0.9	1.5
Patent Share by Entrants		
New Entrants - 1 year	2.3	1.9
New Entrants - 4 years	21.6	31.6
Lateral Entrants - 1 year	1.8	1.2
Lateral Entrants - 4 years	5.5	3.6
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
Geography		
Top 10 MSA share	52	12
Top 10 County share	16	9
Firm in Top 5 in Previous Period		
AT&T	40	49
Motorola	30	46
IBM	44	50

Notes: The sample includes patent stock values from 1986 to 2007, calculated from patent applications from all levels of quality in the period from 1976 to 2007 that are ultimately granted by USPTO on or before 2010. The averages are across the thirty ICT equipment industry patent technology classes and years. $\mathrm{C25}_{\mathrm{stock}}$ is the patent *stock* share of top twenty-five companies within a 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 five patent *stock* holders in the previous period.

Table C6: OLS analysis of patent *stock* ownership concentration

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
M&A Intensity (No of patents transferred in M&A / All Telecom)		-9.30	-9.10	-8.85	-8.76	1.60	1.71	2.26	2.28
		(12.08)	(11.91)	(11.89)	(11.85)	(8.42)	(8.43)	(8.81)	(8.87)
Location Top 10 MSAs		-0.05	-0.00	0.46	0.30	5.68	5.70	4.91	4.43
		(16.72)	(16.73)	(16.31)	(16.44)	(13.61)	(13.68)	(13.79)	(13.97)
New Entry Share	(1 year)	-38.61	-38.49	-43.81	-43.92				
		(19.08)*	(19.36)*	(17.44)**	(17.99)**				
	(4 years)					-48.53	-48.36	-48.87	-48.98
						(11.28)***	(11.39)***	(10.36)***	(10.39)***
Lateral Entry Share	(1 year)	-2.59	-2.74	-3.55	-3.71				
		(49.82)	(50.23)	(51.47)	(51.75)				
	(4 years)					-5.53	-5.41	-10.42	-10.50
						(11.30)	(11.57)	(12.32)	(12.04)
Total Growth in No of Firms		-5.27				5.49			
		(7.36)				(4.57)			
	US only		-4.09				3.02		
			(5.72)				(4.59)		
	Foreign only		-1.01				2.42		
			(4.47)				(3.67)		
Total Growth in No of Patents				-1.77				5.05	
				(4.53)				(2.89)*	
	US only				-1.49				1.42
					(3.60)				(2.51)
	Foreign only				-0.13				4.00
					(3.52)				(2.70)
Lagged Dummies if Firm is in Top 5									
	AT&T	-1.19	-1.18	-1.17	-1.17	-1.30	-1.30	-1.25	-1.24
		(0.77)	(0.77)	(0.75)	(0.75)	(0.62)**	(0.62)**	(0.61)**	(0.62)*
	Motorola	0.52	0.52	0.53	0.53	0.20	0.20	0.21	0.21
		(0.51)	(0.51)	(0.50)	(0.51)	(0.49)	(0.49)	(0.50)	(0.50)
	IBM	0.49	0.48	0.48	0.47	0.88	0.87	0.84	0.83
		(0.93)	(0.93)	(0.93)	(0.93)	(0.91)	(0.91)	(0.91)	(0.91)
Intercept		60.85	60.79	60.25	60.31	103.10	102.92	104.03	104.26
		(10.17)***	(10.15)***	(9.67)***	(9.71)***	(17.67)***	(17.91)***	(17.19)***	(17.28)***
N		660	660	660	660	660	660	660	660
Number of Classes		30	30	30	30	30	30	30	30
R-Squared		0.49	0.49	0.49	0.49	0.58	0.58	0.58	0.58

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 from 1976 to 2007 that are ultimately granted by USPTO on or before 2010.

Table C7: 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%
C5	-4.71 (1.64)***	-7.36 (1.80)***	-5.28 (1.98)**	1.04 (1.50)	0.66 (1.81)	-0.11 (2.21)
C25	-7.76 (2.43)***	-7.19 (1.71)***	-4.86 (1.78)**	-1.21 (1.54)	-1.81 (1.07)*	-2.75 (1.42)*
HHI	-172.91 (49.52)***	-347.89 (155.26)**	-293.27 (122.90)**	90.98 (95.43)	29.85 (167.13)	31.46 (186.73)

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%
C5	-16.50 (8.95)*	-21.25 (8.29)**	-39.83 (14.33)***	-6.84 (5.08)	-4.72 (5.21)	-5.41 (5.72)
C25	-5.27 (7.36)	-50.01 (11.65)***	-82.11 (26.49)***	-1.77 (4.53)	-11.56 (7.07)	-11.13 (7.76)
HHI	-250.17 (206.57)	-580.42 (213.49)**	-957.00 (323.74)***	25.63 (83.33)	31.96 (124.36)	14.46 (159.76)

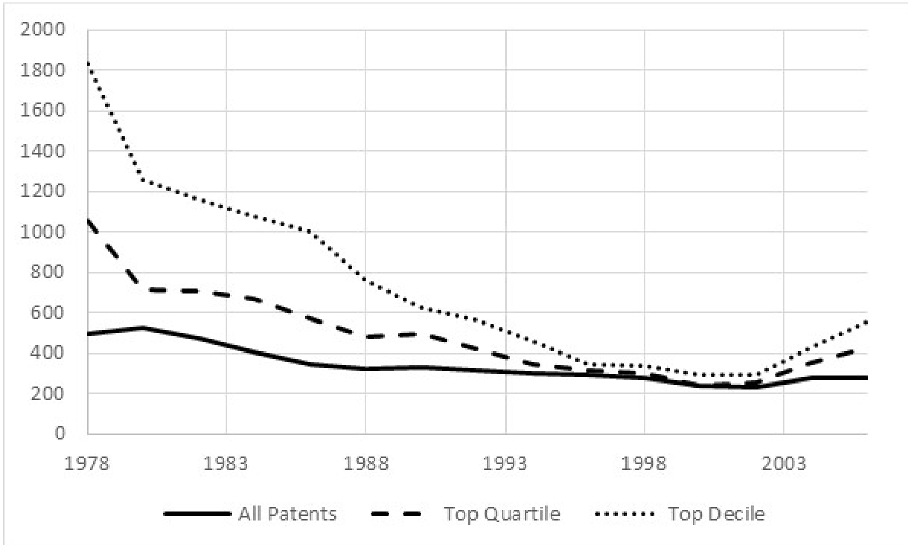

Figure C1: Average patent ownership HHIs across ICTE technology classes

Notes: The sample includes patent applications from the thirty 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.

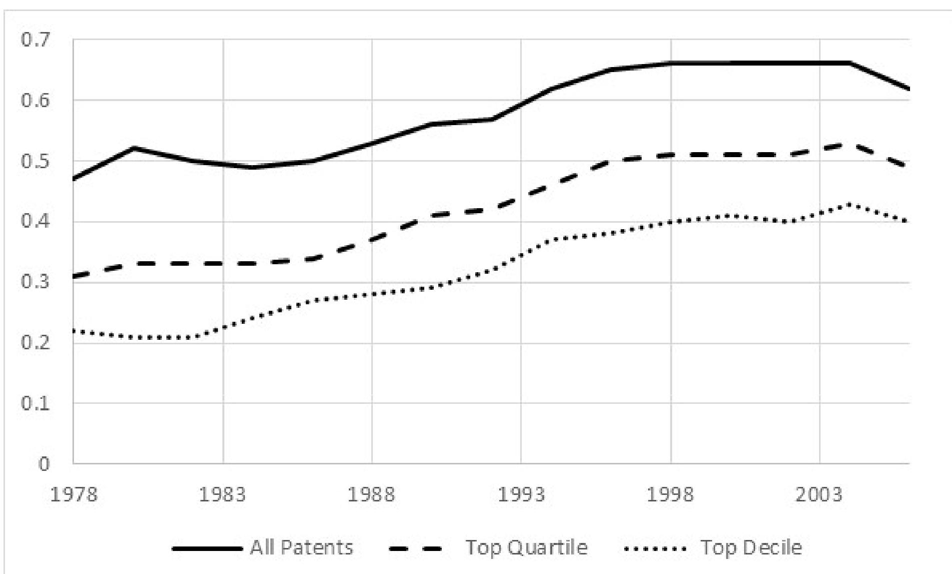

Figure C2: Average gini coefficients for patent ownership across ICTE technology classes

Notes: The sample includes patent applications from the thirty 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.

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