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Learning by Supplying

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Working Paper

12-093

April 20, 2012

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Abstract

Learning processes lie at the heart of our understanding of how firms build capabilities to generate and sustain competitive advantage: learning by doing, learning by exporting, learning from competitors, users, and alliance partners. In this paper we focus attention on another locus of learning that has received less attention from academics despite popular interest: learning by *supplying*. Using a detailed panel dataset on supply relationships in the mobile telecommunications industry, we address the following questions: What factors contribute to a firm's ability to learn by supplying and build technological and market capabilities? Does it matter *to whom* the firm supplies? Is involvement in product design important, or is manufacturing the key locus of learning? How does a supplier's initial resource endowment play into the dynamic? Our empirical analysis yields interesting findings that have implications for theory and practice, and that suggest new directions for future research.

Learning by Supplying

How do firms build capabilities and resources to generate and sustain competitive advantage? This question lies at the very heart of strategic management and has long pre-occupied scholars and practitioners alike. While no simple prescriptions have emerged from the decades of study on the topic, scholars have identified some key industry dynamics and firm-level processes that appear to underlie capability development in different contexts. A common thread running through many of these explorations is a focus on learning: learning by doing (Lieberman, 1984; Irwin and Klenow, 1996); learning from co-located competitors (Baum and Ingram, 1998); learning from users (Von Hippel, 1986, 1988); learning by exporting (MacGarvie, 2006; Salomon and Shaver, 2005); and learning through joint ventures and alliances (e.g., Mowery, Oxley and Silverman, 1996; 2002).

In this paper we focus our attention on a locus of learning that has garnered significant interest in the practitioner-oriented literature of late, but that has received much less attention from academics: learning by *supplying*. Interest in this dynamic is driven in part by the rise in offshore outsourcing of manufacturing and related activities, particularly to China and other emerging economies. Interest is also fueled by the observation that some firms in these countries have successfully parlayed their experience as 'Original Equipment Manufacturers' (OEMs) supplying to major branded producers into positions as viable world-class players in their industry, possibly at the expense of previous market leaders. Take for example this observation by Khanna and Palepu in their 2006 *Harvard Business Review* article subtitled "Building World-Class Companies in Developing Countries":

> Taiwan-based Inventec…is among the world's largest manufacturers of notebook computers, PCs, and servers, many of which it makes in China and sells to Hewlett-Packard and Toshiba… Inventec has mastered the challenges associated with sourcing components from around the world, assembling them into quality products at a low cost, and shipping them to multinational companies in a reliable fashion. Recently Inventec started selling computers in Taiwan and China under its own brand name. The computers have a Chinese operating system and software, so Inventec doesn't compete directly with its customers – yet. (Khanna and Palepu, 2006: 66-67)

This last possibility – that Inventec may eventually emerge as a direct competitor to its erstwhile customers – taps into a concern that has worried policy makers and commentators in the US and other developed countries for decades: i.e., that offshore outsourcing may lead to a migration of capabilities to foreign suppliers (Cohen and Zysman, 1987; Pisano and Shih, 2009). However, prominent examples of firms 'breaking out' of their role as suppliers to major branded producers to become viable world-class competitors are few and far between. Indeed, many suppliers apparently feel trapped in a subordinate role, confined to low-margin manufacturing activities, and unable to support the investments in technology and marketing resources necessary for independent success.[1] Meanwhile, U.S. multinationals and other leading companies are bombarded with advice on how to minimize the migration of capabilities – and profits - to suppliers (e.g., Arrunada and Vazquez, 2006).

This situation raises intriguing strategic questions for OEM suppliers as they attempt to climb up the value chain in search of greater profits: What factors contribute to a firm's ability to learn by supplying, to build capabilities and advance in terms of technological and market success? Does it matter *to whom* the firm supplies? For example, is it more beneficial to supply to market leaders or to team up with market laggards? And does it matter *what* the firm supplies? Must the firm be actively involved in product design to effectively learn by supplying, or is manufacturing the key locus of learning? How does a supplier's own initial resource endowment and capabilities play into the dynamic? To date, researchers and managers contemplating these questions have operated in a virtual empirical vacuum, as there have been, to our knowledge, no systematic empirical studies focused on the phenomenon of learning by supplying. In this paper we address this gap, documenting the extent of learning by supplying in the mobile telecommunications handset industry, a dynamic industry within the electronics manufacturing sector often featured in popular debates about offshore outsourcing and the migration of capabilities.

For the purposes of our study we have collected comprehensive data on significant supply relationships for the design and manufacture of complete handsets for major branded producers and operators over the entire history of the industry. By marrying this data with information on the patenting activities of customer and supplier firms, as well as introduction

[1] Careful study by economists on the impact of offshore outsourcing on wages and employment has also yielded little conclusive evidence to back up doomsday scenarios related to the 'hollowing out' of US technological capability (see Trefler, 2005, for a recent review).

dates and sales of mobile handsets over the period 1995-2010, we are able to generate an unusually complete picture of outsourcing in this industry. We leverage these data in our empirical analysis to assess the extent of technological and market learning achieved by supplier firms, and begin to disentangle sources of heterogeneity in the extent of learning. Consistent with our definition of learning as the accumulation of capabilities, our primary measure of technological learning is supplier patenting. We also assess the 'dyadic' nature of learning by examining the technological overlap between a supplier and its customer(s). To evaluate market learning we track the introduction and sales of a supplier's own-brand mobile handsets.

Our empirical analysis yields several interesting findings. We find significant and robust evidence of learning by supplying in terms of both technological and market learning. For the suppliers in our sample, patenting increases as the firm accumulates experience in handset supply relationships, particularly if they are involved in both handset manufacturing *and* design. Our dyadic analysis of technological overlap also reveals a pattern of convergence in supplier and customer capabilities over the course of a supply relationship. More generally, our findings indicate that it matters a lot to whom you supply in this industry, although sometimes in counterintuitive ways. For example, even though operators are more likely to delegate design activities to their suppliers, relative to branded producers, they do not appear to be a robust source of technological learning for suppliers. Conversely, when it comes to *market* learning, selling to operators represents a particularly important 'pathway' to own-brand introduction and sales, while supplying to market leaders strongly inhibits sales of own-brand products. This finding is consistent with observations in the industry that market leaders, although technologically more advanced, tend to write more restrictive outsourcing agreements, particularly when they perceive that transfer of capabilities to their suppliers could pose a competitive threat.[2]

In addition to providing the first systematic firm-level evidence of learning by supplying, our study contributes to developing understanding of firm boundaries and capabilities, particularly in emerging industries. In particular, our results point to the existence of quite

[2] This and other qualitative assessments of supplier learning in the mobile handset industry are derived from field research in the industry carried out through interviews with managers in 7 suppliers (among them 3 top brand producers) and 5 operators over the period 2007-2012.

distinct pathways to technological and market learning for suppliers in the mobile handset industry. Counter to the received wisdom, it does not appear that accumulation of technological capabilities is a necessary or sufficient condition for successful introduction of own-brand products. Moreover, our analysis of supplier selection models indicates that the initial choice of suppliers is somewhat haphazard, and that there are significant switching costs and inertia in customer-supplier matches. This in turn implies that initial supplier choices of branded producers and operators may have a strong influence on suppliers' long-term capability development and strategic alternatives. Finally, our study reinforces the importance of examining both the *means* and the *motives* for knowledge sharing in inter-firm arrangements. Suppliers working with leading branded producers may find themselves effectively locked into a subordinate role, thwarting ambitions to move up the value chain and develop as viable independent participants in the industry.

Theoretical Background and Related Studies

Although learning by supplying has been subject to little direct academic study, there are several streams of relevant prior research that shape our expectations about the phenomenon and guide our empirical analysis. The importance of learning from direct production experience, or learning-by-doing, has been well documented in the economics literature, dating back to early theoretical work by Arrow (1962). The first empirical studies focused on the shape of individual firms' "learning curves" in different manufacturing industries, and generated robust evidence that costs tend to decline (albeit at a decreasing rate) as a firm's cumulative production volumes increase (Alchian,1963; Rapping, 1965). Later extensions also found evidence of industry-level learning curves (Lieberman, 1984; Irwin and Klenow, 1996), indicative of learning-by-doing spillovers, although these studies also reinforce the notion that it is a firm's own direct experience that has the greatest effect on learning.[3] This conclusion has found further support in research in the strategy and organizations field, which also relates the steepness of the learning curve to choices related to organizational design, product positioning and geographic location (e.g., Baum and Ingram, 1998; Darr, Argote and Epple, 1995; Ingram and Baum, 1997).

[3] Irwin and Klenow (1996), for example, show that firms learn three times more from an additional unit of their own cumulative production than from an additional unit of another firm's cumulative production.

While the conventional learning-by-doing literature has focused primarily on the impact of cumulative experience on production costs, recent extensions of the basic concept have examined the impact of learning-by-doing on other measures of firm performance (e.g., survival and innovation) and have also begun to explore other types of experience-based learning. For example, a recent literature rooted in models of trade and endogenous growth (Romer, 1990; Grossman and Helpman, 1993) examines the link between international trade and innovation.[4] Starting from the premise that trade exposes firms to sources of knowledge that would otherwise be unavailable to them, scholars have looked for – and found – convincing evidence of "learning by exporting," (e.g., Salomon and Shaver, 2005) as well as "learning by importing" (MacGarvie, 2006).[5] In an empirical model that allows for positive feedback between innovation and exporting, for example, Salomon and Shaver (2005) find that exporting leads to significant increases in both technological innovation (as indicated by an increase in patent applications) and product innovation (i.e., new product introductions) at the firm level.

Explanations of learning by exporting resonate particularly well with the concept of learning by supplying, introduced here. In contrast to simple learning-by-doing arguments, which link performance to the focal firm's accumulated volume of production, learning by exporting posits that the identity or characteristics of the firm's customers (or intended customers) may also matter for the extent of learning:

> For instance, exporters might benefit from the technological expertise of their buyers (Clerides et al, 1998). Moreover, exporters might receive valuable information about consumer product preferences and competing products… [And as] the information collected from these sources filters back to the parent firm, it should incorporate the knowledge into its production function. (Salomon and Shaver, 2005: 434)

[4] In addition to the firm-level studies discussed below, there is a very large body of literature examining the effect of international trade and foreign direct investment (FDI) on technological and economic convergence or 'catch-up' at the country level. This research, primarily undertaken by international economists and international business researchers, suggests that significant technological catch-up has indeed taken place over the latter half of the twentieth century. Understanding of the mechanisms underlying this general trend nonetheless remains quite incomplete – see Athreye and Cantwell (2007) for a useful review and discussion.

[5] As discussed in these papers and elsewhere, evidence on the effect of trade on firm-level productivity is more equivocal: although there are significant differences in the average productivity of exporting and non-exporting firms, this is almost entirely attributable to selection effects rather than learning (see, e.g., Clerides *et al*, 1998).

Salomon and Shaver (2005) thus relate the extent of learning to one particular buyer characteristic - location - suggesting that buyers encountered in export markets are more advanced and/or have different requirements than domestic buyers. Similarly, in the context of the current study, we conjecture that the extent of learning (i.e. accumulation of technological and marketing expertise) by firms supplying handsets to branded producers and operators in the mobile telecommunications industry will depend not only on the supplying firms' own characteristics, but also on characteristics of the buyers with whom it works. Relevant characteristics in this case relate to the buyer's level of technological and marketing expertise as well as its willingness to share that expertise with the supplier.

Prior research on learning in inter-organizational alliances reinforces the notion that firms can gain access to valuable technological and market knowledge through vertical and horizontal linkages, and this research generates additional nuanced findings that may be particularly relevant in the context of learning by supplying. One stream of research, for example, has developed the idea that learning from alliance or exchange partners is conditioned on the focal firm's initial stock of knowledge, both in absolute terms and in reference to the knowledge stock of the partner firm: firms with a higher initial stock of knowledge have greater "absorptive capacity" (Cohen and Levinthal, 1990) and thus are able to acquire new knowledge from customers or alliance partners more readily. Moreover, to the extent that absorptive capacity is partner-specific, learning will also be enhanced when there is substantial overlap in the technological or knowledge domains of the firms involved in the exchange (Lane and Lubatkin, 1998). Empirical analysis of changes in the patents granted to firms involved in technology alliances and licensing agreements has generated evidence consistent with these claims. In particular, several studies have shown that the technological overlap between alliance partners increases as they work together, consistent with the notion that firms share technology and learn from each other in these relationships (Mowery *et al.*, 1996, 2002; Oxley and Wada, 2007).

Prior alliance research suggests that we should also expect the extent of learning by supplying to be affected by the organizational and management decisions of the buyers with whom a supplier works. If the outsourcing firm is concerned about the competitive consequences of a transfer of capabilities to the supplier firm, they may act to narrow the scope of activities carried out by the supplier and, in particular, may retain tight control over the most technologically sophisticated elements of production and/or design. In this case, the extent of learning by supplying will be reduced, *all else equal*. Prior research on the scope of technology alliances again provides some evidence that supports this line of reasoning. Oxley and Sampson (2004), for example, show that when alliances bring together firms that are direct product market competitors, the scope of alliance activities tends to be reduced such that the alliance is significantly less likely to encompass manufacturing and/or marketing activities along with Research and Development (R&D). This tendency is less common when alliance partners are industry laggards, suggesting that, "when laggards team up in an R&D alliance they are more willing to expose competitively significant know-how to their partners, perhaps in the hope of leapfrogging industry leaders" (Oxley and Sampson, 2004: 737-738). Although the consequences of observed variation in alliance scope for partner learning have yet to be fully explored, the findings of this prior research nonetheless suggest that learning by supplying may depend in part on the extent to which buyers perceive the supplier as a potential rival, as well as on the scope of activities transferred to the supplier (for example, whether design is outsourced in addition to manufacturing).[6]

The final stream of research that informs our empirical analysis is the emerging literature on the co-evolution of outsourcing and firm capabilities. As suggested in the introduction, there is as yet very little large-scale empirical evidence to support or refute the importance of learning by supplying, but case studies on the rise of multinationals from emerging economies frequently point to the role of OEM relationships in the accumulation of capabilities (e.g., Khanna and Palepu, 2006; Duysters *et al.*, 2009; Pisano and Shih, 2009). Some of these case studies also suggest that the accumulation of *technological* capabilities by supplying firms tends to occur more readily – and faster – than the accumulation of the marketing capabilities and resources necessary to sustain the introduction of an independent brand. In their discussion of the rise of Haier in the domestic appliance industry, for example, Duysters *et al.* (2009) note that Haier sold its products into the US under OEM arrangements with major branded producers for many years and built up significant technological capabilities prior to the eventual introduction of its own brand.

[6] This expectation is also consistent with previous research in technology and operations management (See, e.g., Terwiesch & Loch, 1999).

In sum, although there has been little systematic study of the magnitude and significance of learning by supplying, prior research in related areas suggests that such learning may be a significant phenomenon, with suppliers climbing up the value chain and achieving independent success in technological and marketing domains. The prior literature also points us to several factors that may influence the extent of learning. In the following section we introduce the empirical context of our study – the mobile telecommunications handset industry, and develop more specific predictions regarding the extent of learning by supplying that we are likely to observe in this context.

Empirical context

The empirical setting for our study is the mobile telecommunications handset industry. This is a relatively new industry: the first commercial mobile handsets emerged circa 1985, but demand did not take off until the early 1990s (see Figure 1); since then, production has increased exponentially. From the beginning of the industry, the market has been dominated by a handful of powerful branded producers - Nokia, Motorola, Sony and Ericsson[7], later joined by Samsung and LG. Industry concentration remains high, and indeed has increased slightly during the last decade: in 2010 the five leading firms accounted for over 80% of global handset sales (see Figure 2). Demand growth was particularly strong during the 'telecom boom' of the late 1990s, when demand outstripped available supply. In contrast to other industries in the electronics sector, however, outsourcing of manufacturing among the leading branded producers was quite rare throughout this period, as firms invested heavily in their own manufacturing plants in response to the supply shortfall.[8]

[Figure 1 & Figure 2 about here]

It was only in the post-boom crash of 2000-2001, with significant excess global production capacity emerging in the industry, that major branded producers turned to outsourcing as a way to rationalize operations: many firms sold manufacturing plants to existing electronics manufacturing services (EMS) firms, most notably Flextronics, Foxconn and

[7] Sony and Ericsson merged their handset businesses in 2001, forming Sony-Ericsson.
[8] This decision reflects the rapid pace of technological change in the handset industry during this period, as well as the dearth of capable suppliers available at the time.

Solectron, so opening the door to significant outsourcing in the industry. This door has since been flung wide open as many more suppliers came on line, with production at first centered in Europe and North America, but rapidly shifting to East and South East Asia. The scope of outsourced activities has also increased over this period: initially outsourcing was typically limited to manufacturing-only (OEM) agreements, but in later periods some branded producers began to outsource handset design responsibilities as well, entering into ODM (Original Design and Manufacturing) agreements with their suppliers. In these agreements the branded producer specifies performance requirements and selects key components such as the display and core chips, but the supplier does much of the mechanical and electrical design (Engardio and Einhorn, 2005).

Branded producers sell handsets direct to consumers through retail outlets, and also through mobile telecom operators around the globe (e.g., Cingular, Sprint and Verizon in the US, Virgin Mobile and Vodafone in the UK, or NTT Docomo in Japan, to name a few). During the 1990s' telecom boom these operators sought greater control of handset supply, in part to counter the threat of shortages, but also to more directly influence handset design and increase hardware and service integration. Because operators had little or no prior experience in handset production this was typically accomplished through ODM agreements with established suppliers; the resulting handsets were then distributed exclusively by the operator under the operator's own brand name (Yoffie, Alcacer and Kim, 2012).

Today, the industry continues to be dominated by a core group of branded handset producers, but there is a vibrant and growing set of peripheral providers – many of whom are suppliers that have successfully introduced their own branded handsets. The incentives for suppliers to climb up the value chain and operate independently are clear, as profit margins for branded producers still significantly exceed those of OEM suppliers. Thus, for example, when Taiwan's HTC Corp. successfully introduced its own branded handsets in 2006, it saw its profit margin increase from 18% in 2004 (in line with peer OEM suppliers at the time) to 33% in 2008. This latter figure compares quite favorably with leading brand producers such as Nokia, Samsung, Motorola, etc., whose profit margins were in the range of 25-30% during this period.[9]

[9] Author estimates based on IQ Capital data, various years.

It should be noted that while a significant fraction of suppliers have introduced own-brand handsets in recent years, few have been able to match HTC's success in global markets. Most own-brand introductions have been limited to the supplier's home markets (examples include Ningbo Bird in China, Sewon and Telson in South Korea) and OEM relationships continue to account for the largest share of these companies' revenues. Outsourcing suppliers have made significant leaps forward in terms of technological innovation since the beginning of the outsourcing era: while as a group these firms held almost no telecommunications-related patents in the early 1990s, many are now active innovators and regularly patent their innovations in the US and elsewhere.[10]

Placing these features of the mobile telecommunications industry's evolution alongside the prior research discussed above generates several predictions regarding the extent of learning by supplying that we may observe in this context. A simple extension of learning-by-doing logic suggests that supplier learning (both technological and market learning) will be positively related to the duration and extent of supply activity (including, for example, the number of customers supplied.) Prior research on learning by exporting and learning through alliances also suggest that learning is likely to be conditioned by the technological endowments of the supplier firm as well as those of the customers that it supplies, with increased technological sophistication enhancing learning, *ceteris paribus.*

The alliance literature further highlights potential complexities in the link between customer capabilities and market position and supplier learning, however: as emphasized by Oxley and Sampson (2004), we must be careful to consider both the 'means and the motives' for knowledge sharing and transfer in such arrangements since at times these may be in tension. In our empirical setting this issue is brought to the fore as we compare suppliers' relationships with branded producers and those with operators: branded producers tend to have significantly stronger technological capabilities than operators and, as such, suppliers to branded producers potentially gain access (or at least exposure) to more advanced technologies. Branded manufacturers have also traditionally been quite 'protective' of their core technologies in

[10] Among the suppliers in our dataset we observe that over three-quarters of the firms had obtained one or more telecom-related patents by the end of the observation period, and about two-thirds had introduced one or more own-brand handsets.

relationship to suppliers however, limiting outsourcing to less technologically-advanced and low cost handsets (known as feature phones) or to handsets based on standards in which they had not previously invested significantly.[11] Quoting Motorola CEO Edward J. Zander, one article noted that "You have to draw a line…core intellectual property is above it, and commodity technology is below" (Engardio and Einhorn, 2005). The same article notes that branded producers have also tended to limit suppliers' involvement in 'customer facing' aspects of the handset design process, jealously guarding their customer relationships. This last point is significant in that prior research indicates that learning opportunities will be greatest when a supply relationship combines design and manufacturing activities, i.e. in ODM contracts.

In contrast, most operators have willingly outsourced manufacturing of even high-end cell phones (e.g., smart phones), and to involve suppliers in all aspects of handset design and manufacture. For example, in describing HTC's relationship with its operator clients (prior to introduction of its own-brand phones) Yoffie *et al*. (2012) note that

> Carriers embraced HTC as they gained a greater sense of control over their product portfolio. "HTC's willingness to listen to what we [operators] wanted was like a breath of fresh air," recalled Richard Brennan, a former Orange executive who later moved to HTC as a marketing consultant. "Because HTC were bending over backwards to deliver, you wanted to make your relationship with HTC work and help the underdog become successful.

In sum, we indeed observe an apparent tension between the means and the motives for knowledge sharing by branded producers and operators and their handset suppliers. As such it remains an open empirical question as to whether suppliers are likely to learn more from operators or branded producers, and the implications that this has for suppliers' ability to progress along the value chain to become independent players in the industry.

Data

Data for our empirical study comes from a wide variety of sources. Our goal for this project was to assemble a comprehensive dataset covering handset design and manufacturing

[11] Nokia, for example, has outsourced most CDMA handsets while producing GSM handsets in-house. More generally, according to data from THT Research, 70% of outsourcing by leading producers was for relatively low-cost feature phones..

supply relationships for all of the major branded producers and operators active in the mobile telecom handset industry from the beginning of the outsourcing era to the present day. Extensive search revealed that (as we suspected), no single source existed that could accomplish this goal. We therefore drew on a variety of proprietary datasets and web-based resources. For the web-based data search we crawled and compiled relevant information from current and archived pages of electronic product comparison websites, as well as industry association, news media, and government sites, to gather information on mobile handset production and outsourcing relationships. Appendix 1 provides information on the different data resources accessed, and the scope of data coverage for each source. To increase our confidence in the validity of the outsourcing dyads (customer-supplier relationships) in our dataset, we include only those dyads that appeared in at least two of these data sources.

Identification of valid outsourcing dyads is further complicated by the frequent occurrence of mergers and acquisitions in the mobile telecommunications and electronic manufacturing service industries during the period of study, and the complex and shifting ownership pattern that resulted from this process. To ensure that supply relationships identified in our data are in fact arrangements between independent firms, we documented the ownership history for each identified firm using the Directory of Corporate Affiliations (DCA), Mergent Online, ISI Emerging Markets, Orbis, and archived editions of the IT news website, Digitimes (http://www.digitimes.com);[12] any outsourcing relationships where the customer and supplier were joined by common ownership were omitted from the dataset.

Consistent with our focus on supplier learning, the unit of observation in most of our empirical specifications is supplier-year, and we aggregate the outsourcing dyads identified in our data search to the firm level for each supplier in each year. For our indicators of supplier learning, as well as firm and relationship characteristics that may condition the extent of learning by supplying, we drew on data from several additional sources: patent data come from Thomson Innovation's Derwent World Patents Index (DWPI) database; financial data come from Compustat's Worldscope Global, ISI Emerging Markets, Orbis, and Capital IQ; global sales data

[12] Using a variety of sources for ownership data was necessary because our sample firms vary widely in terms of location, size, and public/private ownership. This diversity also necessitated the use of a variety of sources for the compilation of financial data (see below).

for branded handsets come from International Data Corporation. Information collected from each of these sources was matched by hand to the firms (both customers and suppliers) in our dataset.

The process used for compilation of the patent data deserves particular attention: for this we sampled all patents from DWPI with telecom-related EPI Manual Codes W01 (Telephone and Data Transmission Systems) and W02 (Broadcasting, Radio and Line Transmission Systems) for the period 1990-2010.[13] We then used the Directory of Corporate Affiliations (DCA) to assign patents to firms, ensuring that we captured all relevant patent applications for each firm by matching sample firms with all related subsidiaries listed in DCA, and in turn matching these to patent assignees in the DWPI database. Finally, to eliminate potential bias arising from differences in the scope of claims across technology classes (Alcacer and Gittelman, 2006), the assigned patents were collected into 'patent families,' (i.e., patents based on the same invention disclosed by a common inventor and patented in more than one country). Application dates used in our analysis are based on the year of the first patent application within the family, i.e., the earliest priority year.

The dataset emerging from this compilation process comprises observations on 114 unique firms that supplied complete handsets to 154 branded producers or operators between 1994 and 2010; 13 of these supplier firms were subsequently dropped in preparing the dataset for our empirical analysis because they are also branded producers and derived a significant portion of their revenues from branded handset sales throughout the period of study: as such, it would be unreasonable to attribute changes in patenting, etc. to learning by supplying for these firms.[14] Table 1 shows the distribution of these supplier firms across countries, as well as the time period in which they began supplying handsets. This table illustrates the shifting geography of the

[13] DWPI has created a proprietary system of patent classifications called Manual Codes. These are in part based on the International Patent Classification System but provide an alternative more technologically-grounded view of the patenting landscape. EPI Manual Codes cover patents in the electrical field. Using Manual Codes W01 and W02 as the basis of our patent sampling ensures that we maintain a tight focus on telecom-related technologies. See http://ip-science.thomsonreuters.com/m/pdfs/epi_manualcodes1.pdf for further details. Note that we chose 1990 as the beginning year for the patent sample to ensure that we would be able to calculate our patent 'stock' variables for the first outsourcing dyads observed in our data, which turned out to be in 1995.

[14] The dropped firms are Alcatel, Apple, Ericsson, Hewlett Packard, LG, Motorola, Nokia, Panasonic, Philips, RIM, Samsung, Sony and Sony Ericsson. Note that all of these firms are also important customers to OEM suppliers and, as such, are still accounted for in our final dataset in that capacity.

supply base in this industry: operators and producers mainly outsourced handset production to suppliers in Europe, North America and Japan in the early period, but when outsourcing took off in the early 2000s, the centre of gravity of the handset supply industry shifted towards emerging markets in Asia. Chinese, South Korean and Taiwanese firms together account for 76% of new suppliers in the period since 2005.

[Table 1 about here]

While we cannot claim that our data are exhaustive and capture *every* significant handset supply contract, we are confident that we have assembled the most comprehensive database of outsourcing relationships to date in this industry, and that there are few major omissions. This view is bolstered by our conversations with industry experts, who were unable to identify any significant handset supply relationships that we had missed. The variables and estimation strategy used in our empirical analysis are described in detail below, followed by a discussion of supplier selection and endogenous matching issues.

Empirical approach

The goal of our empirical analysis is to understand the relationship between changes in suppliers' technical and market capabilities and the duration and extent of a supplier's cumulative supply experience, along with relevant characteristics of the supplier, its customers, and the supply relationships themselves. We use four measures of supplier capabilities as dependent variables in our analysis – two related to technological learning and two related to market learning – and all models share the following basic structure:

$$Supplier\ capabilities_{it} = E_{it} + S_{it} + C_{it} + R_{it} + \delta_t + \eta_i + \epsilon_{it}$$

here, E_{it} is the duration and extent of supply experience for supplier *i* up to time *t*, S_{it} captures characteristics of supplier *i* at time *t*, C_{it} captures characteristics of supplier *i*'s customers to year *t*, and R_{it} aggregates relationship characteristics of supplier *i* to time *t*; δ_t, η_i are year and supplier firm (or supplier-customer dyad) fixed effects and ϵ_{it} is an error term.

The estimation method used in specific regressions depends on the nature of the dependent variable in the model, as detailed below. The use of fixed effects regressions with year and firm (or dyad) fixed effects means that in each case we are focusing on within-firm (or within-dyad) variation rather than cross-sectional variation in capabilities.

Dependent Variables

We construct two measures of a supplier's technological capabilities to assess the extent and direction of technological learning by supplying. The first of these is $PATENTS_{it}$, a firm-level measure based on a count of patent families in telecom-related technology classes. More specifically, $PATENTS_{it}$ is an annual count of the number of 'patent families' in (ultimately successful) US patent applications filed by $supplier_{i,}$ averaged over a three year window beginning in year t.[15] A three-year window is used to smooth the patent application series which is typically quite lumpy, especially for firms with relatively small numbers of applications overall (as is the case for many of the suppliers in our sample), and to account for the possibility that patent applications may be a lagging indicator of innovation activity.[16] Since $PATENTS_{it}$ is a count variable, we use fixed effect negative binomial estimation in models with this dependent variable.

For our analysis of partner-specific technological learning we construct a dyadic measure of the technological overlap (TECH $OVERLAP_{ijt}$) between every potential supplier-customer pair in every year of the sample period. The precise construction of this variable is as follows:

$$TECH\ OVERLAP_{ijt} = \frac{F_{it} * F_{jt}^{'}}{\sqrt{\left(F_{it} * F_{it}^{'}\right) * \left(F_{jt} * F_{jt}^{'}\right)}}$$

where F_{it} the patent class distribution vector for firm *i* in year *t* (See Jaffe, 1986, for further details.) Models that have TECH $OVERLAP_{ijt}$ as the dependent variable are estimated using fixed effects linear regressions.

For our analysis of *market* learning we construct two firm-level proxies for market capabilities: The first, OWN $BRAND_{it}$ is an indicator variable marking the first introduction of

[15] We obtain virtually identical results if we use counts of individual patent applications. This is unsurprising in this context, since the average number of patents per family in telecom-related patent classes is quite low. Our results are also robust to the inclusion of patents filed in other countries.

[16] Because the patent data series is censored in 2011, observations in 2008 and beyond use fewer years of patent data for these forward counts.

one or more own-brand mobile handsets by supplier *i*. This variable takes a value of 0 in every year preceding the year in which supplier *i* introduces its first own brand handset and changes to 1 in the year of introduction.[17] These models are estimated using random effects logit with year dummies. Our second proxy for market capabilities is BRANDED $SALES_{it}$, the total number of units of own-brand handsets sold by supplier *i* in year *t*. These sales data, which come from International Data Corporation (IDC, 2011), are available for only a subset of suppliers (27 firms in all) for the years 2004-2010, and these are fixed effects linear regressions.

Independent Variables

Our first set of independent variables measures the duration and extent of a focal firm's supply experience in the mobile telecom handset industry. SUPPLY $TIME_{it}$ indicates how long $supplier_i$ has been supplying mobile telecom handsets by year *t*, i.e., the number of years from the first observation of a supply relationship for $supplier_i$ in our data to year *t*. CUM. $CUSTOMERS_{it}$ is then our measure of the *extent* of the accumulated supply experience. This measure is based on the number of customers supplied in each year by $supplier_i$, cumulated to year *t*.

Our second set of firm-level independent variables captures other relevant characteristics of the supplier firms. Most important among these is the technological sophistication of the supplier, which may generate absorptive capacity and thus impact the extent of learning by supplying. To capture suppliers' evolving technological sophistication we include a variable PRIOR $PATENTS_{it}$ a dummy variable equal to 1 if the supplier has successfully applied for one or more patents prior to year *t*.[18] In addition, to account for the possible effect of changes over time in firm size, revenues and R&D investments, we also include LOG $ASSETS_{it}$, LOG $SALES_{it}$,, LOG $R\&D_{it}$, and LOG FIRM AGE in all model specifications. The financial variables

[17] In the results reported in Table 4a, below, the supplier exits the sample in years following the introduction of its first brand since this is the focal event for our analysis: in this way our analysis mimics the structure of a hazard rate model. Our results are nonetheless quite robust to alternative model specifications and methods, including estimation of a Cox proportional hazards model, as discussed in the robustness section.

[18] In robustness tests we have also estimated models where this variable is replaced by a 3-year lagged dependent variable (the number of patent families in $supplier_i$'s patent applications averaged over a three year window *ending* in year *t)*. These models produce qualitatively identical results. Because inclusion of a lagged dependent variable can result in inconsistent estimates in fixed effects panel estimations (Nickell, 1981) we also implemented a Bond – Arellano model (with OLS). This model also produces qualitatively similar results, although the statistical significance of some coefficients is slightly reduced. These results are available from the authors on request.

are contemporaneous dollar-denominated logged values; log transformations are used to account for the significant skewness in these variables.[19]

Our third set of independent variables focuses on learning-relevant characteristics of the customers served by a supplier over time. To capture the extent to which a supplier's customers can provide a window on the technological frontier we include a variable CUSTOMER PATENTS_{it} equal to the maximum number of patent families in the patent applications of any one of supplier_i's customers, averaged over a three year window ending in year *t*.[20] We also create additional customer counts that distinguish different types of customers: CUM. OPERATORS_{it} is the summation to year *t* of supplier *i*'s customers that are operators; similarly, CUM. LEADERS_{it} is the summation to year *t* of supplier *i*'s customers that are among the top 5 branded producers in terms of market share in the mobile telecom handset market in a given year.[21]

To provide an indication of the *nature* of the outsourcing relationships that the supplier has developed to date, in some specifications we partition the cumulative customer count according to whether the outsourcing relationship with a given customer (in a given year) involves an OEM agreement, i.e., manufacturing only, or an ODM agreement (design *and* manufacturing).[22] Similar to our basic customer count, these variables, CUM. OEM_{it} and CUM.ODM_{it} are cumulative measures to year *t.*

[19] Missing financial data reduces the number of supplier firms available for our empirical analysis to 76 firms. Most of the results reported below are nonetheless robust to the exclusion of financial data (and a concomitant increase in sample size).

[20] By using the maximum number of patents held by a single customer rather than the total number of patents held by all customers we avoid conflating our measures of customers' technological sophistication with the number of customers served by a supplier. We obtain qualitatively identical results if we use the average number of patents held by customers.

[21] Market share data comes from Gartner group's "Mobile device – markets share" reports for 2000-2011.

[22] There are a very small number of design-only agreements in our data, which we combine with ODM agreements in the results reported here. Breaking out these agreements as a separate category produces essentially identical results and the lack of significance of the design-only category in these regressions is consistent with the idea that enhanced learning is associated with design *and* manufacturing rather than design *per se*. The sparseness of this data category limits our ability to draw inferences in this regard however.

Finally, for the dyadic analysis of technological overlap we reconstruct relevant variables at the dyad level.[23] DYAD SUPPLY TIME$_{ijt}$ is a measure of the duration of dyad-specific supply experience and is defined as the accumulated number of years that supplier$_i$ has served customer$_j$ by year *t*. We supplement this with a second measure, ACTIVE DYAD$_{ijt}$, which indicates whether supplier *i* is *currently* supplying customer *j*. OEM$_{ijt}$, and ODM$_{ijt}$, are dummy variables equal to 1 if the relationship between supplier$_i$ and customer$_j$ in year *t* involves 'pure' manufacturing, or manufacturing and design.

Descriptive statistics for all of the variables included in the empirical analysis are shown in Table 2.

[Table 2 about here]

Addressing Endogenous Matching Issues

A major concern with any empirical analysis of the co-evolution of resources and organization is of course endogenous matching and unobserved heterogeneity (Hamilton and Nickerson, 2003). The primary concern in the context of our study is that a branded manufacturer will choose the 'most capable' candidate firm as its supplier and that these chosen suppliers are also more likely to innovate (i.e., to patent or to successfully introduce one or more own-brand handsets) not because of their supply activity *per se*, but rather as a natural consequence of the firm's particular (perhaps unobservable) capabilities. Absent any truly exogenous shocks, such as a policy change that impacts supplier choice but has no direct impact on learning outcomes, we cannot *fully* unravel this potential source of bias. There are nonetheless several features of our empirical context and methodology that significantly mitigate such concerns. First and foremost, we include supplier (or buyer-supplier dyad) fixed effects and year effects in our regressions so that we are examining *within-firm* variation in our measures of learning, rather than cross-sectional differences. In this way we rule out the possibility that

[23] Because we include dyad fixed effects in these regressions, only variables that vary within a dyad across time are relevant. For example, we do not have an indicator variable for whether the customers is an operator or a market leader: operator is time-invariant at the dyad level, and market leadership changes are rare, so that there is within-dyad variance for only a very few dyads: including an indicator for whether the customer is a market leader does not change the reported results, and the indicator variable is insignificant in these regressions.

observed differences in the extent of learning are simply a reflection of different starting points in supplier capabilities.

We of course recognize that the inclusion of fixed effects is only a partial fix for potential selection bias, since it does not exclude the possibility that the learning curves of some firms (i.e., more 'capable' firms) have steeper slopes. We address this issue in two ways: First, our dyadic analysis of technological overlap examines the direction, not just the rate or extent, of learning: by computing dyadic measures of technological overlap (described above) between all potential supplier-customer pairs in each year of the sample and employing dyad fixed-effects regressions we evaluate whether (and to what extent) a supplier's technological portfolio becomes more similar to the portfolios of its customer(s) over the course of a supply relationship, relative to those of other potential customers – in other words, whether supplying is associated with 'convergence' of supplier and customer technological capabilities.[24] Second, we examine the extent of two types of learning - technological *and* market learning – and two types of customers – branded producers and operators. Here again we are looking not just at the overall learning rate of a supplier, but rather at how different types of learning varies depending on the type of customer. This analysis thus effectively controls for unobserved supplier quality that increases the overall learning rate of a supplier.

The idea that different types of customers may foster different types of learning highlights a final source of potential bias which is more difficult – indeed impossible - to mitigate entirely: potential assortative matching between different types of buyers and suppliers. Here the concern is that learning outcomes are influenced by the particular buyer-supplier matches observed in the data. And although we control for as many observable differences in buyer and supplier characteristics as possible in our regressions, some aspects of these matches may be unobservable. To assess the importance of assortative matching in this setting, we follow our main analysis of learning by supplying with an examination of the selection decisions of different types of customers from the beginning of the 'outsourcing era'. This allows us to more directly assess the extent to which *observable* customer characteristics that are associated with

[24] This dyadic panel dataset is also used in our supplementary analysis of supplier selection where we explore potential endogenous matching issues (see discussion following presentation of the main results).

differential supplier learning are also associated with differences in the selection criteria that they apply when choosing suppliers with whom to work. To foreshadow the results of this analysis (presented immediately following our main results), while all customers show a preference for technologically-advanced suppliers and for stability in supply relationships, we find little evidence of systematically different selection criteria for the various types of customers served by the suppliers in our sample. This provides us with some reassurance that assortative matching is not the primary driver of our empirical results. However, we stress that we do not claim (nor in fact would we wish to claim) that we are documenting an 'average learning effect' across all *potential* customer-supplier dyads; rather, we believe that we are able to effectively document the learning effect in *observed* dyads.[25]

Results

Our first set of estimation results, displayed in Table 3, examines the relationship between supplying and technological learning as evidenced by changes in supplier patenting in the three years subsequent to the observation year. The dependent variable in these negative binomial regressions is PATENTS[26] and all models include firm and year fixed effects. Missing financial data and inclusion of fixed effects reduces the number of supplier firms in these models to 58, since suppliers that never patent are dropped from the analysis.[27]

[Table 3 about here]

Models 1 and 2 explore the basic relationship between the duration and extent of supplying activity and technological learning. These results indicate that it is not merely the duration, but rather the *extent* of supply activity that appears to matter for supplier learning: the coefficient on SUPPLY TIME in Model 1 is insignificant, and in fact becomes negative and marginally significant when we add CUM. CUSTOMERS in Model 2. In contrast, CUM. CUSTOMERS is positive and significant in all specifications. Of the supplier-related variables we see that patenting is positively and significantly related to sales revenue and prior patenting,

[25] Thus we are essentially estimating the 'effect of the treatment on the treated.' See Kellogg (2011: 1797) for a very useful discussion of this approach in the context of 'learning by drilling.'
[26] For convenience, firm and time subscripts are omitted from variable names hereafter.
[27] Starting from the 101 firms in the initial dataset, we lose 25 firms due to a lack of financial data. Of the remaining firms, 18 did not hold a patent at any time during the observation period.

consistent with absorptive capacity arguments; these effects are also consistent across specifications. Age is also positive and significant in some specifications, while firm size (assets) is negatively related to patenting and R&D does not carry a significant coefficient.[28]

When it comes to the type of customers served by the supplier (Models 3-5) we see some particularly interesting results. Model 3 introduces our measure of the technological sophistication of customers served by the supplier (CUSTOMER PATENTS) and subsequent models add cumulative counts of operators (CUM. OPERATORS, in Model 4) and market leaders served by the supplier (CUM. LEADERS, Model 5). From these models we see a strong positive association between the technological sophistication of a supplier's recent customers and the firms' own subsequent patenting activity, suggesting that the supplier is indeed learning from its customers. And while it does not appear to matter whether the customers are market leaders, it *does* matter if they are operators: CUM. OPERATORS carries a *negative* and significant coefficient in all specifications, suggesting that technological learning is lower for firms supplying to operators, all else equal.

Finally, in Model 6 we replace the cumulative customer count with the partitioned count separately cumulating OEM and ODM customers. As discussed earlier, received wisdom suggests that there are more opportunities for suppliers to engage in learning if they are involved in a combination of design and manufacturing. Our results provide support for this received wisdom, as CUM. ODM carries a positive and significant coefficient, while CUM. OEM is insignificant. Thus, OEM experience alone does not appear to foster technological learning, and design activities are indeed an important pathway to technological learning.

Turning to the relationship between supplying and *market* learning, the results of our analysis of suppliers' introduction of own-brand mobile handsets into the market and sales of own-brand phones are presented in Tables 4a and 4b respectively. These models mirror the specifications in the previous table and they reveal patterns that are interesting in of themselves, but particularly so when compared with the results for technological learning. The only significant predictor of own-brand introduction in Table 4a is the supplier's cumulative

[28] R&D is significant and positive in models that do not include prior patenting, as one would expect (results not shown); these alternative specifications do not generate any other notable changes to the results reported here.

experience producing handsets for operators. Recall that this is *opposite* to the observed effect of operator experience on technological learning, where supplying to operators was associated with reduced learning, but is nonetheless consistent with the idea that operators by necessity involve their suppliers more deeply in design and other market-facing activities. This inference is further reinforced in the results for BRANDED SALES (Table 4b): despite the very small sample size in these regressions we see a positive and significant coefficient for CUM. OPERATORS when this variable is added in Model 4, and the coefficient remains positive, albeit losing significance, as we add additional variables. Perhaps even more interesting, we see that supplying to branded producers that are market leaders has a significant dampening effect on sales of own-brand phones (Models 5 and 6), even though in Table 4a there was no apparent effect on brand introductions *per se*. The small sample size and lack of robustness in the observed effects in these regressions prompt caution in interpretation, but the evidence is at least consistent with the observation that suppliers are better able to capture valuable market-related knowledge when they supply to operators than when they supply to other branded producers, particularly if these branded producers are market leaders. In other words, the extent of learning by supplying - and the ability to capitalize on that learning - is shaped to a significant extent by *who* a firm supplies to, not just on the extent of supply activity.

[Table 4a and 4b about here]

The contrasting patterns of learning observed in Tables 3 and 4 also point to the existence of quite distinct pathways to technological and market learning for suppliers in the mobile handset industry. For example, counter to the received wisdom, it does not appear that accumulation of technological capabilities is a necessary or sufficient condition for successful introduction of own-brand products (the coefficient on PRIOR PATENTS is insignificant in Tables 4a and 4b). And since supplying to operators appears to dampen technological learning while enhancing market learning it cannot simply be the case that operators are selecting firms that are somehow more able learners than those selected by branded producers.

Our next set of results further reinforces the idea that the identity of the customer matters for supplier learning, as we examine technological learning at the dyad level. These models, (presented in Table 5) show quite clearly that the technological overlap between a supplier and its customer increases with relationship-specific experience – the coefficient on DYAD SUPPLY

TIME is positive and significant in all of the models shown. Moreover, these results appear to be inconsistent with a pure selection story: when we add the variable ACTIVE DYAD in Model 2 which is equal to one in all years in which the supplier serves the focal customer this variable, while positive, does not weaken the observed effect of DYAD SUPPLY TIME. Interestingly, when we replace ACTIVE DYAD with two dummy variables capturing the different types of supply relationship we again see some evidence that technological learning (here partner-specific learning) is greatest for ODM relationships, although this effect is only marginally significant from a statistical standpoint.

[Table 5 about here]

The results presented above are quite robust to a variety of alternative measures and methods: For all of the different regressions, qualitatively identical results have been obtained using different methods of cumulating supply experience, as well as with random effects estimation that allow for inclusion of suppliers that have never patented or introduced their own branded handsets. For own-brand introduction, estimation of a survival (Cox proportional hazards) model also yields very similar results.

As discussed in the previous section, our empirical approach effectively allows us to rule out two alternative explanations based on endogenous selection – i.e., that observed differences in the extent of learning are simply a reflection of different starting points in supplier capabilities, or of unobserved quality that increases the overall general learning rate of a supplier. We are nonetheless left with the possibility that differential learning reflects assortative matching of buyers and suppliers. In the Table 3 results, for example, we saw that supplier patenting was positively associated with suppliers' own prior patenting, and with customer patents. This begs the question of whether 'high tech' buyers (those with a strong patent portfolio) are matching with 'high tech' suppliers (i.e. those that already hold telecom-related patents), and whether this may in part be driving the observed results.[29] Or perhaps since operators tend to delegate more design activities to their suppliers, they are matching with more high tech suppliers, so that we

[29] Estimation of a model similar to that in Table 3 but interacting dummy variables based on whether the supplier and/or buyer are high patenters produces results that run counter to this view (not shown; available from authors on request) – 'high tech' suppliers learn significantly more than their lower-tech brethren, regardless of whether they are matched with high tech or low tech buyers.

see less evidence of technological learning by these suppliers mainly because they have less to learn. To investigate this issue directly, in Table 6 we show estimation results for supplier selection models, first for all buyers, and then separately for different subsets of buyers. These are conditional logit models, estimated on a dyadic dataset comprising all potential buyer-supplier dyads over the study period.[30] The dependent variable in each case is ACTIVE DYAD, and independent variables include the supplier characteristics used in the Table 5 regressions, plus a dummy variables capturing whether the buyer and supplier are located in the same region, and how long they have been working together. If there is indeed active assortative matching among buyers and suppliers then we would expect to see significant differences in the observed selection criteria for different categories of buyers.

[Table 6 about here]

These selection models generate some interesting results, but none that are indicative of active assortative matching among different classes of buyers and suppliers. In Model 1, using the full sample of dyads, the most significant positive predictors of an active dyad are DYAD SUPPLY TIME and SAME REGION. Thus there is strong evidence of the perceived benefits of proximity, and of continuity or path dependence in buyer-supplier relationships – the probability that a supplier will serve a particular buyer in a given year is strongly related to the length of time that the buyer and supplier have worked together up to that point. Buyers also show a preference for younger, smaller and more R&D-intensive suppliers with high revenues, all else equal. Surprisingly, SUPPLIER PATENTS, is not significantly associated with selection. Models 2-5 show similar estimation results for subsamples of buyers – operators only, branded producers, market leaders, and high-tech buyers (i.e. buyers that are in the top 5% of patenters among the firms in our data). While there are some small differences in these results – branded producers seem slightly less concerned with choosing a supplier located in the same region for example – the general logic guiding supplier selection seems to be quite similar for all of the different subsets of firms that we can observe.

[30] The results shown are based on a sample wherein a supplier is deemed to be at risk of selection as soon as it comes into existence. Qualitatively identical results were obtained for a variety of different sample definitions, e.g., when suppliers were considered to be at risk of selection only in a 3-5 year window around the observation of an active dyad in our data.

Model 6 replicates the selection analysis just for the first few years that we observe in our data, leading up to the take-off in outsourcing around 2000: It is particularly interesting to see that in these early years, virtually the *only* strong positive predictor of supplier selection, other than dyad-specific experience, is that the buyer and supplier are located in the same region. Not only is a supplier's telecom-related patenting inconsequential here (not so surprising given that few suppliers had relevant patents during this period), but R&D intensity is actually *negatively* associated with selection. This seems to suggest that buyers took a quite opportunistic and haphazard approach to supplier selection in the early days of outsourcing in the industry. When combined with the strong path dependence in buyer-supplier relationships, this again reinforces the notion that the patterns of capability development observed in our data indeed reflect a process of learning by supplying, and are not merely an artifact of endogenous selection or assortative matching between buyers and suppliers in the industry.

Discussion and Conclusion

The findings reported above, while not definitive, are strongly suggestive of both technological and market-related learning by supplying in the mobile telecommunications handset industry. For the suppliers in our sample, patenting increases as a firm accumulates experience in handset supply relationships, particularly when they are involved in both handset manufacturing and design. Our dyadic analysis reinforces this inference, as the technological overlap between a buyer and a supplier increases significantly as dyad-specific experience accumulates. Our findings also suggest that it matters a lot to *whom* you supply, although sometimes in counterintuitive ways. Even though operators are more likely to delegate design activities to their suppliers, they do not appear to be a robust source of technological learning for suppliers, relative to serving branded producers; conversely, engaging with the most technologically sophisticated customers increases suppliers' technological learning significantly, as one would expect. When it comes to *market* learning, however, selling to operators appears to facilitate own-brand introduction and sales while supplying to market leaders strongly inhibits sales of own-brand products. Thus, our results point to the existence of quite distinct pathways to technological and market learning for suppliers in the mobile handset industry. Moreover, our analysis of supplier selection indicates that the initial choice of suppliers is somewhat haphazard, and that there are significant switching costs and inertia in customer-supplier matches. This in turn implies that initial supplier choices of branded producers and operators may have a strong influence on suppliers' long-term capability development and strategic alternatives.

We believe that these findings provide important new evidence on the extent of learning by supplying in an industry that has witnessed significant offshore outsourcing in the last decade, a first-order issue given continuing debates on the implications of outsourcing for the migration of technological and market leadership. Contrary to some of the more alarmist commentary in the popular press, our observations suggest that the progression from trusted supplier to threatening competitor among electronics manufacturing firms is far from inevitable. Our findings also reinforce anecdotal evidence that leading producers have a tendency to write tight outsourcing agreements that may severely limit the ability of a supplier to sell own-brand phones, particularly in markets currently served by the customer. There is also some evidence that leading producers take these provisions seriously and react strongly to violations: When BenQ began selling phones in China under its own brand name in 2004, for example, Motorola promptly pulled the contract under which BenQ had previously designed and manufactured millions of handsets for the company (Engardio and Einhorn, 2005).

The contrasting patterns of capability development by suppliers to operators and branded producers observed in our study have potentially interesting implications for the way that we should think about learning in this context. As is also true in some other learning contexts, while producers (here suppliers) may be the beneficiaries of direct, purposive knowledge transfers from customers, this is not the only potential source of learning: learning and innovation may also be the result of efforts by suppliers to respond to the particular demands of sophisticated buyers, such as overseas customers (Saloman and Shaver, 2005) or "lead users" (von Hippel 1986). In this case there may be little direct knowledge transfer; rather, learning occurs because responding to customer demands stimulates investment by the supplier in new domains. We remain quite agnostic about the different potential mechanisms underlying the process of capability building by suppliers captured by our definition of learning by supplying. We nonetheless believe that the greater room for strategizing and conflict over supplier learning represents a key difference between learning by supplying in an OEM supply context, and learning from users in the final product markets that have been the focus of prior research on learning from users and learning from exporting. In particular, our findings on the divergent learning outcomes for suppliers serving operators and branded producers are consistent with the idea that operators grant access to and involve suppliers in more customer-facing activities, and that branded producers strictly limit access – and thus opportunities for learning – in this domain. In sum, we believe that our study represents an important first step towards understanding learning by supplying, but there is much still to do; continued exploration of the interplay between buyers and sellers in learning and innovation represents a fascinating avenue for future research.

References

Alchian A. 1963. Reliability of progress curves in airframe production. *Econometrica* **31**: 679-93.

Arrow K. 1962. The economic implications of learning by doing. *Review of Economic Studies* **29**: 155-173.

Arrunada B, Vazquez XH. 2006. When your contract manufacturer becomes your competitor. *Harvard Business Review* (September): 135-144.

Athreye S, Cantwell J. 2007. Creating competition? Globalisation and the emergence of new technology producers. *Research Policy* **36**: 209-226.

Alcacer JA, Gittelman M. 2006. How do I know what you know? Patent examiners and the generation of patent citations. *Review of Economics and Statistics* **88**(4): 774-779.

Baum JAC, Ingram P. 1998. Survival-enhancing learning in the Manhattan hotel industry, 1898-1980. *Management Science* **44**: 996-1016.

Clerides SK, Lach S, Tybout JR. 1998. Is learning by exporting important? Micro-dynamic evidence from Colombia, Mexico and Morocco. *Quarterly Journal of Economics* **113**(3): 903-948.

Cohen WM, Levinthal DA. 1990. Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly* **35**: 128-152.

Cohen WM, Zysman J. 1987. *Manufacturing Matters: The Myth of the Postindustrial Economy*. Basic Books: New York.

Darr ED, Argote L, Epple D. 1995. The acquisition, transfer and depreciation of knowledge in service organizations: productivity in franchises. *Management Science **42***: 1750-1762.

Duysters G, Jacob J, Lemmens C, Jintian Y. 2009, Internationalization and technological catching up of emerging multinationals: A comparative case study of China's Haier group. *Industrial and Corporate Change **18***(2): 325-349.

Engardio P, Einhorn B. 2005. Outsourcing innovation. *Bloomberg BusinessWeek.* March 21. http://www.businessweek.com/magazine/content/05_12/b3925601.htm [April 13 2012].

Grossman G, Helpman E.1993. *Innovation and Growth in the Global Economy.* MIT Press: Cambridge MA.

Hamilton B, Nickerson J. 2003. Accounting for endogeneity in strategic management research. *Strategic Organization* **1**: 53-80

Ingram P, Baum JAC. 1997. Opportunity and constraint: Organizational learning from operating and competitive experience. *Strategic Management Journal* **18**: 75-98.

Irwin D, Klenow PJ. 1994. Learning-by-doing spillovers in the semiconductor industry. *Journal of Political Economy* **102**: 1200-1227.

Jaffe AB. 1986. Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review* **76**: 984-1001.

Kellogg R. 2011. Learning by drilling: Interfirm learning and relationship persistence in the Texas oilpatch. *The Quarterly Journal of Economics* **126**: 1961-2004.

Khanna T, Palepu KG. 2006. Emerging giants: Building world-class companies in developing countries. *Harvard Business Review* (October): 60-69.

Lane PJ, Lubatkin M. 1998. Relative absorptive capacity and interorganizational learning. *Strategic Management Journal* **19** (5): 461-477.

Lieberman MB. 1984. The learning curve and pricing in the chemical processing industries. Rand *Journal of Economics* **15**: 213-28.

MacGarvie M. 2006. Do firms learn from international trade? *Review of Economics and Statistics* **88** (1):46-60.

Mowery DC, Oxley JE, Silverman BS. 1996. Strategic alliances and inter-firm knowledge transfer. *Strategic Management Journal* **17** (Winter): 77-91.

Mowery DC, Oxley JE, Silverman BS. 2002. The two faces of partner-specific absorptive capacity: Learning and co-specialization in strategic alliances. In *Cooperative Strategies and Alliances,* Contractor F, Lorange P (eds). Elsevier: London, UK.

Nickell SJ. 1981. Biases in dynamic models with fixed effects. *Econometrica* **49**(6): 1417-26.

Oxley JE, Sampson RC. 2004. The scope and governance of international R&D alliances. *Strategic Management Journal* **25**: 723-749.

Oxley JE, Wada T. 2009. Alliance structure and the scope of knowledge transfer: Evidence from US-Japan agreements. *Management Science* ***55***(4): 635-649.

Pisano G, Shih W. 2009. Restoring American competitiveness. *Harvard Business Review* (July): 1-13.

Rapping L. 1965. Learning and World War II production functions. *Review of Economics and Statistics* **47**: 81-86

Romer P. 1990. Endogenous technological change. *Journal of Political Economy* **98**(5): S71-S102.

Salomon R, Shaver JM. 2005. Learning by exporting: New insights from examining firm innovation. *Journal of Economics and Management Strategy* **14** (2): 431-460.

Terwiesch C, Loch CH. 1999. Measuring the effectiveness of overlapping development activity. *Management Science* **45**(4): 455-465.

Trefler D. 2005. *Policy responses to the new offshoring: Think globally, invest locally.* Paper prepared for Industry Canada’s March 30, 2005 Roundtable on Offshoring. Available at http://homes.chass.utoronto.ca/~trefler/Outsourcing_Final_TeX.pdf

von Hippel E. 1986. Lead users: A source of novel product concepts. *Management Science* **32**(7):791-805.

von Hippel E. 1988. *The Sources of Innovation*. Oxford University Press: New York.

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Table 1: Frequency of new suppliers by country of origin-year

	1994-1999	2000-2004	2005-2009	Total firms
FINLAND	0	1	0	1
FRANCE	2	0	1	3
GERMANY	3	0	1	4
ITALY	1	0	0	1
SPAIN	0	0	1	1
SWEDEN	1	0	0	1
SWITZERLAND	0	1	0	1
UNITED KINGDOM	2	0	0	2
Europe	**9**	**2**	**3**	**14**
CANADA	0	3	0	3
USA	4	7	1	12
North America	**4**	**10**	**1**	**15**
CHINA	1	11	4	16
HONG KONG	0	1	1	2
JAPAN	16	0	0	16
MALAYSIA	0	1	0	1
SINGAPORE	0	1	1	2
SOUTH KOREA	2	10	1	13
TAIWAN	2	13	6	21
Asia	**21**	**37**	**13**	**71**
ISRAEL	0	1	0	1
Other	**0**	**1**	**0**	**1**
Total	**34**	**50**	**17**	**101**

Table 2a: Summary statistics supplier dataset

Variable	Obs	Mean	Std. Dev.	Min	Max
PATENTS	851	51.86	111.58	0	672
OWN BRAND	419	0.08	0.27	0	1
BRANDED SALES	132	13.89	2.42	5.74	17.74
LOG ASSETS	851	7.57	2.28	0.08	11.84
LOG SALES	851	7.74	2.24	0.06	12.33
LOG R&D	851	4.03	2.23	0	8.77
LOG FIRM AGE	851	3.33	0.98	0	5.10
PRIOR PATENTS	851	0.87	0.34	0	1
SUPPLY TIME	851	3.44	3.40	0	16
CUM CUSTOMERS	851	9.88	16.25	0	159
CUSTOMER PATENTS	851	103.19	210.48	0	1157
CUM OPERATORS	851	4.02	7.90	0	79
CUM LEADERS	851	1.26	3.40	0	25
CUM OEM	851	5.69	11.72	0	84
CUM ODM	851	4.19	9.09	0	117

Table 2b: Summary statistics dyadic dataset

Variable	Obs	Mean	Std. Dev.	Min	Max
TECH OVERLAP	14,935	0.788	0.195	0	1
LOG SUPPLIER ASSETS	14,935	8.325	1.982	3.039	11.802
LOG SUPPLIER SALES	14,935	8.581	1.962	3.336	12.326
LOG SUPPLIER R&D	14,935	4.582	2.166	0	8.765
LOG SUPPLIER AGE	14,935	3.390	0.923	0.693	5.094
DYAD SUPPLY TIME	14,935	0.253	1.003	0	14
ACTIVE DYAD	14,935	0.062	0.241	0	1
OEM	14,935	0.040	0.196	0	1
ODM	14,935	0.022	0.146	0	1
PRIOR PATENTS	14,935	0.978	0.145	0	1
SAME REGION	14,935	0.425	0.494	0	1

Table 3: Technical Learning - Supplier Patenting

Negative binomial regressions; dependent variable = PATENTS; firm and year fixed effects in all models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LOG ASSETS	-0.1971	-0.1973	-0.203	-0.2502	-0.25	-0.2892
	[2.88]**	[2.91]**	[2.99]**	[3.58]**	[3.58]**	[4.14]**
LOG SALES	0.4885	0.4772	0.468	0.5035	0.5029	0.5586
	[6.27]**	[6.16]**	[6.05]**	[6.47]**	[6.44]**	[7.18]**
LOG R&D	-0.0029	-0.0075	-0.0074	-0.0058	-0.0058	-0.0021
	[0.18]	[0.46]	[0.45]	[0.34]	[0.34]	[0.13]
LOG FIRM AGE	0.1488	0.1627	0.1882	0.234	0.2352	0.2188
	[1.62]	[1.68]+	[1.87]+	[2.27]*	[2.27]*	[2.11]*
PRIOR PATENTS	1.5318	1.5228	1.4935	1.4638	1.4656	1.4292
	[7.46]**	[7.43]**	[7.27]**	[7.12]**	[7.11]**	[6.96]**
SUPPLY TIME	-0.0041	-0.0288	-0.0308	-0.0092	-0.0097	0.0253
	[0.31]	[1.87]+	[1.99]*	[0.51]	[0.53]	[1.29]
CUM CUSTOMERS		0.0079	0.0071	0.0113	0.0109	
		[3.32]**	[2.96]**	[3.87]**	[2.43]*	
CUSTOMER PATENTS			0.0003	0.0002	0.0002	0.0003
			[2.45]*	[2.11]*	[2.10]*	[2.22]*
CUM OPERATORS				-0.0164	-0.0159	-0.0389
				[2.74]**	[2.01]*	[4.01]**
CUM LEADERS					0.0019	0.0241
					[0.12]	[1.45]
CUM OEM						-0.0019
						[0.36]
CUM ODM						0.0335
						[4.81]**
Constant	-2.8257	-2.7487	-2.705	-2.7576	-2.7588	-2.7734
	[8.08]**	[7.70]**	[7.46]**	[7.58]**	[7.58]**	[7.58]**
Observations	851	851	851	851	851	851
Number of firm ids	58	58	58	58	58	58

Absolute value of z statistics in brackets

+ significant at 10%; * significant at 5%; ** significant at 1%

Table 4a: Market Learning – Own Brand Introduction

Logit regressions; dependent variable = OWN BRAND; year dummies in all models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LOG ASSETS	0.0363	0.0492	0.0755	0.1235	0.1242	0.1334
	[0.09]	[0.12]	[0.18]	[0.30]	[0.31]	[0.31]
LOG SALES	-0.0399	-0.0513	-0.0631	-0.1272	-0.1234	-0.1182
	[0.10]	[0.13]	[0.16]	[0.34]	[0.32]	[0.29]
LOG R&D	0.2868	0.2808	0.2661	0.1649	0.1629	0.1597
	[1.27]	[1.25]	[1.15]	[0.76]	[0.75]	[0.70]
LOG FIRM AGE	0.4296	0.4326	0.4283	0.3697	0.3677	0.4048
	[0.80]	[0.81]	[0.81]	[0.75]	[0.74]	[0.73]
PRIOR PATENTS	0.2773	0.275	0.3273	0.296	0.2956	0.3527
	[0.42]	[0.42]	[0.48]	[0.44]	[0.44]	[0.50]
SUPPLY TIME	0.2271	0.1917	0.2669	-0.0785	-0.0667	0.0228
	[1.11]	[0.72]	[0.94]	[0.27]	[0.21]	[0.06]
CUM CUSTOMERS		0.0121	0.0153	0.0126	0.0146	
		[0.21]	[0.26]	[0.20]	[0.22]	
CUSTOMER PATENTS			-0.0011	-0.0007	-0.0006	-0.0006
			[0.95]	[0.56]	[0.51]	[0.48]
CUM OPERATORS				1.1848	1.1722	1.33
				[2.53]*	[2.41]*	[2.16]*
CUM LEADERS					-0.0222	-0.1291
					[0.09]	[0.44]
CUM OEM						0.0279
						[0.40]
CUM ODM						-0.1432
						[0.62]
Constant	-4.9508	-4.9249	-5.0166	-4.4253	-4.4498	-4.8659
	[1.65]+	[1.66]+	[1.74]+	[1.59]	[1.58]	[1.44]
Observations	549	549	549	549	549	549
Number of firm ids	69	69	69	69	69	69

Absolute value of z statistics in brackets

+ significant at 10%; * significant at 5%; ** significant at 1%

Table 4b: Market Learning – Sales of Own-Brand Handsets (2005-2010)

OLS regressions ; dependent variable = BRANDED SALES; firm and year fixed effects in all models

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
LOG ASSETS	-0.9219	-1.0352	-0.9671	-0.9286	-1.0053	-1.0125
	[1.67]+	[1.92]+	[1.79]+	[1.75]+	[1.90]+	[1.89]+
LOG SALES	1.2185	1.326	1.3065	1.2962	1.3666	1.3906
	[2.40]*	[2.69]**	[2.66]**	[2.68]**	[2.86]**	[2.88]**
LOG R&D	0.175	0.1396	0.1066	0.0366	0.0268	0.0214
	[1.24]	[1.02]	[0.78]	[0.27]	[0.20]	[0.16]
LOG FIRM AGE	-0.1145	0.3828	0.4662	0.035	0.0045	-0.0234
	[0.21]	[0.65]	[0.78]	[0.06]	[0.01]	[0.04]
PRIOR PATENTS	-0.526	-0.71	-0.8879	-0.5254	-0.4434	-0.419
	[0.61]	[0.83]	[1.03]	[0.61]	[0.51]	[0.48]
SUPPLY TIME	0.1808	0.0211	-0.004	-0.0609	-0.0017	-0.0012
	[1.58]	[0.17]	[0.03]	[0.48]	[0.01]	[0.01]
CUM CUSTOMERS		0.0337	0.0353	-0.0206	0.0337	
		[3.13]**	[3.30]**	[0.81]	[0.87]	
CUSTOMER PATENTS			0.0017	0.0021	0.0019	0.0019
			[1.58]	[1.96]*	[1.87]+	[1.87]+
CUM OPERATORS				0.1196	0.0477	0.0457
				[2.45]*	[0.75]	[0.62]
CUM LEADERS					-0.308	-0.3286
					[1.89]+	[1.78]+
CUM OEM						0.0379
						[0.67]
CUM ODM						0.0353
						[0.67]
Constant	8.86	7.9084	7.687	9.3943	9.0822	9.0237
	[5.41]**	[4.75]**	[4.55]**	[5.09]**	[4.73]**	[4.61]**
Observations	141	141	141	141	141	141
Number of firm ids	27	27	27	27	27	27

Absolute value of z statistics in brackets
+ significant at 10%; * significant at 5%; ** significant at 1%

Table 5: Customer-Specific Technical Learning: Dyad- Year Observations

OLS regressions; dependent variable = TECH OVERLAP; dyad and year fixed effects in all models

	Model 1	Model 2	Model 3
LOG SUPPLIER ASSETS	0.046	0.046	0.046
	[8.29]**	[8.29]**	[8.29]**
LOG SUPPLIER SALES	-0.0348	-0.035	-0.0351
	[6.72]**	[6.76]**	[6.76]**
LOG SUPPLIER R&D	0.0024	0.0024	0.0024
	[1.70]+	[1.74]+	[1.75]+
LOG SUPPLIER AGE	-0.0201	-0.0207	-0.0208
	[1.74]+	[1.79]+	[1.80]+
DYAD SUPPLY TIME	0.004	0.0038	0.0038
	[2.34]*	[2.22]*	[2.20]*
ACTIVE DYAD		0.0094	
		[1.68]+	
OEM			0.0046
			[0.66]
ODM			0.017
			[1.91]+
Constant	0.8044	0.8068	0.8072
	[20.64]**	[20.69]**	[20.70]**
Observations	18130	18130	18130
Number of dyad ids	5691	5691	5691
R-squared	0.07	0.07	0.07

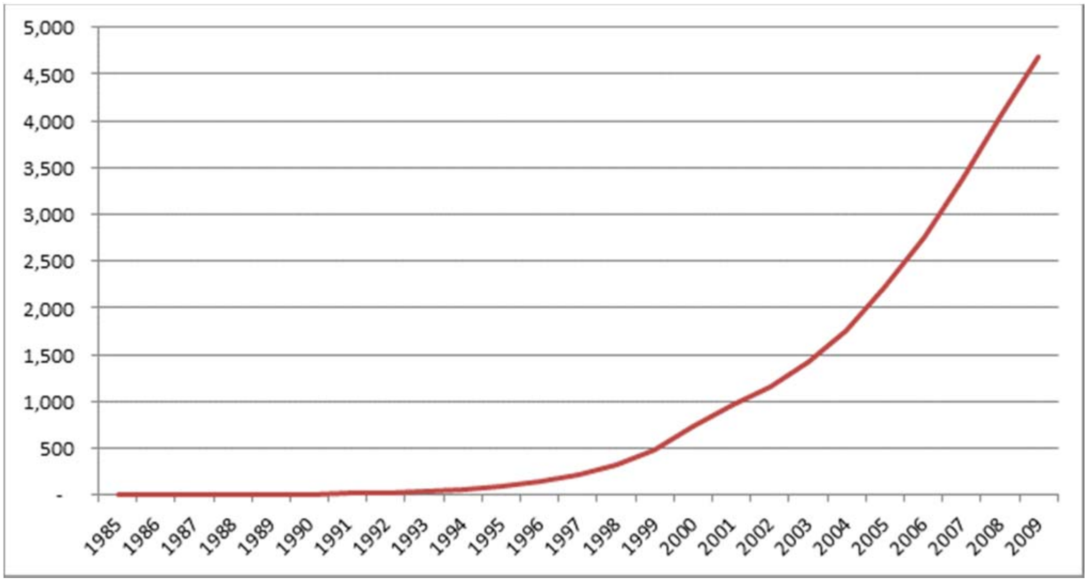
Absolute value of z statistics in brackets
+ significant at 10%; * significant at 5%; ** significant at 1

Table 6: Supplier Selection Models

Conditional logit regressions; dependent variable = ACTIVE DYAD

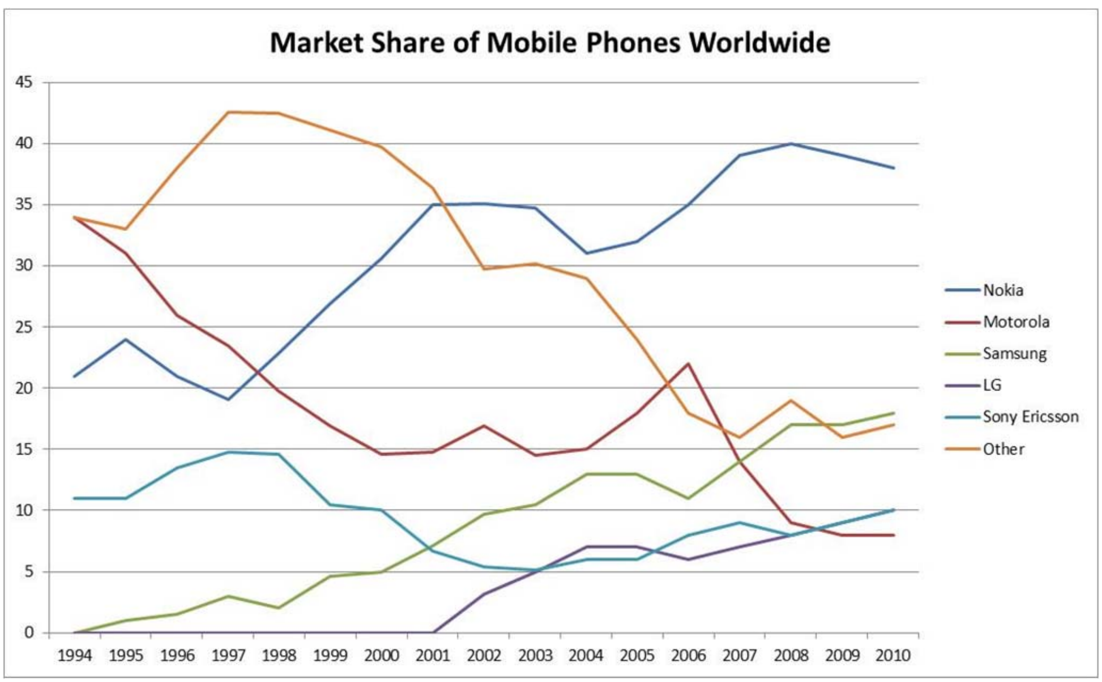
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	All	Operators only	Branded Producers	Market Leaders	High Tech Buyers	1995-2000 only
LOG SUPPLIER ASSETS	-0.2795	-0.1038	-0.38	-0.2148	-0.123	-0.1368
	[2.93]**	[0.67]	[3.40]**	[0.90]	[0.49]	[0.49]
LOG SUPPLIER SALES	0.2341	0.2634	0.2594	0.247	0.1273	0.2657
	[2.62]**	[1.92]+	[2.36]*	[1.01]	[0.46]	[0.99]
LOG SUPPLIER R&D	0.1128	0.1124	0.105	0.082	0.0919	-0.0963
	[3.76]**	[2.50]*	[2.51]*	[1.87]+	[1.59]	[2.01]*
LOG SUPPLIER AGE	-0.4683	-0.8437	-0.4166	-0.4866	-0.5013	-0.011
	[8.03]**	[5.09]**	[7.24]**	[5.30]**	[3.84]**	[0.05]
SUPPLIER PATENTS	0.3238	0.8583	0.416	-0.0821	0.1733	0.8726
	[1.65]	[1.46]	[1.87]+	[0.29]	[0.44]	[1.37]
YEARS SUPPLYING	-0.1132	0.0595	-0.1614	-0.2478	-0.2394	-0.438
	[4.02]**	[1.01]	[5.07]**	[2.32]*	[2.50]*	[2.72]**
DYAD SUPPLY TIME	2.0374	2.1577	1.9331	1.1768	1.5221	4.5272
	[8.23]**	[3.16]**	[7.68]**	[9.91]**	[6.59]**	[12.72]**
SAME REGION	0.6856	0.878	0.5995	0.2472	0.3568	1.194
	[4.19]**	[2.50]*	[3.13]**	[0.61]	[1.17]	[3.07]**
Observations	24207	6307	17900	2117	3893	1742
Robust z-statistics in brackets						
* significant at 5%; ** significant at 1%						

Figure 1: Global output in the mobile telecom handset industry



Source: Dataquest

Figure 2: Global market share of leading producers



Source: Dataquest

Appendix 1: Data Sources for Supply Relationships and Branded Handset Introductions

Data Source	Data Description and Scope
THT Business Research http://www.thtresearch.com/	(1) Announcement data on specific outsourcing orders for a sample of 87 customers and 43 suppliers. Years covered: 1999-2010. Proprietary. (2) Customized report on significant handset outsourcing (OEM/ODM) relationships for 11 major branded producers sourcing from 24 suppliers, including aggregate shipment data; some data on phone type (e.g., operating system, low-, middle-, high-end phone). Years covered: 2000-2007. Proprietary.
World Cellular Information Service (WCIS) http://www.informatandm.com/about/wcis/	Comprehensive tracking of global handset introductions. Data includes model name/number, date of introduction, OEM manufacturer, and detailed product features. Years covered, 1990-2008. Proprietary.
World Cellular Handset Tracker (WCHT) - http://www.telecomsmarketresearch.com/research/TMAAAQIV-World-Cellular-Handset-Tracker--mobile-phone-industry-data.shtml	Detailed information on handset introductions by mobile telecom operators in 17 countries. Data includes model name/number, operator, manufacturer, date of introduction and detailed product features. Years covered, 1990-2009. Proprietary.
PDAdb.net - http://pdadb.net/	Product comparison data covering PDAs, smartphones, tablets, netbooks; includes introduction year, brand, manufacturer, designer, detailed product features. Years covered (for smartphones), 1999-2010. Non-proprietary.
Federal Communications Commission Equipment Authorization System- https://fjallfoss.fcc.gov/oetcf/eas/	Provides public information on FCC approvals for handsets (and other telecommunications devices) introduced into the US. Information includes model information, date of introduction and name of applicant (product manufacturer). Years covered, 1998-2011. Non-proprietary.
Phone Scoop - http://www.phonescoop.com/	Detailed information on handset introductions into the US market. Data includes model name/number, brand, date of introduction and FCC approval ID and date (see below) and detailed product features. Years covered, 1998-2011. Non-proprietary.
Detectright http://detectright.com/	Information on handset data such as introduction date and basic features. Period covered: 2005-2011. Proprietary.
GSM Arena http://gsmarena.com	Information on handset data such as introduction date and basic features. Period covered: 1995-2011. Non-proprietary.
GSM Choice http://gsmchoice.com	Information on handset data such as introduction date and basic features. Period covered: 1995-2011. Non-proprietary.