

RESEARCH NOTES AND COMMENTARIES

CHICKEN, OR THE EGG, OR BOTH? THE INTERRELATIONSHIP BETWEEN A FIRM'S INVENTOR SPECIALIZATION AND SCOPE OF TECHNOLOGIES

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Firms with different scope of technologies experience different firm growth. Understanding such heterogeneity requires knowing not only what drives technologies' scope but also why these drivers remain different across firms. I propose inventor specialization as a driver of technologies' scope: firms with more specialized inventors create narrower scope technologies. I also propose that these narrower scope technologies themselves in turn induce these firms' inventors to remain more specialized. I empirically demonstrate this two-way interrelationship in the U.S. communication equipment industry using policy shocks as natural experiments and a new measure of scope. This interrelationship has important implications for why resources and organization appear isomorphic within a firm but heterogeneous across firms. Copyright © 2013 John Wiley & Sons, Ltd.

INTRODUCTION

A central theme in the Penrosian theory is that a firm's growth is driven by its internal resources (Penrose, 1959; Helfat and Eisenhardt, 2004). Emerging from this theme is an insight that wider scope technological resources, that is, technologies with wider uses, are more effective in supporting a firm's expansion, relative to technologies with specific applications (Montgomery and Wernerfelt, 1988; Silverman, 1999). For firms to act on this insight, however, an accompanying question,

which has, thus far, received little attention in strategy research, needs to be addressed: what influences a firm to create wide or narrow scope technologies?

A natural response is to examine the firm's inventors who create these technologies. How these inventors are organized must surely influence their technological outputs, as evidenced by the vast literature on research and development (R&D) organization (Damanpour, 1991; Cardinal *et al.*, 2011). Conceivably, a knowledge-based or search-based theory (Nickerson and Zenger, 2004; Ahuja and Katila, 2004; Leiponen and Helfat, 2010) could suggest that technological specialists, being constrained in breadth of knowledge, will invent technologies of specific uses and vice versa.

However, theories of this nature suffer a shortcoming: they do not explain why the causal factor—in this case, the firm's extent of inventor

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specialization—is sustained. Many of these causal factors, such as whether the firm has technological specialists versus generalists, can presumably be adjusted by the firm. For a theory to propose that firms with less inventor specialization create wider scope technologies that facilitate their growth, it should ideally also explain why inventor specialization remains different across firms within an environment. Otherwise, a lingering puzzle remains as to why the other firms do not reduce their inventor specialization as well to facilitate growth or why firms do not all converge in their extent of inventor specialization to conform to common external pressures (Lawrence and Lorsch, 1967). Hence, a more comprehensive question is: how does a firm's inventor specialization influence its creation of wide or narrow scope technologies and what sustains this extent of inventor specialization?

To address this question, I examine the interrelationship between a firm's inventor specialization and the scope of its technologies. I propose that a firm with greater inventor specialization creates more narrow scope technologies. Importantly, I also propose that these narrow scope technologies in turn exert pressure on the firm to increase its inventor specialization. A key theoretical novelty here is that it is the very output of inventor specialization itself (i.e., scope of technologies) that sustains the firm's extent of inventor specialization. A firm having more technological specialists is induced to remain so because of the narrow scope technologies these specialists create. These propositions simultaneously identify a causal factor for the firm's scope of technologies and explain why the causal factor persists. The two-way causal nature of this interrelationship is not uncommon; indeed, it has similarities with interrelationships between other firm-level constructs that prior research has demonstrated, such as complementarities between a firm's scale and its scope of product offerings (Basker, Klimek, and Van, 2012), between product innovations and competencies (Danneels, 2002), or between project designs and performance outcomes (Cardinal *et al.*, 2011).

I examine the propositions using longitudinal data on the U.S. communication equipment industry from 1985 to 2003. I use a new measure of technologies' scope based on textual coding of the dependence-independence nature of patent claims. Empirically testing the interrelationship poses significant challenges of simultaneity and

unobserved heterogeneity. Both inventor specialization and scope of technologies are simultaneously determined by each other, and both are likely concurrently driven by unobserved factors such as a firm's overall strategy. To overcome these challenges, I use two-stage estimations for each side of the causal effects. Each first-stage estimation uses a policy shock to predict a change in a main variable (Berry and Waldfogel, 2001), with a difference-in-difference approach to fine-tune the shock (Card and Krueger, 1994). The corresponding second-stage estimation then uses this predicted change from the first stage to explain the resulting change in the other main variable. I use the Pennsylvania R&D state tax credit implementation in 1997 and the Telecommunications Act of 1996 as policy shocks for inventor specialization and scope of technologies, respectively. This empirical design, while relatively unconventional in the strategy literature, is particularly useful in capturing interrelationships of this sort. I elaborate more on the details in the Methods section.

This article potentially conveys new insights on firm heterogeneity and isomorphism. Scope of technologies and inventor specialization can be viewed as specific dimensions of a firm's resource and organization, respectively. While firms differ in their resources and organization of activities (Thompson, 1967; Henderson and Cockburn, 1994), within a firm, resource and organization often appear isomorphic, in that they seem to align with and support each other (Henderson and Clark, 1990; Baldwin and Clark, 2000). This prompts conjectures that one causes the other. For instance, firms organizing their search differently result in heterogeneous resources (Ahuja and Katila, 2004; Nickerson and Zenger, 2004). Conversely, resource heterogeneity causes firms' organization to evolve differently (Nelson and Winter, 1982; Birkinshaw, Nobel, and Ridderstrale, 2002). However, when put together, these conjectures pose a fundamental puzzle, much like the classic 'chicken or the egg' dilemma: does the isomorphism arise from organization shaping resource, from resource driving organization, or from both? This study hints that both effects exist to reinforce the isomorphism within firm. In fact, they together sustain the heterogeneity of resource and organization across firms.

THEORY AND HYPOTHESES

Inventor specialization refers to the extent that the firm's inventors are individually focused on particular technological areas. It affects how inventors search for new technologies and what type of knowledge they acquire (Eisenhardt and Tabrizi, 1995; Katila and Ahuja, 2002). The firm with a collection of technological specialists likely has greater knowledge depth, whereas the firm with technological generalists likely has greater knowledge breadth.

Scope of technologies refers to how widely the individual technology can potentially be applied.¹ It is an *ex ante* concept, as the firm often cannot perfectly predict the technology's eventual uses. It is inextricably tied to the technology's scope of novelty, as in how widely such novelty can be represented. When the technology's novelty can be portrayed in various ways, the technology can likely be applied in various ways as well. This allows the firm to form an expectation of the eventual scope of use, based on the technology's scope of novelty.

Inventor specialization reduces scope of technologies through two mechanisms. The first is problem identification (Cyert and March, 1963; Nickerson and Zenger, 2004). Specialized inventors have greater knowledge depth which helps them identify and evaluate domain-specific (narrow scope) problems and constraints (Hatfield, Liebeskind, and Opler, 1996; Jones, 2009). Technological generalists can better identify generic problems. By being repeatedly exposed to these problems across domains, they are more equipped to understand and formulate the problems (Dougherty, 1992) and also accurately assess the full value of finding solutions to these common problems.

The second mechanism is solution identification. Specialized inventors have the requisite domain information (Hatfield *et al.*, 1996) to recognize

which solution to a nuanced problem is viable, and they have the skills to tweak the solution to fit this nuanced problem. This comes from their search depth, reuse of knowledge, and familiarity of inherent concepts and scientific principles (Eisenhardt and Tabrizi, 1995; Katila and Ahuja, 2002), which is especially crucial in advanced domains (Jones, 2009). Consequently, they are better at generating narrow scope inventions. Generic problems are exposed to more settings where potential solutions may be found, and technological generalists familiar with multiple domains are more apt at identifying such solutions (Ahuja and Katila, 2004). Their exposures to diverse perspectives accords the creativity and skills needed to transfer solutions across domains (Allen, Lee, and Tushman, 1980; Dougherty, 1992; Leiponen and Helfat, 2010) and also the abilities to select appropriate settings for experimentation (Thomke, 1998). Thus, they are better at generating wide scope inventions.

The effect of inventor specialization can be more closely identified at the level of R&D location within a firm (Chacar and Lieberman, 2003; Gambardella and Giarratana, 2010). Knowledge sets are different across R&D locations (Howells, 1990; Kenney and Florida, 1994; Almeida and Kogut, 1999). Even when spillovers occur, they tend to be geographically confined (Shaver and Flyer, 2000; Carrincazeaux, Lung, and Rallet, 2001). Because inventors have access to different knowledge depending on their R&D locations, the problems and solutions they systematically identify are accordingly different. Thus, based on the two mechanisms explained earlier, I arrive at the first hypothesis.

Hypothesis 1 (H1): In an R&D location of a firm, greater inventor specialization will subsequently narrow the scope of technologies.

Scope of the firm's technologies in turn reduces inventor specialization. First, with changes in scope, inventor specialization evolves to maximize use of these technologies. To exploit the flexibility in wide scope technologies at a particular R&D location (Argyres and Silverman, 2004), the firm is induced to have more technological generalists at that location, as they are more able to recognize commonalities across domains. Likewise, given more narrow scope technologies, the firm tends to have more technological specialists who are

¹ Scope reflects individual technologies' potential use and is different from the overall breadth of inventive activities. To illustrate scope: generic painkillers (e.g., aspirin) have wider scope as they can be used for various types of pain. Specific painkillers (e.g., Celebrex, which is meant for arthritis) have narrower scope as they are less appropriate for other types of pain. Scope is also different from search scope, which refers to the range of knowledge inputs generating the technology. To illustrate: the binary code is used widely in applications ranging from computer programming to various data transmissions, but was not invented based on a wide span of knowledge inputs.

skilled in foreseeing potential issues related to these technologies (Hatfield *et al.*, 1996) and can determine how feasible it is to apply these technologies to specific problems (Jones, 2009).

Second, with changes in scope, inventor specialization evolves to optimize coordination in using these technologies. Applying wide scope technologies requires greater cross-domain coordination (Burns and Stalker, 1966; Chacar and Lieberman, 2003), which can be problematic when language, norms, and processes differ across domains (Becker and Murphy, 1992; Kretschmer and Puranam, 2008). The firm opts for more generalists who are cognizant of these differences and other diverging objectives or constraints across domains and who are, hence, equipped to reduce frictions and coordinate such applications (Howells, 1989). Use of narrow scope technologies requires more within-domain coordination, crucial for dealing with errors during applications and making small tweaks on the ground (Kenney and Florida, 1994). The firm is induced to have more specialists with the domain expertise to manage such coordination.

Third, when scope reduces, the corresponding shift in knowledge pushes the firm toward greater inventor specialization and vice versa. Knowledge accumulation is path dependent (Nelson and Winter, 1982; Helfat, 1994); use of skills begets further similar skills. Applying wide scope technologies across domains induces inventors to learn about other domains and become generalists. Using narrow scope technologies in a particular domain encourages inventors to dwell deeper and specialize. The presence of other similar specialists further guides incremental building of expertise (Jones, 2009). Based on these arguments, I arrive at the second hypothesis.

Hypothesis 2 (H2): In an R&D location of a firm, narrower scope of technologies will subsequently increase inventor specialization.

METHOD

I examine the hypotheses in the setting of the U.S. communication equipment industry from 1985 to 2003. Decisions on inventors and technologies are consequential here, as firms in this industry exhibit some of the highest R&D intensities

across all industries,² technological changes occur frequently, and substitution threats are high.³ This industry also uses wide varieties of related technologies, providing ample variance for scope and inventor specialization.⁴

To form the sample, I match firms in the U.S. communication equipment industry (SIC codes 366 and 367) from the Compustat database to their assignee numbers by the U.S. Patent and Trademark Office (USPTO) with the matching file in the National Bureau of Economic Research (NBER) patent database. Next, I identify all patents assigned to these firms within the sample range (70,218 patents) from USPTO's database. I then trace all inventors and their geographical locations listed in the patents, using their first name initials and last names (43,545 inventors). This trace of inventors is done for each firm-year, which prevents errors of inventors across different firms having the same first name initials and last names or from inventor mobility.⁵

The unit of analysis is a firm's R&D location in a year. I use the cities in which inventors reside as proxies for the firm's R&D locations (Gambardella and Giarratana, 2010).⁶ To ensure that no spurious locations are created because of spelling errors or differences in how a city is named across observations, I manually check the city names

² Firms' R&D intensities in this industry are comparable to those of pharmaceutical firms (Fransman 2002). In 1999, R&D expenses for Cisco, Ericsson, and Nortel were 18.7, 14.5, and 13.9 percent of sales, respectively. Equivalent figures for Roche, Glaxo Smithkline, and SmithKline Beecham were 15.5, 14.4, and 10.8 percent, respectively.

³ E.g., for data transmission, there are multiple competing transmission media, such as light wave, wireless radio wave, power lines, and satellite. Within each medium, there often exist multiple competing technologies as well.

⁴ For telecommunication applications alone, related technologies include circuit switch and signaling systems, data transmission, customer premise equipment (like servers and routers), communications protocol connecting networks, and network technologies like (ethernet and voice-data convergence technologies).

⁵ To check that this procedure is not corrupted by a firm's location having multiple inventors with same first name initials and last name in a year, I randomly select 50 patents that each has other patents with (matched) inventors of the same first name initials and last name within the firm, location, and year. I then manually check these 50 sets of patents and find no instance where matched inventors have different first names or middle names. Alternatively, I reconstruct the entire sample based on inventors' full first names and last names. All findings remain robust.

⁶ Manual tracing of firms' historical R&D locations is likely impractical and inaccurate given the large sample panel and that the information is not available in public documents such as 10K statements or annual reports.

within each state in all 10,005 observations against a reference list (www.city-data.com).⁷ I further drop all cities corresponding to only one patent, to remove spurious locations due to spelling errors in the name. The remaining sample contains 3,449 R&D locations and 10,863 observations.⁸

Variables

To measure scope of technologies, prior research has used counts of technology classes a patent is assigned to or the claims in a patent (Lerner, 1994; Lanjouw and Schankerman, 2004). I conducted informal conversations with patents lawyers and corporate licensing experts who expressed that these measures, while they have merits, may not adequately capture scope.⁹ The practitioners suggested that scope is more closely reflected in the text used to describe the technologies, particularly in the patent claims. While claims, reflecting scope of novelty, do not perfectly capture the *ex post* scope of applications, they nonetheless offer a closer prediction.

In response, I create a new measure of scope using textual coding of patent claims. There are

two types of claims: independent and dependent (Radack, 1995). An independent claim states an unprecedented element of novelty that is not partially described elsewhere in the patent, whereas a dependent claim represents an extension or elaboration over a claim previously described in the patent.¹⁰ I create a Java-based language parser program to access patent texts on the USPTO Web site and code the dependence-independence nature of all individual claims with the following heuristics: a dependent claim always contains a reference to an earlier claim number within the same patent. References always include the word structure 'claim #' (where # is a number). The program identifies a dependent claim as one that incorporates this word structure. It captures all references in the form of 'as defined in claim #', 'according to claim #', 'as claimed in claim #', 'as set forth in claim #', or 'the method of claim #', etc. All other claims are coded as independent. Table 1 shows some examples of claims coding. These heuristics are formulated via extensive readings of actual claim texts and legal literature, and they are verified with practitioners who are patent lawyers and corporate licensing experts. Prior to coding, I iteratively pretest the program on 100 random patents to manually check for programming errors and robustness to various structures of claim texts. I then use the program to code the claim of all 70,218 patents in the sample. Next, I aggregate this coding at the patent level and map patents to R&D locations based on inventors listed in the patents. Note that one patent is assigned to more than one R&D location when it involves inventors residing in multiple locations. This is appropriate, as my objective is not to count patents, but rather to trace scope and inventor specialization within each location. Finally, I construct the measure *Scope_{ijt}* as the average number of independent claims per patent that firm *i* in R&D location *j* applies for in year *t*.¹¹

⁷ I treat city names within a state that are based on the same root words, and that do not show up as separate cities in the reference list, as the same city (e.g., 'Anaheim Hills' and 'Anaheim' in California). I also match city names with differences in spacing between words (e.g., 'Sugar Hill' and 'Sugarhill'). I then check for inconsistent acronyms across city names (e.g., 'Fort Lauderdale' and 'Ft. Lauderdale'). Finally, I match city names within state with small differences in spellings (e.g., 'Rancho Palos Verdes' and 'Racho Palos Verde').

⁸ This procedure does not capture instances where a firm's inventors from the same location commute from different cities. Using larger geographic areas, such as Metropolitan Statistical Areas (MSA) or states, mitigates this problem but suffers from overaggregation, i.e., the firm's R&D activities may be conducted in multiple locations within an MSA or state. For robustness, I match cities to MSAs using the scheme in Thompson (2006), and I reconstruct the sample with MSA as proxy. Findings remain largely robust. Even with city as proxy, overaggregation may still occur. A corporate headquarters with an attached R&D lab may have other labs in other functional units within the same city. Inventor specialization constructed at the city level may not be indicative of the actual inventor specialization for the R&D lab that created technologies with a particular scope. However, this problem is likely to work against finding results supporting the propositions.

⁹ For instance, a patent assigned to one technology class, with broad applications within the class, may not be narrower in scope than another patent assigned to multiple classes covering only narrow applications in each class. Similarly, a patent with one generic claim constituting a vital component in numerous subsequent uses may not have narrower scope than another patent with multiple incremental claims of small and insignificant improvements.

¹⁰ To illustrate with hypothetical examples: an independent claim may be 'a table comprising of three legs,' whereas a corresponding dependent claim would be 'a table, as described in claim # (where # refers to a number), wherein one of the legs has a wheel attachment.' Accordingly, an independent claim typically contains greater novelty than a dependent claim, and the potential scope of application covered by the independent claim is usually larger.

¹¹ Note that this measure, strictly speaking, captures technologies' scope of novelty and relies on the notion that such scope corresponds to the technologies' potential scope of use, as explained in an earlier part of the article.

Table 1. Examples of patent claims coding

Patent number	Title	Claim	Claim text	Coding
6603206	High bandwidth, low power, single stage cascode transimpedance amplifier for short haul optical links	1	An amplifier comprising: an input port; an output port; a ground to provide a ground voltage; a power rail to provide a power voltage; a bias circuit to provide a bias voltage between the ground voltage and the power voltage; a common-gate transistor comprising a gate biased by the bias circuit, a source connected to the input port; and a drain connected to the output port; and a pMOSFET and a nMOSFET to provide bias current to the common-gate transistor, the pMOSFET comprising a gate connected to the ground, and a drain; and the nMOSFET comprising a gate connected to the power rail, and a drain.	Independent
		2	The amplifier as set forth in <i>claim 1</i> , wherein: the common-gate transistor is a pMOSFET with its source connected to the drain of the pMOSFET, and its drain connected to the drain of the nMOSFET.	Dependent
6613660	Metallization process sequence for a barrier metal layer	1	An in situ method of forming a barrier metal layer above a surface of a substrate including a layer of dielectric material, the method comprising: cleaning the surface of the substrate; depositing, in a plasma ambient, the barrier metal layer on the surface of the substrate; and controlling the temperature of the surface below a predefined critical temperature so as to inhibit void generation underneath the barrier metal layer.	Independent
		2	The method of <i>claim 1</i> , wherein controlling the temperature of said surface includes cooling the surface prior to depositing the barrier metal layer.	Dependent
		4	The method of <i>claim 2</i> , wherein cooling the surface includes allowing the substrate to dissipate heat by at least one of thermal conduction, radiation, and convection for a predefined time period.	Dependent
		15	An in situ method of forming a barrier metal layer above a surface of a substrate, the method comprising: cleaning the surface of said substrate; depositing, in a plasma ambient, a barrier metal layer on the surface of the substrate; and performing at least one sequence interrupt, each of which defines a time period of reduced deposition activity on the surface of the substrate, said at least one sequence interrupt inhibiting the formation of voids in the barrier metal layer.	Independent
		16	The method of <i>claim 15</i> , wherein cleaning the surface of said substrate comprises pre-degassing the surface of said substrate.	Dependent

Table 1. Continued

Patent number	Title	Claim	Claim text	Coding
6611477	Built-in self test using pulse generators	6	A method of measuring a first signal-propagation time required for a rising edge of a signal to traverse a test circuit from a data input node of the test circuit to a data output node of the test circuit, the method comprising: (1) providing sequential, alternating falling and rising signal transitions on the test-circuit data input node, thereby producing a corresponding series of alternating falling and rising signal transitions on the test-circuit data output node; and (2) for each one of a plurality of the rising signal transitions that occur on the test-circuit data output node over a selected time period: (a) instigating a subsequent one of the rising signal transitions on the test-circuit data input node in response to the one rising signal transition; and (b) instigating a subsequent falling signal transition on the test-circuit data input node in response to the one rising signal transition on the test-circuit data output node.	Independent
		7	The method of <i>claim 6</i> , further comprising developing a clock transition for each one of the plurality of the rising signal transitions that occur on the test-circuit data output node over the selected time period, thereby creating a clock signal having a clock period proportional to the first signal propagation time.	Dependent

To measure inventor specialization, I compile inventors at each R&D location j in a given year t . For each inventor k , I trace the patent applications the inventor is involved in for year t and their assigned main technology classes. I then calculate a concentration ratio of technology classes for all patents involving inventor k in year t , reflecting how focused this inventor is on particular technological areas. Finally, I take the average of this concentration ratio across all inventors in firm i at R&D location j in year t to create the variable *Inventor Specialization_{ijt}*.¹²

¹² E.g., firm i at location j has two inventors, Brian and Stewie, and two patents in year t assigned to different classes. Brian is involved with one patent, while Stewie is involved with both. Concentration ratios of technology classes, i.e., sum of squares of ratios, for Brian and Stewie are 1 and $0.25 + 0.25 = 0.5$, respectively, and *Inventor Specialization_{ijt}* is $(1 + 0.5) / 2 = 0.75$. If Brian and Stewie are involved with one patent each, then greater inventor specialization would have occurred. *Inventor Specialization_{ijt}* would reflect this by taking on a greater value of $(1 + 1) / 2 = 1$.

These measures may not have incorporated all relevant inventions, since not all inventions are patented (Cohen, Nelson, and Walsh, 2000). But this is likely not problematic in this single-industry study, since patenting propensities are stable within an industry (Griliches, 1990). *A priori*, it is also not apparent why unpatented inventions would systematically differ from patented ones in scope or inventor specialization, and it is unlikely that motivation for nonpatenting will systematically bias or spuriously create the proposed negative interrelationship. The empirical design further mitigates potential omission bias, as I explain later.¹³

¹³ Alternatively, *Inventor Specialization_{ijt}* could be the average technological breadth across inventors instead of a concentration ratio, i.e., it need not be weighted by the inventors' actual use of knowledge across technological classes. I create a variable, *Domain_{ijt}*, by calculating the average count of technological classes that inventors are involved with and then taking the inverse, such that the higher the value, the more focused inventors are on a particular technology. The correlation between *Domain_{ijt}* and *Inventor Specialization_{ijt}* is high at 0.90. I repeat all analyses with *Domain_{ijt}* instead. The difference-in-difference

I control for *Total Patents_{ijt}* for firm *i* at location *j* in year *t* to account for inventive activities inducing inventors to both operate in many technological areas and create wide scope technologies. A location covering more technological areas may use wider scope technologies and require inventors to be individually less specialized. I control for such *Technological Breadth_{ijt}* measuring the number of patents' assigned technological subcategories, based on NBER's classification, associated with the location. This variable is different from *Inventor Specialization_{ijt}*, as it measures overall breadth for the location rather than average inventor specialization. Inventors drawing more on science may create wider scope technologies and concurrently are less constrained to particular technological area. I add *Science_{ijt}* to capture the science-based prior art used to generate the technologies, measured as the average proportion of nonpatent-based citations made in patents. I also add *Knowledge Inputs_{ijt}*, which counts citations in patents, to control for span of knowledge inputs (which may both widen scope and induce inventors to be less specialized). Additionally, I control for the firm's number of employees (*Firm Size_{it}*), cash and short-term assets (*Cash_{it}*), and profits (*Profits_{it}*). I add year dummies to capture intertemporal heterogeneities.

Econometrics issues and policy shocks

Tests of the propositions are vulnerable to the simultaneity problem.¹⁴ Also, unobserved heterogeneity, e.g., the firm's strategy to be a specialist, may both discourage wide scope technologies and encourage inventors to individually specialize. These issues cause nonrandom assignment

estimator *Tax_Pennsylvania_{ijt}* in Model 2 of Table 3 loses its significance, though still has the right sign. All other findings remain robust.

¹⁴ Consider the following interrelationship: (1) $Scope_{ijt} = \beta_0 + \beta_1 Specialization_{ijt} + \mu_{ijt}$. (2) $Specialization_{ijt} = \gamma_0 + \gamma_1 Scope_{ijt} + \varepsilon_{ijt}$. Where $E(\mu_{ijt}) = 0$, $E(\mu_{ijt}^2) = \sigma^2$, $E(\varepsilon_{ijt}) = 0$, and both β_1 and γ_1 are non-zero. Substituting equation (1) into (2), we arrive at: $Specialization_{ijt} = (1 - \beta_1 \gamma_1)^{-1} [\gamma_0 + \gamma_1 \beta_0 + \gamma_1 \mu_{ijt} + \varepsilon_{ijt}]$. Hence, $E(Specialization_{ijt}) = (1 - \beta_1 \gamma_1)^{-1} (\gamma_0 + \gamma_1 \beta_0)$, and $Specialization_{ijt} - E(Specialization_{ijt}) = (1 - \beta_1 \gamma_1)^{-1} [\gamma_1 \mu_{ijt} + \varepsilon_{ijt}]$. Thus, $Cov(Specialization_{ijt}, \mu_{ijt}) = E\{ [Specialization_{ijt} - E(Specialization_{ijt})][\mu_{ijt} - E(\mu_{ijt})] \} = E\{ [(1 - \beta_1 \gamma_1)^{-1} (\gamma_1 \mu_{ijt} + \varepsilon_{ijt})][\mu_{ijt}] \} = (1 - \beta_1 \gamma_1)^{-1} [\gamma_1 \sigma^2 + E(\mu_{ijt} \varepsilon_{ijt})] \neq 0$ since $\sigma^2 > 0$. This nonzero covariance between specialization and the error term in the estimation violates the assumption of OLS and leads to biased estimates of coefficients in Equations 1 and similarly for Equation 2.

of observations to different levels of the two main variables, resulting in biased coefficient estimates (Holland, 1986).¹⁵ To address these issues, I use two-stage least square (2SLS) estimation to test each proposition, with a policy shock in the first stage to predict an exogenous change in a main variable (Berry and Waldfogel, 2001). I also use difference-in-difference estimators (Card and Krueger, 1994) to identify how this change on a treatment group (locations that experienced the shock) is different from any concurrent changes on a control group (locations that did not experience the shock). In the second stage, I trace how this change in one main variable results in a change in the other main variable.

For *Inventor Specialization_{ijt}*, I use the Pennsylvania R&D state tax credit enactment in 1997 as a policy shock. Following a federal R&D tax credit in the U.S. Economic Recovery Tax Act of 1981, Pennsylvania, along with various other states, introduced a similar state tax credit for within-state firms in addition to the federal tax credit, so as to attract firms' R&D activities into the state.¹⁶ This mainly induced firms to relocate projects that would otherwise have been allocated to other states to Pennsylvania, so as to reduce R&D costs, without inducing firms to change either their overall investment levels or project type (Wilson, 2006).¹⁷ With these project relocations, locations

¹⁵ Consider the effect of *Specialization_{ijt}* on *Scope_{ijt}*. Suppose *Specialization_{ijt}* takes two levels: high and low. Conceptually, the effect of *Specialization_{ijt}* refers to the average difference between *Scope_{ijt}* under high (Y_h) and low (Y_l) *Specialization_{ijt}*, across all locations. Yet, empirically, each location has only one level of *Specialization_{ijt}* at any point in time, and the researcher cannot observe what its *Scope_{ijt}* would have been had it adopted a different level of *Specialization_{ijt}* at that point. In an estimation equation, the coefficient of *Specialization_{ijt}* captures $(Y_h|i=h) - (Y_l|i=l)$, where $(Y_h|i=h)$ and $(Y_l|i=l)$ refer to the average *Scope_{ijt}* among locations with high and low levels of *Specialization_{ijt}*, respectively. A problem arises when $(Y_h) \neq (Y_h|i=h)$, and $(Y_l) \neq (Y_l|i=l)$, because some unobserved factors are selecting the locations into their respective groups ($i=h$ or $i=l$). This nonrandom assignment of locations to either level of *Specialization_{ijt}* constitutes the source of biases arising from unobserved heterogeneity.

¹⁶ The federal tax credit was 25 percent of qualified R&D expenses over a base level of a firm's average R&D in the past three years. Qualified expenses include wages, intermediate or materials expenses, and rental costs of property and equipment incurred in performing research undertaken to discover information that is technological in nature for a new or improved business purpose. Structure of the state tax credits largely resembles that of the federal tax credit.

¹⁷ Through interviews with officers at R&D-performing firms, OTA (1995) concludes that while tax and financial directors were aware of the R&D tax credits and their relevance to firm

in Pennsylvania were effectively assigned more projects with different technological nature than before; and inventors on average have to operate in more technological areas than they would otherwise have, resulting in a decrease in *Inventor Specialization_{ijt}*. *StateTax_{ijt}* captures observations up to five years after the enactment, i.e., it is ‘1’ from 1998 to 2002 and ‘0’ otherwise. Redefining *StateTax_{ijt}* as one, two, three, or four years post-enactment yields robust findings. *Pennsylvania_{ijt}* equals ‘1’ (treatment) for locations in Pennsylvania (which experienced the state tax credit) and ‘0’ otherwise (control). The difference-in-difference estimator *Tax_Pennsylvania_{ijt}* combines the two dummy variables and captures observations in Pennsylvania occurring up to five years after enactment.

For *Scope_{ijt}*, I use the Telecommunications Act of 1996 as a policy shock. This act was meant to increase competition in the local telephony markets previously monopolized by the incumbent local exchange carriers (ILECs), while allowing the ILECs to enter long distance service markets.¹⁸ While many questioned its effectiveness (Fransman, 2002), it nonetheless resulted in firms being involved in more markets, even if not in the envisioned manner.¹⁹ These market entries and new applications by downstream network firms such as AT&T and ILECs created demand of wide scope technologies for upstream R&D firms, as technologies now can and need to be applied across different settings. Also, the Act fostered an emphasis on interconnectedness between technologies, evident

from the numerous standards bodies set up subsequently (e.g., IEEE, EIA, ITU, etc.). When firms entered new markets, they created massive requirements for interoperability of different networks and standardization of communication protocols between networks (Economides, 2004),²⁰ resulting in lower technological obstacles for wide scope technologies to span various networks and applications. *Act_{ijt}* captures observations occurring after the Act’s enactment year, i.e., it takes the value of ‘1’ for observations occurring after 1996 and ‘0’ otherwise.²¹ The Act likely affects firms’ R&D locations that are more focused on technologies related to communication equipment (treatment) than those less so (control). I group patents’ technology classes into 36 technology subcategories, based on NBER’s categorization. Of these subcategories, I identify 10 as being less related to communication equipment.²² *Telecommunications_{ijt}* is ‘0’ for locations involved in these 10 subcategories (control group) and ‘1’ otherwise (treatment group). *Act_Telecommunications_{ijt}* combines the two dummy variables to capture observations occurring after the enactment for locations working on technologies related to communication equipment.

Model specifications

To test H1 using 2SLS estimations, I first estimate the effect of the Pennsylvania R&D state tax credit on *Inventor Specialization_{ijt}* in the first stage.

$$\begin{aligned}
 \text{Inventor Specialization}_{ijt} = & \beta_0 + \beta_1 \text{StateTax}_{ijt} \\
 & + \beta_2 \text{Tax_Pennsylvania}_{ijt} + \beta_3 \text{Pennsylvania}_{ijt} \\
 & + \beta_h \text{Controls} + \varepsilon_{ijt}
 \end{aligned}
 \tag{1}$$

value, the tax credits have little influence on the nature of R&D activities for the overall firm. Likewise, other studies show that supply of scientists is inelastic and R&D subsidies tend to go to scientists’ wages without accordingly increasing R&D expenses (Goolsbee, 1998).

¹⁸ To facilitate entry in local exchange markets, the Act mandated ILECs’ leasing of unbundled network elements to new entrants ‘at cost’ and their sale of services to competitors at ‘wholesale prices.’

¹⁹ By 2003, ILECs successfully entered the long distance service market in all states (Economides 2004). Long distance service providers initially tried to enter the local exchange markets by leasing the ILEC’s existing network. However, when leasing procedures were substantially delayed by lack of agreement on terms and long-drawn lawsuits, they reacted by acquiring the ILECs for rapid entries (Fransman, 2002). Also, the Act corresponded with a time of rapid development in Internet telephony, and cable companies actively entered the local exchange markets with Internet telephony as a substitute for the traditional copper wire local loops. In response to these threats, the ILECs themselves started offering long distance Internet telephony services as well (e.g., AT&T in 1998).

²⁰ Section 251(c)(2) of the Act mandates interconnection between local and long distance networks, to facilitate entry in local exchange markets. Also, the Act, by promoting integration of markets, spurred a near-euphoric optimism within the financial markets in the stock valuations of telecommunication firms (Fransman, 2002). Share prices rose steadily for four years following the Act, and the financial markets were ready to reward firms that were able to progress on this trend of interconnectedness and integration of different networks and technologies.

²¹ Restricting *Act_{ijt}* to 1997 to 2000 to account for the stock market decline thereafter does not change findings.

²² (i) agricultural, food, textile, (ii) organic compounds, (iii) surgery and medical Instruments, (iv) biotechnology drugs and med, (v) motors and engines + parts, (vi) transportation mechanicals, (vii) amusement devices, (viii) apparel and textile, (ix) furniture, house fixtures, and (x) receptacles (not otherwise classified under communications).

$\beta_2 Tax_Pennsylvania_{ijt}$, narrows the change in *Inventor Specialization_{ijt}* to the portion arising from the policy enactment and not from other events occurring concurrently. I then predict *Inventor Specialization_{ijt}*, lag it by one year, and estimate its effect on *Scope_{ijt}* in the second stage.²³

$$Scope_{ijt} = \delta_0 + \delta_1 Predicted\ Inventor\ Specialization_{ijt-1} + \delta_h Controls + \xi_{ijt} \quad (2)$$

Test of H2 follows a similar set-up.

$$Scope_{ijt} = \beta_0 + \beta_1 Act_{ijt} + \beta_2 Act_TeleCommunications_{ijt} + \beta_3 TeleCommunications_{ijt} + \beta_h Controls + \varepsilon_{ijt} \quad (3)$$

$$Inventor\ Specialization_{ijt} = \gamma_0 + \gamma_1 Predicted\ Scope_{ijt-1} + \gamma_h Controls + \mu_{ijt} \quad (4)$$

FINDINGS

Table 2 contains descriptive statistics of variables.²⁴ To check if the Pennsylvania R&D tax credit is a viable shock for *Inventor Specialization_{ijt}*, I plot in Figure 1 the average *Inventor Specialization_{ijt}* separately for before and after shock (1997) and for treatment and control group. This figure shows that *Inventor Specialization_{ijt}* reduces on average after the shock for the treatment group (locations in Pennsylvania) as expected, and this reduction appears larger than that for the control group (locations not in Pennsylvania). I similarly check the effectiveness of the Telecommunications Act in Figure 2. After the shock in 1996, the average *Scope_{ijt}* increases

as expected; and such increase appears larger for the treatment group than for the control group. These figures provide some assurance that the respective shocks are effective instruments.

The left panel of Table 3 holds results for H1. Models 1–2 predict *Inventor Specialization_{ijt}* in the first stage. *StateTax_{ijt}* is significantly negative in Models 1–2, suggesting that *Inventor Specialization_{ijt}* is lower on average for all locations in the five years post-tax credit enactment. Consistent with Figure 1, *Tax_Pennsylvania_{ijt}* is significantly negative in Model 2 (t-statistics –2.09), indicating that the tax credit induces a sharper decline in *Inventor Specialization_{ijt}* for locations in Pennsylvania than elsewhere over the same time period. This adds confidence in the policy shock as an effective instrument. I predict *Inventor Specialization_{ijt}* with Model 2 and use the one-year lagged prediction to estimate *Scope_{ijt}* in the second stage in Model 3. *Predicted Inventor Specialization_{ijt-1}* is significantly negative (t-statistic –4.92), suggesting that a lowering of *Inventor Specialization_{ijt}* induces the particular R&D location of the firm to subsequently generate technologies with wider scope. This supports H1.

The right panel of Table 3 contains results for H2. In the first-stage estimations (Models 4–5), *Act_{ijt}* is in generally positive, suggesting that scope may be wider across all locations after 1996. Importantly, as in Figure 2, the significantly positive *Act_TeleCommunications_{ijt}* (t-statistics 3.22) suggests that the Act increases *Scope_{ijt}* more so for R&D locations focused on communication equipment technologies than elsewhere. This further assures that the policy shock is appropriate. I predict *Scope_{ijt}* with Model 5 and use the one-year lagged prediction to estimate *Inventor Specialization_{ijt}* in the second stage in Model 6. *Predicted Scope_{ijt-1}* is significantly negative (t-statistic –4.41), suggesting that a widening of *Scope_{ijt}* causes the R&D location of the firm to subsequently reduce its *Inventor Specialization_{ijt}*. This supports H2.²⁵

²³ The model calculates *Specialization_{ijt}* on a yearly basis but does not assume that it changes from year to year. The model allows five years for *Specialization_{ijt}* to react to the shock and captures its average difference between the shock period versus the nonshock period for the treatment group, relative to the control group.

²⁴ The variables *Total Patent Applications_{ijt}*, *Technological Breadth_{ijt}*, *Knowledge Inputs_{ijt}*, and *Profits_{it}* exhibit high pairwise correlations with other variables. To ensure that findings are not affected by multicollinearity, I drop each variable individually, as well as all four variables together, from the main analyses in Table 3 in separate robustness tests. All results remain robust.

²⁵ *Scope_{ijt}* may take more than a year to react to changes in *Inventor Specialization_{ijt}* (H1) or vice versa (H2). I vary lags in the second-stage estimations to two, three, and four years separately for all analyses. Findings remain fully robust. I also repeat all analyses allowing for robust errors. In Model 2, *Tax_Pennsylvania_{ijt}* becomes significant only at 10 percent (t-statistics –1.76), which is arguably still meaningful given the test's one-tail nature. All other findings remain robust.

Table 2. Descriptive statistics

	Obs	Mean	Std.Dev.	i	ii	iii	iv	viii	viii	viii	viii	ix
i Scope _{ijt}	11,310	3.39	1.63	1.00								
ii Inventor specialization _{ijt}	11,310	0.80	0.21	-0.06	1.00							
iii Total patent applications _{ijt} ^a	11,310	0.10	0.33	0.03	-0.01	1.00						
iv Technological breadth _{ijt}	11,310	2.79	2.56	0.00	-0.03	0.66	1.00					
viii Science _{ijt}	11,310	0.11	0.13	0.13	-0.03	0.04	0.05	1.00				
viii Knowledge inputs _{ijt} ^b	11,310	0.12	0.57	0.06	-0.02	0.92	0.49	0.04	1.00			
viii Firm size _{it} ^b	10,863	0.05	0.05	0.00	0.03	0.03	0.13	-0.05	-0.01	1.00		
viii Cash _{it} ^c	10,942	0.00	0.00	0.10	-0.02	0.04	0.10	0.01	0.03	0.33	1.00	
ix Profits _{it} ^c	10,942	0.00	0.00	0.08	-0.05	0.04	0.09	0.01	0.02	0.25	0.73	1.00

a, b, c: variables scaled in (a) hundreds, (b) thousands (c) millions respectively.

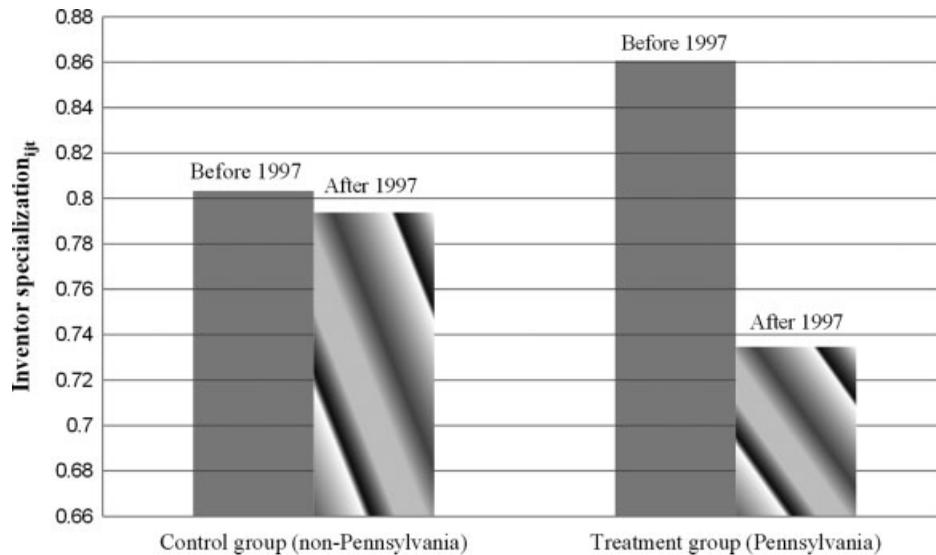


Figure 1. Effect of policy change on specialization

Analysis of scope measure

To examine the distributional properties of *Scope_{ijt}*, I reconstruct the dataset at the patent level. The average scope, i.e., number of independent claims in a patent, is 3.24 (26% of all claims), with a standard deviation of 2.27 and range of 1 to 50 per patent. I then compare it with other alternative scope measures: the patent’s number of technology classes, number of citations made, number of citations received, and generality of patents (Lerner, 1994; Lanjouw and Shankerman, 2004). The pair-wise correlations between these measures, as reported in Table 4, are low even among the alternative measures, suggesting that each measure contains substantively different information about the patented technology. Next, I regress my scope measure on the alternative

measures separately, controlling for the total number of claims and year dummies (Table 4). Each alternative measure is significantly and positively related to my scope measure across models, suggesting that while these measures may contain different information, the scope component is common and present across all measures.²⁶

²⁶ *Scope_{ijt}* depends on both the technology’s nature and the intellectual property (IP) component, i.e., how claims are drafted. A concern could be that such IP component may confound findings. However, the empirical design mitigates this concern: it is unlikely that the Telecommunications Act changes the way lawyers draft claims. Thus, variations in *Scope_{ijt}* predicted by the Act likely reflect changes in underlying technologies as intended. Likewise, it is unlikely that changes in *Inventor Specialization_{ijt}* arising from the tax credit will alter lawyers’ drafting techniques. Hence, *Inventor Specialization_{ijt}* likely affects the subsequent technologies’ nature and not the IP component.

Table 3. 2SLS regressions for the interrelationship between inventor specialization and scope of technologies

Dependent variable	Effect of inventor specialization on scope of technologies (H1)			Effect of scope of technologies on inventor specialization (H2)				
	First stage		Second stage	First stage		Second stage		
	(1)	(2)	(3)	(4)	(5)	(6)		
Statetax _{ijt}	-0.0533 (-3.11)	*** -0.0513 (-2.98)	***	Act _{ijt}	0.678 (5.19)	***	0.220 (1.14)	
Pennsylvania _{ijt}	0.0209 (1.49)	0.0326 (2.16)	**	Telecommunications _{ijt}	0.0349 (0.46)		-0.175 (-1.75)	*
Tax_Pennsylvania _{ijt}		-0.0848 (-2.09)	**	Act_telecommunications _{ijt}		0.466 (3.22)	***	***
Predicted inventor specialization _{ijt-1}				Predicted scope _{ijt-1}				-0.0436 (-4.41)
Total patents _{ijt}	0.148 (7.11)	*** 0.148 (7.11)	***	Total patents _{ijt}				0.0727 (3.51)
Technological breadth _{ijt}	-0.0077 (-6.61)	*** -0.00777 (-6.63)	***	Technological breadth _{ijt}				-0.00596 (-5.57)
Science _{ijt}	-0.0317 (-2.00)	** -0.0312 (-1.96)	**	Science _{ijt}	1.478 (12.6)	***	1.479 (12.6)	*** -0.0289 (-5.17)
Knowledge inputs _{ijt}	-0.0667 (-6.51)	*** -0.0667 (-6.51)	***	Knowledge inputs _{ijt}	0.602 (7.96)	***	0.619 (8.17)	*** -0.0305 (-2.88)
Firm size _{it}	0.223 (4.70)	*** 0.225 (4.73)	***	Firm size _{it}	-0.223 (-0.64)	**	-0.207 (-0.59)	0.112 (2.19)
Cash _{it}	0.729 (0.50)	0.638 (0.43)		Cash _{it}	2.207 (0.20)		4.168 (0.38)	3.084 (2.03)
Profits _{it}	-4.484 (-2.14)	** -4.422 (-2.11)	**	Profits _{it}	73.31 (4.73)	***	70.25 (4.53)	*** -3.018 (-1.38)
Year dummies included			included	Year dummies included				included
Constant	0.857 (58.6)	*** 0.856 (58.5)	***	Constant	2.587 (19.5)	***	2.785 (19.0)	*** 0.994 (30.9)
Observations	10863	10863	7576	Observations	10863		10863	7576

t statistics in parentheses.
 *** $p < 0.01$,
 ** $p < 0.05$,
 * $p < 0.1$

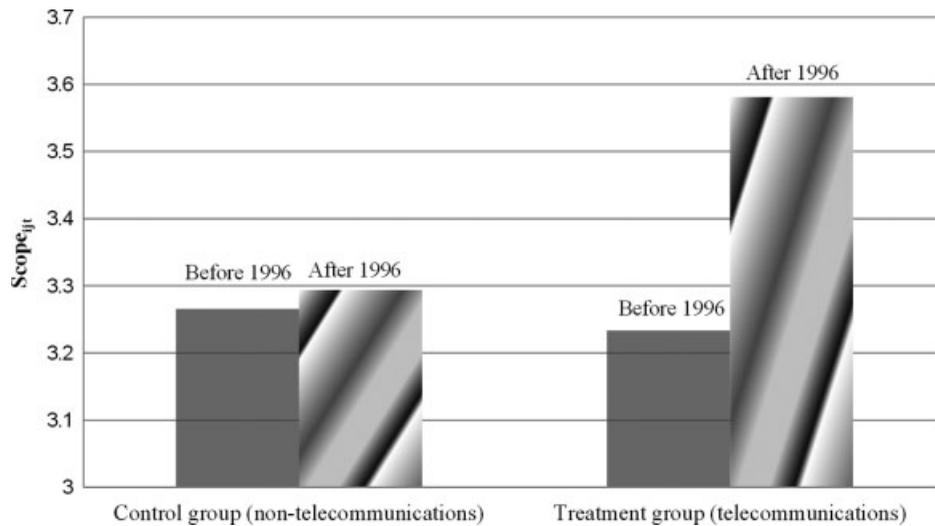


Figure 2. Effect of policy change on scope

Table 4. Analyses of scope measure

	OLS regressions, dependent variable: $Scope_{ijt}$				Pairwise correlations				
	(1)	(2)	(3)	(4)	(i)	(ii)	(iii)	(iv)	(v)
Scope (i)					1.00				
Number of technology classes (ii)	0.042 (3.55)	***			0.04	1.00			
Number of citations made (iii)		0.00825 (7.64)	***		0.10	0.03	1.00		
Number of citations received (iv)			0.00682 (6.27)	***	0.06	0.06	0.02	1.00	
Generality (v)				0.0861 (1.98)	**	0.02	0.25	0.00	0.34
Number of claims	0.11 (123)	***	0.11 (123)	***	0.108 (102)	***	0.109 (103)		
Year dummies	included		included		included		included		
Constant	2.171 (8.03)	***	1.445 (22.8)	***	1.622 (22.3)	***	1.614 (22.2)		
Observations	37258		36937		25954		25954		

t statistics in parentheses.
 *** $p < 0.01$,
 ** $p < 0.05$

CONCLUSIONS

The core proposition in this article is that a firm with more specialized inventors creates more narrow scope technologies and, importantly, these narrow scope technologies induce the firm to increase its inventor specialization. This not only explains why firms differ in their technologies' scope, which is by itself an important inquiry given its role in heterogeneous firm growth, but also explains how this difference across firms

is sustained. I find empirical support for this proposition in the U.S. communication equipment industry from 1985 to 2003.

Viewing technologies' scope as a resource attribute and inventor specialization as a form of R&D organization, this article aims to shed light on the commonly observed isomorphism between a firm's resource and organization. A potential explanation of this isomorphism, informed by prior research, is that how a firm organizes its search

activities determines the types of resources it creates and enforces the isomorphism. Yet, without recognizing that such organization is itself shaped by the firm's resources, this simplistic attribution falls short of comprehensively explaining why a firm's resource and organization appears isomorphic, and it misses the inherent 'chicken or the egg' dilemma in this inquiry. The same theoretical shortfall exists in research explaining how a firm's resources shape its organization of activities.

Conceptually, this article suggests a different approach to examining firm heterogeneity. Past research typically attributes firms' different performances to resource heterogeneity (Henderson and Cockburn, 1994) and then further attributes such heterogeneity to other forms of firm heterogeneity, spurring a perpetual inquiry for antecedents in the upstream. For instance, resource heterogeneity is caused by variations in search, which results from different R&D organization, which is, in turn, a consequence of distinct strategies, and so on. This article instead breaks away from such perpetual inquiry and suggests that two forms of firm heterogeneities, in scope of resource and organization of inventors, can both be antecedents of each other. The two forms of firm heterogeneities, once in place, may be mutually reinforcing and difficult to change.

Such two-way interrelationships are by no means uncommon. For instance, a firm's resources driving strategy selection are, in turn, shaped by the firm's strategy; a firm's reputation facilitating alliance formation is itself enhanced by the firm's alliances; firm-specific capabilities expanding a firm's boundaries will themselves grow with increasing internalization. This article serves as a call to examine these other interrelationships in strategy research and offers an empirical tool for such examination. Fundamentally, at the heart of the propositions lies a more generic interrelationship between how one organizes activities and what skills one possesses, and this interrelationship could well extend beyond the realm of firm decisions. Future research has more opportunities to reveal the process of how such interrelationship unfolds over time, such that specialization begets further specialization while a generalized entity strives for greater generalization. Further, intriguing questions remain as to how initial differences across firms arise before interrelationships of this sort kick in to sustain such differences. Hence, while this article lay but modest claims,

the potential future discoveries it aspires to catalyze are plentiful.

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