Center for Economic Institutions
Working Paper Series

CEI Working Paper Series, No. 2002-14

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Center for Economic Institutions
Working Paper Series

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October 15, 2001 (Version: two_faces1n.doc) -- Work in progress: Please do not cite

Professors F. M. Scherer, Cynthia Montgomery, and Tarun Khanna provided insightful comments and suggestions on earlier drafts of this paper. This research has benefited from the Saltonstall Fellowship at Harvard University.

Two Faces: Effects of Business Groups on Innovation in Emerging Economies

Abstract

This paper argues that business groups in emerging economies exert dual effects on innovation. While groups encourage innovation by providing institutional infrastructures, groups also discourage innovation by creating entry barriers for small and non-group firms and inhibiting the proliferation of new ideas. Using OLS and panel data estimation techniques, followed by nonparametric analysis and semiparametric kernel regression, we find evidence of an inverted-U relation between group market share and innovation in industrial sectors of both Korea and Taiwan, during the 1981-1995 period. Institutional differences between Korea and Taiwan in terms of market structure and industrial policies provide useful conceptual implications from the empirical comparison.

Two Faces: Effects Of Business Groups On Innovation In Emerging Economies

This paper studies how business groups affect innovation in emerging economies. Diversified business groups dominate private sector activities in most emerging markets (Khanna and Palepu, 2000), arising in response to market failures (Leff, 1978; Amsden and Hikino, 1994; Khanna and Palepu, 1997,1999; Ghemawat and Khanna, 1998; Toulan, 2001) and policy inducements (Chang and Hong, 1998; Chang and Choi, 1988). Such groups take names such as groups economicos in Latin America, business houses in India, *chaebols* in South Korea, family holdings in Turkey, and mining houses in South Africa. Although the precise definition of groups varies across countries, business groups are conglomerations of nominally independent firms under common administrative and financial management that often are controlled by distinct families (Chang and Hong, 1998). The groups often control a substantial fraction of a country's productive assets and account for the largest and most visible of the country's firms (Amsden and Hikino, 1994; Granovetter, 1994; Khanna and Palepu, 1997).

The ubiquity of business groups suggests that they may affect technological activities in emerging economies, either facilitating or hindering innovation. Groups might facilitate innovation by providing institutional infrastructure, such as internal capital markets in weak external capital markets (Teece, 1996), business reputations and government ties that attract foreign technology providers (Hobday, 1996), and concentrated ownership that provides long term perspectives on R&D investments (Claessens, Djankov, and Lang, 2000). By contrast, groups might hinder innovation by creating entry barriers to new entrants and thereby limiting opportunities to experiment with new technology. To date, little empirical research addresses the interface between business groups and innovation in emerging economies.

We argue that the positive effects of institutional innovation infrastructures and the negative effects of entry barriers for non-group firms interact as group market share rises in an industry. At low levels of group market share, the marginal benefits of group infrastructure override marginal costs. As group share increases, however, the rising marginal cost in terms of lack of access to new ideas offsets the marginal benefits from access to infrastructure, so that beyond a threshold, higher group share leads to lesser innovation. When group share is at an intermediate stage, meanwhile, the mix of groups and independent firms provides both infrastructure and new ideas, resulting in the maximum amount of innovation. Recognition of the group structure-innovation linkage contributes to our understanding of innovation in the context of market imperfections, and also highlights the tradeoff between the need for new ideas and the need for resources and infrastructure to successfully commercialize those new ideas.

The empirical analysis uses panel data estimation techniques as well as nonparametric and semiparametric methods to examine data from two emerging economies: Korea and Taiwan. The institutional differences between the countries' market structures and industrial policies make the empirical comparison conceptually interesting.

1. Theory And Hypotheses

1.1 Groups provide infrastructures for innovation

Innovation requires access to finances, talents, and technology. In developed economies, relatively efficient markets for capital and labor, easy access to complementary business activities, and stringent enforcement of property rights, as well as relatively corruption-free government and independent judiciary all permit individual entrepreneurs to raise capital, hire talent, learn about customer demands, and play by the rules of the game. In emerging economies where many of these institutions exist in relatively weak form, business groups can contribute to innovation by substituting for functions that stand-alone institutions provide in developed economies. The descriptive literature on groups in emerging economies emphasizes a panoply of benefits that arise out of the intermediation functions that business groups play in lieu of capital markets (Leff, 1979) and labor markets (Khanna and Palepu, 1997). The earliest econometric evidence concerning the prevalence of group intermediation came from studies of Japanese keiretsu (Caves & Uekusa, 1976; Nakatani, 1984). More recently, Lincoln, et al. (1996) describe coordination mechanisms within Japanese keiretsu and their role in reducing the variability of returns of affiliates. Chang and Hong (1999) suggested Korean chaebols might create value through product and capital market intermediation. Other studies demonstrate that business groups in Chile and India add value through product, labor, and capital market intermediation (Fisman & Khanna, 1998; Khanna & Palepu, 1999, 2000).

Consider four elements of institutional infrastructure: capital, scientific labor markets, knowledge sourcing, and vertical intermediation. First, innovation requires access to capital. Most generally, firms that are seeking capital for new projects can use internal cash flow or external funds. When firms in advanced economies lack internal cash flow, they may turn to venture capital organizations or other external sources for funding. By scrutinizing firms before providing capital and then monitoring them afterwards, external capital organizations alleviate information gaps and reduce capital constraints (Kortum and Lerner, 2000). However, the under-developed, illiquid status of capital markets and lack of explicit market for corporate control in emerging economies mean that firms face a more difficult task in communicating the value of their ideas and their ability to execute their projects to would-be investors. Under these circumstances, access to internal capital markets within multi-product and multidivisional groups allows groups to act as de facto venture capitalists and allocate resources for new innovative opportunities more effectively than the available external markets.

In addition to allocating capital from internal funds, groups may be able to raise external capital more easily than unaffiliated entities, due to lower bankruptcy risks and greater ability to attract foreign capital. Larger fixed assets tend to lead to lower bankruptcy risks, which is a substantial concern in nations with poor mechanisms for dealing with financial distress (Khanna and Yafeh, 2000). Moreover, business groups can more easily acquire new bank credits if banks believe that governments will step in to prevent group bankruptcies that could jeopardize the banking system. Such government support of struggling business groups has been common in emerging economies such as Korea. Further, foreign investors expect groups to evaluate new opportunities and to exercise auditing and supervisory functions. As a result, groups become conduits for large amounts of domestic and foreign investment.

Second, innovation requires good research facilities and a pool of talented scientists. In economies with an acute scarcity of scientific talent, groups can create value by acting as incubators for such talent. Business groups can incur the fixed costs of setting up infrastructure to develop scientific talent, amortizing the expenses over the businesses in the group. Moreover, groups' intervention in the labor market can extend beyond creating talent incubators. Groups can also facilitate innovation by developing efficient internal labor markets. As Khanna and Palepu (1997) pointed out, the flow of information within the group structure means that group management will be able to allocate available scientific talent to the most suitable jobs. To incubate scientific talent and develop internal labor markets, groups sometimes concurrently perform the functions of research institutes, engineering universities, and vocational schools. Hence, groups develop extensive virtual internal talent markets, which help counteract the rigidities and variations of the external labor market. On the other hand, with more desirable facilities and conditions, scientific personnel are willing to accept intra-group relocation, providing business groups with reliable intellectual human resources that they can use to launch new innovation activities. In contrast, unaffiliated firms in emerging markets usually must recruit publicly in order to build their operations, which is a difficult proposition in countries where the quality of labor varies widely and lacks certification from respected educational institutions.

Third, groups can use relationships with foreign firms to gain knowledge needed for developing and commercializing new ideas (Reddy and Zhao, 1990). Such relationships include research joint ventures, co-production, and co-marketing agreements (Chesbrough and Teece, 1996). Hobday (1996) argues that it is important for firms in emerging markets to create technological linkages with firms in advanced economies. However, weak property rights in many emerging markets mean that firms have only limited ability to negotiate enforceable arms length contracts. Fearful that their intellectual property will be expropriated, firms from developed economies may hesitate to license technology in emerging economies. A group company may overcome this reluctance by putting the entire group's reputation at stake. In addition, groups may utilize their strong political and bureaucratic ties to protect property rights and enforce contracts more efficiently than their independent counterparts. Foreign providers of technology are likely to prefer groups with a reputation of honoring contracts than independent firms (Khanna and Palepu, 1999; Amsden and Hikino, 1994). Moreover, to the extent that group firms have better access to financial capital, research facilities, and talent, as we discussed above, they will be more productive sites for foreign firms to provide technological knowledge. Guillen (1997), focusing on Argentina, Spain, and South Korea, emphasizes the role of business groups as agents that combine factors of production within the country with resources from outside the country.

Fourth, developed economies tend to possess robust pools of vertical intermediaries such as suppliers and distributors. Such complementary firms often play key roles in a given firm's innovative efforts, by providing access to skills, equipment, and customers (Afuah, 2000). In emerging economies, by contrast, such complementary sectors of the economy tend to be much weaker. Rather than rely on complementary external firms, then, business groups tend to provide internal intermediation of such vertical business activities (Khanna and Palepu, 1997; Khanna and Rivkin, 2001). Such internal vertical intermediation then provides innovation infrastructure.

The availability of such elements of innovation infrastructure in an industrial sector of an emerging economy will be greatest when business groups hold large market shares in the sector. When groups in aggregate hold small market shares in an industry, the size of the pie may be too small to justify the fixed investments involved in creating various industry-specific innovation infrastructures. For a fixed aggregate market share for groups, the incentives for setting up these industry-specific infrastructures will decline with the number of groups operating in that sector. Thus, when groups hold small market shares, the availability of infrastructure will be low. On the contrary, when groups hold large market shares, the incentive to protect market positions will provide incentive for setting up the required innovation infrastructures.

This implies that a sector with in which groups hold high market share will possess group-based innovation infrastructures. If there are only a few groups operating in a sector with high group share, then at least one group will hold large enough share to create innovation infrastructure. As the number of groups operating in that industry increases, a sector will tend to have multiple infrastructures. Even if each group holds, on average, a relatively small share, there will be multiple players that possess access to capital, research facilities, and know-how that they can apply to projects in the sector. In turn, this availability of multiple infrastructures will contribute to innovation. Thus, market share is a reasonable measure of group presence in an industry, with or without controlling for the number of groups.

1.2 Groups erect entry barriers

While groups may facilitate innovation by providing the infrastructure for innovation, they may also discourage innovation by erecting entry barriers for small and independent firms, either deliberately or as a consequence of group ubiquity. Entry barriers are facets of market structure, basic conditions, and/or conduct that allow incumbent firms to earn positive economic profits while making it unprofitable for newcomers to enter an industry. In his seminal work, Bain (1956) identified two kinds of barriers: structural and strategic. Structural entry barriers arise when incumbent firms have cost advantages, marketing advantages, or benefits from a favorable policy regime. Newcomers must overcome the advantages to compete on equal terms. Strategic entry barriers arise when incumbent firms take explicit actions aimed at deterring entry by newcomers. Such entry-deterring strategies include activities such as capacity expansion, limit pricing, and predatory pricing (Besanko, Dranove, and Shanley, 1996).

Theoretical reasons for the existence of business groups emphasize how groups resolve several market imperfections in capital and intermediate product markets. Large firms have the opportunity to secure financial resources at significantly lower interest rates from bankers who know them well and can assess their credit-worthiness. According to Leff (1978), this marginal advantage in the procurement of funding often provides groups with an incentive to diversify. Secondly, in the absence of markets for risk and uncertainty, diversification of product lines provides an alternative to shareholder portfolio diversification and a way of eliminating problems that arise from bilateral monopoly or oligopoly. In many countries, such as Korea and India, governments' preferential treatment of group firms in specific sectors also played a critical role in the origin and growth of groups. Thus, in the presence of market imperfections, group structure influences the appropriation of quasi rents that accrue from groups' access to scarce and imperfectly marketed resources such as capital, information, and political connections.

The same resources that allow groups to earn rents in the presence of market imperfections also help groups to erect entry barriers, for at least three reasons. First, groups are diversified companies with access to deep pockets that enable them to reduce competition with preemptive price-cutting in focal businesses (Berger and Ofek, 1995). Second, groups that meet each other in multiple markets often recognize their interdependence and moderate their competition with each other (Bernheim and Whinston, 1996). Third, diversified groups may establish favorable reciprocal arrangements with firms that are both buyers and suppliers. As Weinstein and Yafeh (1995) show for the Japanese keiretsus, such collusion among large diversified groups could have the effect of foreclosing markets to smaller competitors.

Groups' ability to erect barriers that deter independent firms has implications for innovation. Innovation requires not only the access to effective infrastructure that we discussed earlier, but also an access to new ideas. These new ideas can arise through either recombination, which involves drawing together existing pieces of ideas into novel blends (Weitzman, 1998), or mutation, which involves the emergence of new ideas or variations of existing ideas (Mokyr, 1994). An empirical regularity emerging from studies of technological innovation is the role of new entrants (Jewkes, Stawers, and Stillerman, 1958; Acs and Audretsch, 1988; Hall, 1993; von Hippel, 1988; Hirshleifer, 1973; Kamien and Schwartz, 1982). Several models of technological competition also anticipate innovative roles for industry entrants (Reinganum, 1989). While many studies suggest that established firms have advantages in producing incremental innovation, and some studies show that they also are common sources of major innovations

(Methé, Mitchell, and Swaminathan, 1997), independent inventors, small firms, and diversifying entrants undoubtedly play key roles in conceiving major new ideas and radical breakthroughs (Mansfield, 1996).

For instance, smaller entrants pioneered two recent major areas of technological innovation in Europe and North America — bio-technology and Internet — typically with the backing of venture capital investors (Lerner, 1996). The small entrants tended to be among the first to seize upon the commercial opportunities. On some occasions, these entrants—utilizing the capital, expertise, and contacts provided by their venture capital investors—established themselves as market leaders. In other cases, they were acquired by larger firms or entered into licensing arrangements with them.

According to Mansfield (1996), it is the existence of such complementarities and interdependencies among existing firms and new entrants that hold the key to successful innovation. Geroski (1991), meanwhile, shows that industry entry tends to lead to innovation, rather than the reverse relationship. Thus, if group members prevent independent firms from entering an industry, a lack of diversity in existing source of ideas would suggest, ceteris paribus, a lower rate of technological creativity and innovation (Mokyr, 1994). Moreover, in the absence of threat from small and medium sized enterprises, groups may choose to collude and focus on existing technology, rather then compete with each other through innovation.

In parallel with the relationship between innovation infrastructure and business group market share in an industrial sector, the prevalence of entry barriers also will increase with group share in an industry. That is, the more that groups dominate a sector, the more difficult it will be for other firms to enter, owing to the entrenched market and political positions of the groups.

We note that high entry barriers do not mean that there cannot be competition among existing groups. In Korea, for instance, evidence of competition among a few large business groups operating in the semiconductor industry provides a case in point. For a fixed aggregate market share for groups, competition will tend to rise with the number of groups operating in that industry. Thus, it is possible for an industrial sector in which groups hold large market share to be competitive even though high entry barriers deter non-groups firms from entering the sector.

Nonetheless, competition is not in itself a sufficient condition for innovation. Instead, as we discussed above, innovation requires the introduction of new ideas for recombination and mutation. Even if there are several groups operating in a sector, to the extent that groups share relatively similar structures, backgrounds, approaches to governmental negotiation, hiring policies, and other practices, then high group share will lead to limits in generating new ideas. Thus, group dominance of a sector will lead to less diversity in the source of ideas in the sector. In turn, the sector's access to new ideas will tend to decline with the level of entry barriers, regardless of the number of groups operating in that industrial sector.

As this discussion suggests, market share is a reasonable measure for a sector's access to new ideas, with or without controlling for the number of groups operating in that sector. In the end, whether to control for the number of groups is an empirical matter. In this paper, we address this issue by explicitly controlling for the number of groups in a sector.

1.3 Group share thresholds: Within and across countries

In summary, we argue business groups have offsetting influences on innovation in emerging economies. (1) Access to the infrastructures needed for innovation increases with business groups' share in an industrial sector, but (2) access to new ideas decreases with groups' share in an industrial sector.

Combining these two arguments, one can trace an empirical link between business groups' share in a sector and that sector's innovative performance. When group share in a sector is very high, firms in that sector often have the infrastructure needed to carry out innovation, but lack access to new ideas. When group share is very low, the sector has access to new ideas but lacks the institutional infrastructure to commercialize those ideas. Only when group share is at an intermediate stage does the mix of groups and independent firms provide both infrastructure and new ideas, resulting in greater innovation.

Thus, group share both facilitates and inhibits innovation in an industry. At low levels of group share, the marginal benefits of group structure may override associated marginal costs. As group share increases, however, the rising marginal costs in terms of lack of access to new ideas are likely to offset resulting marginal benefits from access to infrastructure, so that beyond a threshold, still higher level of group share leads to a decrease in innovative performance. This suggests an inverted-U relationship between group share and innovative performance.

> **Hypothesis 1:** Innovative performance in an industry first increases with the market share that business groups hold in that industry, but then declines after group share crosses a threshold.

The inverted-U relationship is a useful starting point for understanding how the threshold for group share may vary across countries. In theory, as long as the marginal benefit of infrastructure declines with the level of group share while the marginal cost of group share increases with it, there is an optimal level of group share beyond which groups are no longer innovation maximizing. However, countries differ in terms of their innovative infrastructures (Nelson, 1993) and the differences in the market-based institutional development and technological capability may cause variation in the group share – innovation thresholds. In general, the closer a country is to the "institutional frontier" of strong market institutions, the fewer benefits that group structure will provide.

For at least four reasons, which parallel our earlier discussion of business group benefits, the stronger the market institutions in a country, the less that business groups will contribute to innovation. First, benefits from access to internal capital markets will be least critical when alternative sources of capital such as venture capital are available. Second, more robust labor markets and greater availability of external research facilities will limit the scientific labor market benefits of group structure. Third, multinational companies act as alternative suppliers of technology, making groups less critical for industrial development. Fourth, greater availability of complementary firms such as suppliers and distributors can help foster innovation. Thus, when there are alternative sources of institutions needed for innovation, the marginal benefits from group structure will be lower, for every level of group share, suggesting that the threshold will decline with the presence of alternative providers of institutions.

Hypothesis 2: The greater the presence of alternative sources of innovation infrastructures in a country, the lower the threshold at which increasing group share will lead to lower innovation.

The comparison of institutional infrastructures in Taiwan and Korea is particularly relevant for testing hypothesis 2. While the development-oriented governments in both Korea and Taiwan chose to "lead" rather than "follow" the market in terms of encouraging business development and innovation, the two countries used strikingly different policy packages. The logic of the Korean approach was hierarchical, unbalanced, and command-oriented, calling for the intensive use of resources to foster a select and obedient business sector to carry out the specific tasks the leadership assigned (Cheng, 1990: 142). In this approach, the *chaebols* provided most of the business infrastructures in Korea's corporate landscape. By contrast, the logic of the Taiwanese approach was horizontal, balanced, and incentive-oriented, implying a more pluralistic economy and more varied use of resources within the broad parameters that the state delimited (Cheng, 1990: 142). In turn, Taiwan has a more varied infrastructure, comprised of independent companies and government bodies, as well as business groups. In line with our discussion, then, we expect the group share threshold for Taiwan to be lower than for Korea.

2. Methods

2.1 Data and construction of the panel

We use archival data for innovation and group market share. In this paper, we use a patent-based measure of innovation, provided by CHI Research Inc. The CHI data use a concordance developed by the U.S. Patent Office between the U.S. Patent Office Classification (USPOC) and Standard Industrial Classification (SIC) to construct a mapping of US patents granted to Korean and Taiwanese residents, broken down into 42 U.S. SIC-based manufacturing industry groupings.[1] US patents provide a useful measure of innovative activity because the U.S. is a highly desirable market and firms tend to file their most important innovations in the U.S. as well as, or instead of, in their home country. The patent data cover the 1980-1996 period. [2]

For the sector market share of business groups, we use a database on business groups in South Korea and Taiwan prepared by Robert Feenstra (1997), supplemented by more recent information. The Feenstra database contains information for the major business groups in Korea at the aggregate group level as well as at the individual member firm level for the years 1983 and 1986, and 1989. The source of

Feenstra's data for 1983 and 1986 is *Analysis of Financial Statements--Fifty Major Business Groups in Korea,* published by the Management Efficiency Research Institute in 1987. The database contains information on 537 business group member firms in 1983 and on 533 business group member firms in 1986. For each firm belonging to a business group, the data include its sales, assets, debt, equity, capital, profit, year of establishment, number of employees, value added, five digit Korean Standard Industrial Classification (KSIC), and whether it is listed on a stock exchange. Feenstra then pooled firm level data to obtain information at the group level. Both the 1983 and the 1986 datasets include 50 business groups.

Feenstra's primary source for the 1989 data is the *1990 Chaebol Analysis Report,* published by the Korea Investors Services, Inc. The 1989 dataset includes 44 groups, with 499 member firms. In addition to the information provided in the earlier datasets, each member firm received a product sector code. The product sector classification uses the 1988 Input-Output Tables published by the Bank of Korea in 1991, which contained 161-sector classifications (IO numbers). Each group member firm received an IO number according to the firm's main product. The source of information on the firm's products *was Hankuk Kiup Chong Ram (Korea Business Firms) 1990 and 1991,* published by Korea Chamber of Commerce and Industry, and *Yearbook on the Korean Economy and Businesses 1991/1992*, published by Business Korea.

We supplemented Feenstra's dataset of Korean firms by adding 1995 to the analysis.[3] In order to extend the database to 1995, we first had to identify the member firms for each group from the 1989 dataset (which has the most recent roster of group membership). Once the member firms were identified, the relevant information about them was collected from the *Business Korea Yearbook, 1997,* which contains detailed firm-level information on all firms—group members as well as non-member firms, and publicly-listed as well as non-listed firms. Extending the dataset beyond 1989 allows us to include member firms that became part of the groups after 1989. We consulted the individual firm level literature for every firm documented in the *Business Korea Yearbook,* 1997 in order to identify such firms.

For Taiwan, the Feenstra database contains similar data for 1983, 1986, and 1994. For 1983 and 1986, the database draws from Business Groups in Taiwan (1985/86) and Business Groups in Taiwan (1988/89), both published by China Credit Information Service Ltd., Taipei. The 1994 database for Taiwan drew from two sources, both of which relied on the China Credit Information Service (CCIS) in Taipei, Taiwan: (1) Business Groups in Taiwan (1996/1997), published by CCIS and (2) Company annual reports to the Taiwan stock exchange, for the 1994 fiscal year. This data was collected by the CCIS.

For both countries, the Feenstra database contains data for 21 manufacturing sectors, reporting the aggregate share of sales by individual firms that belonged to various business groups within each sector. This data allows calculation of group market share by sector in each year of the study.

It was necessary to collate information from different data sources, which define product categories differently. For instance, whereas the Feenstra database treats *'Food'* and *'Beverage & Tobacco'* as two separate groups, the *Korea Company Yearbook* combines these two into one group known as *'Food, Beverage, and Tobacco*.' Similarly, Feenstra considers *'Rubber'* and *'Plastic'* as two different groups while the *Korea Company Yearbook* treats them as one group. Moreover, while patent data include 42 U.S. SIC based industry groupings, the data on the sector share of business groups are classified according to either 17 (the *Business Korea Yearbook*) or 21 product groups (the Feenstra database). To construct the panels, therefore, we used disaggregated sales figures by product groups to combine two or three product groups into broader product categories. The resulting panel consists of 13 product categories.

For each product category, we divide the patent data into three three-year time periods. Our objective is to create a three-year "patenting window" following each of the three points at which we have group market share data for both countries.[4] Aggregating patent data over several years reduces variations in annual patenting data (Archibugi and Pianta, 1992). Moreover, the mean lag between when a patent application is filed and when it is finally granted in the U.S. is about one to two years (Scherer, 1983), so that patents granted in a particular year may be driven by factors that occurred up to two years earlier. By including patent data for up to two years following a year for which group share data exists, we account for the two-year lag effect in patenting. This procedure provides 39 observations for each of the two countries (3 patent periods x 13 product categories).

2.2 Sector measure of innovation

A problem with patent data is variation across sectors in patenting propensity (Scherer, 1983). To address this problem, we follow research that uses the Technology Revealed Comparative Advantage (TRCA) Index as the sector measure of innovation (Soete, 1987; Archibugi and Pianta, 1992). The TRCA index measures the *relative* distribution of a country's inventive activity in each field, compared to its own total patents and to the overall distribution of patents in the US. This makes the specialization index independent of the countries' size and specific fields, allowing comparison of relative strengths and weaknesses across industries and nations. The TRCA index suits the comparative scope of this paper.

Formally, the TRCA index for country *i* in sector *j* is defined as the ratio of country *i*'s share of total world patents in sector *j* to country *i*'s share of total world patents, such that,

$$TRCA_{ij} \equiv \frac{\left(\frac{\left(n_{ij}\right)}{\sum_i n_{ij}}\right)}{\left(\frac{\sum_j n_{ij}}{\sum_i \sum_j n_{ij}}\right)}, \text{ where } n_{ij} \text{ is the number of patents of country } i \text{ in sector j}$$

By definition, this index equals 1 if the country holds the same share of worldwide patents in a given technology as in the aggregate, and is below (above) 1 if there is a relative weakness (strength). However, it is important to recognize that a value of the index greater than 1 indicates a relative advantage only (i.e., relative to the existing patenting of the country), and should not be confused with an absolute advantage. Shifts in the TRCA over a time frame allows us to observe whether a country has increased its strength in selected areas or shifted its relative advantage to new fields (e.g., Pavitt, 1988).

Because we know the distribution of patenting across the 42 two-digit SIC based classes, we can aggregate them to determine the distribution of patenting across the 13 product groups in this paper. This allows us to calculate a separate TRCA index for each of the 13 product categories in each country.

Table 1A highlights shifts in the TRCA profiles in Korea over the three periods. The Spearman rank correlation between TRCA in period I and TRCA in period III is .31, while between TRCA in period I and TRCA in period II, it is .20. Thus, we observe substantial shifts over time in the sector patterns of specialization in technology, as evidenced by low Spearman rank correlations among the TRCA profiles across time. While Korea's technological comparative advantage in Period I lay in industries such as transportation equipment, chemical materials, non-metallic mineral products (stone, clay, and glass products), metal products, and textiles, the TRCA for each of these sectors had declined by period III. By contrast, there was substantial increase in the TRCA for the electronics/electrical sector by Period III.

************ Tables 1A and 1B about here ************

Table 1B reports the same information for Taiwan. Here, the Spearman rank correlation between TRCA in period I and TRCA in period III is 0.73, while between TRCA in period I and TRCA in period II it is 0.79. The high correlations point to lesser shifts in the sector patterns of technology specialization in Taiwan than in Korea. In parallel with Korea, though, there was a marked increase in the electronics/electrical TRCA in Taiwan during the study period.

2.3 Group market share within sectors

We calculated group market share in each sector as the ratio of total sales of firms that belonged to business groups in a particular sector to the sales of all firms within that sector. Table 2A reports the sector share of groups in Korea across the 13 product groupings for three years: 1983, 1989, and 1995. Table 2A shows that groups accounted for more than 25% of total sector sales for most Korean sectors; in several cases, groups account for more than 50% of sales. In general, Korean groups dominated heavy industries such as *Electronic/electrical products*, *Machinery*, *Transportation equipment,* and *Petroleum and coal*. The major change is that groups were moving out of several established sectors, including *Textiles and apparel*, *Rubber and plastic products*, and *Chemical materials*.

Table 2B reports the sector share of groups in Taiwan across the 13 product groupings at the three points: 1983, 1986, and 1994. Group share in Taiwan tended to be markedly lower than in Korea, reaching 50% only once (*Textiles and apparel* in 1983). Group share declined over time in several sectors, although there were increases in *Machinery, Transportation equipment,* and *Metal products*.

3. Statistical Analyses

3.1 Model specification

We use the following baseline specification to test the hypothesized inverted-U relation between group-share and innovation as measured by TRCA:

$$TRCA_{i,t+1} = \alpha_0 + \alpha_1\left(GroupShare_{it}\right) + \alpha_2\left(GroupShare_{it}\right)^2 + \alpha_3\left(Number_{it}\right) + \alpha_4\left(C5_{it}\right) + \alpha_5\left(CurrentRatio_{it}\right) + \alpha_6\left(Electronics_{it}\right) + \alpha_7\left(Chemicals_{it}\right) + \alpha_8\left(Machinery_{it}\right) + \alpha_9\left(Metals_{it}\right) + \alpha_{10}\left(Traditional_{it}\right) + \varepsilon_i$$

TRCA and *GroupShare* provide our focal measures. The dependent variable *TRCA* measures a sector's relative technological specialization in patenting. *GroupShare* is the ratio of total sales of firms that belonged to business groups within each sector to the sales of all firms in that sector during a particular year. In order to account for the hypothesized non-linearity, in addition to the variable *GroupShare*, we also include a squared term for *GroupShare*. We expect to find a positive coefficient for *GroupShare* and a negative coefficient for its squared term.

The other measures control for alternative explanations. Group share does not necessarily capture the level of competition among groups. Given the same group share, the incentive for innovation may differ depending on the degree of competition among group-affiliated companies. Thus, we want to separate the "pure" group share effect (entry barriers) from the more conventional "market structure" effect (competition). The number of group companies in a sector is a measure of inter-group competition.

We also include a five-firm concentration ratio, *C5*, defined for each sector. Empirical studies often focus on the relationship between market structure and innovation, with market structure measured in terms of concentration ratios. Empirically, there is little consensus regarding the effects of concentration on innovation (Cohen and Levin, 1989) but there is some agreement that the relationship varies with the "technological opportunity" class of the industry (Kamien and Schwartz, 1986: 90).[5]

The *CurrentRatio* variable provides a control for available internal funds. To the extent that innovation must rely on internal financing (Himmelberg and Petersen, 1994: 49), only firms with high liquidity can support sizable R&D efforts. However, access to internal capital markets within diversified structures allows conglomerates to allocate cash generated everywhere to high yield purpose anywhere (Servaes 1996; Teece, 1996), suggesting that internal financing may be less relevant when business groups exist. Thus, the issue of internal financing is an open question. We control for any liquidity effect by including a sector's sales-weighted average current ratio (defined as the ratio of a firm's current assets to its current liabilities). We calculate the sector-specific values by taking a weighted average of all the firm-specific values within a particular sector and weighting them by each firm's share of sales in the total sales of the sector. We expect the *CurrentRatio* variable to have a positive coefficient.

In addition, given the highly leveraged status of many Korean companies, a firm's debt burden (measured by the ratio of its debt to equity, *Debt/Equity*) may influence the level of accessible funds that the firms can use for research and development. We use a sector's sales-weighted average *Debt/Equity* ratio as a measure of for capital market access. We expected *Debt/Equity* to have a negative impact.[6]

Finally, unobservable sector-specific effects might correlate with both the sector share of groups and *TRCA* variables. Technological opportunity will not only increase the possibilities for innovation, it may also increase the sector share of groups. For instance, the Korean government's use of the *chaebols* to create high technological capabilities led to preferential credits for *chaebols* entering high opportunity sectors (Kang, 1996). Failing to account for such sector-specific effects would create a specification error that might bias the estimates of the effects of group-share. We use sector-specific dummy variables to control for variation in technological opportunity and propensity to patent, with the sectors aggregated into five major classifications: *Electrical, Machinery, Chemicals*, *Metals,* and *Traditional* (Scherer, 1965). *Electrical* includes one category: Electronic/Electrical Products; *Machinery* includes three categories: Machinery, Transportation equipment, and Precision instruments; *Chemicals* includes four categories: Chemical materials, Chemical products, Rubber and plastic products, and Non-metallic minerals; *Metals* includes three categories: Primary metals, Metal products, and Petroleum and coal; finally, *Traditional* includes two categories: Food and beverages, and Textiles and apparel.

3.2 Descriptive statistics

Table 3A summarizes Korea data. *TRCA* varies from a minimum of zero (no patents were granted to the *Food and beverage* sector firms during 1983-1985) to a maximum of 2.19 (the *TRCA* of the *Electronics and electrical* sector during 1994-1996). Following the terminology of panel data analysis, 'between-sectors' in Table 3A refers to differences in sector-specific averages across the 13 sectors, with the averages taken within a sector over time. The 'between-sectors' numbers demonstrate that the sector specific averages vary from a minimum of 0.156 (*Rubber and plastics)* to 1.670 (*Electronics and electrical)*. In turn, 'within-sectors' refers to the deviation of variables from all-period sector means. *TRCA* 'within-sector' numbers, measuring the deviation from sector averages, vary from -0.777 to 0.829.

Table 3A shows that the mean (overall) *GroupShare* across sectors and over time was about 45%. The share of groups varied from 11.1% (*Precision instruments*) to 100% (*Petroleum and coal*). These figures appear reliable when we consider the firms that belong to the sectors. For instance, the firms that dominate the *Petroleum and coal* sector are all members of a group; e.g., Yukong is affiliated with the SKC group, Ssangyong Oil Refining belongs to the Ssangyong group, Hanwha Energy is affiliated with the Hanwha group, and Kukdong Oil and Chemical is a member of the Kukdong Oil group. We also observe that, despite a low sector share of groups, a sector can have a high concentration ratio. For instance, none of the four firms that dominate the *Precision instruments* sector in Korea (Orient Watch

Industries, Pan Korea, Shinhung, and Medison) belongs to a group. This is why, despite having the lowest sector share of groups, the *Precision instruments* sector has the highest concentration ratio. The 'within-sector' results for the variable *GroupShare* range from -23.93 to +31.66. The maximum fluctuation over time in the sector share of groups takes place within the *Rubber and plastics* sector. The mean debt to equity ratio of 351.58 reconfirms the highly leveraged state of the Korean corporate structure.

Table 3B summarizes the Taiwan data. *TRCA* has a mean value of about 6.2, with a minimum of 0.06 (for *Petroleum and coal* in period II) and a maximum of 38.98 (the *TRCA* of the *Electronics and electrical* sector during period III). Table 3B also shows that the mean *GroupShare* across sectors and over time was about 19%, much lower than in Korea. Group share varied from 0% (*Petroleum and coal*) to 50.7% (*Textile and apparel*). We observe that the overall *C5* of 28% for Taiwan is smaller than Korea. Both low average *GroupShare* and low average *C5* values suggest greater rivalry among firms in Taiwan than in Korea. The mean *Debt/Equity* ratio of 211% reflects that the Taiwanese firms were less leveraged than their Korean counterparts. Also, the mean *ROS* of 2.9% is much lower than in the Korea data.

Tables 4A and 4B provide correlation matrices for the data from Korea and Taiwan. For Korea, there are moderate correlations among *GroupShare* and *C5*, as well as *Current Ratio* and *Debt/Equity*. There also are moderate negative correlations between *Current Ratio* and *Debt to Equity* and between *Current Ratio* and *C5*. In general, the *GroupShare* measure provides reasonable independence relative to the control variables, other than the C5 measure, which we discuss below.

3.3 Regression results using sector dummies on pooled data

Table 5A reports the initial results for the Korean data, using OLS regression. Column (1) in Table 5A omits *C5* as an explanatory variable, owing to the moderate collinearity between *GroupShare* and *C5* that we noted in the discussion of Table 4A. In model 1, both *GroupShare* and $(GroupShare)^2$ take the expected positive and negative signs and are statistically significant, consistent with the prediction in hypothesis 1 that group share would lead to an inverted-U impact on innovation in a sector. The TRCA innovation benefit in Korea reaches its peak when the sector share of groups is 71.6%. Among the control variables, *Current Ratio, Debt/Eqyuty* and the *Electrical* dummy are statistically significant.

Column (2) in Table 5A adds *C5* as an explanatory variable to the specification as column (1). The results continue to support hypothesis 1, as the *GroupShare* variables retain their statistical significance, although the presence of *C5* leads to a slight decline in the t-statistics for *GroupShare*. *C5, meanwhile,* has a statistically insignificant negative coefficient. The collinearity between *C5* and *GroupShare*, though, likely explains the modest reduction in the magnitude of the *GroupShare* variable.

Column (3) of Table 5A replaces *GroupShare* and its squared term with *C5* and its squared term. The goodness of fit suffers, however, as the R-square value declines. Therefore, *GroupShare* performs better than *C5* as a market structure measure. In later analyses, we focus on *GroupShare* and omit *C5*.

Table 5B reports the results for Taiwan, again supporting hypothesis 1. The statistically significant positive sign for *GroupShare* and the negative sign for $(GroupShare)^2$ in models 1 and 2 are consistent with the prediction of an inverted-U relation between group-structure and innovation.

Comparing the points of *GroupShare* at which innovation measured by TRCA reaches its peak in Korea and Taiwan tests hypothesis 2. Recall that we expected a lower threshold in Taiwan, owing to the greater presence of non-group innovation infrastructure. The results are consistent with the prediction. As we noted, innovation reaches its peak at over 72% group share in Korea (Table 5A, column 2). By contrast, innovation in Taiwan reaches its peak when the sector share of groups is about 29% (Table 5B, column 2).

We note that reverse causation is not a likely problem in these analyses. The first two values for *GroupShare* in Korea are for the years 1983 and 1989, whereas the first two periods for the TRCA variable are for the periods 1983-1985 and 1989-1992. Even if patenting were to influence *GroupShare*, it would take a substantial lag, implying only modest possibility of contemporaneous impacts of patenting on group share. Amsden (1989) also argues that unlike their counterparts in developed economies, the latecomer business groups in Korea generally did not emerge on the basis of Schumpeterian technological breakthroughs, suggesting that possibility of causality from innovation to group share may be low.[7]

3.4 Panel data estimation

Tables 6A and 6B report alternative methodological approaches. Column 1 uses fixed effects in place of sector dummy variables. This approach treats the sector-specific components of the error terms as fixed effects. A standard method for absorbing fixed effects is to transform variables to deviations from their sector means. The error term ε_{it} accommodates measurement errors in the dependent variable and is assumed to be uncorrelated with the explanatory variables and the sector-specific errors.

None of the variables in column (1) of Table 6A is statistically significant, although the signs of the coefficients for *GroupShare* and $(GroupShare)^2$ are consistent with our expectation of an inverted-U relationship between *TRCA* and *GroupShare. TRCA* reaches its peak when the sector share of groups in Korea is 75%, similar to the figures in Table 5A.

The poor performance of the fixed effects model in column 1 of Table 6A is plausible when one considers the standard deviations of the variable *GroupShare* in Table 3A. About 70% of the variance in *GroupShare* appears to be cross-sectional, suggesting that by controlling for sector-specific fixed effects, a fixed effects specification may be throwing away most of the variance that our model seeks to explain.

Column 2 of Table 6A, therefore, replaces the fixed effects model with a between-sector OLS. To obtain the between-sector results, we regressed the sector-specific means of the dependent variable (i.e., averaged over time) on the sector means of the explanatory variables. This involves regressing the sector average of *TRCA* over the study period on the sector averages of *GroupShare* and other variables.

The coefficients of *GroupShare* and *(GroupShare)*^{2} in the between-sector results in column 2 in Table 6A are qualitatively consistent with our hypothesis of a quadratic relationship. *TRCA* reaches its peak when the sector share of groups is 60%. Again, however, the coefficients are statistically insignificant, most likely due to the sample size and the need to include multiple dummy variables.

Given the small sample available, there is a benefit from using random-effects models that do not require fixed-effect dummies but also do not discard information. To permit direct comparisons with the between-sector and within-sector results, column 3 in Table 6A reports the results using a random-effects model with a WGLS (Weighted Generalized Least Square) estimator. The Random effects WGLS estimates of *GroupShare* and *(GroupShare)*^{2} in column 3 of Table 6A are statistically significant. The results reinforce the inference of a nonlinear relationship between *TRCA* and *GroupShare,* where *TRCA* reaches its peak when the sector share of groups is 72%. The control variables have similar outcomes in the random-effects results (column 3) and between-sector OLS analysis (column 2). We believe the random effects approach is appropriate here. In a statistical assessment, the Hausman test fails to reject random effects estimators in favor of the fixed effects estimators, which reinforces the support for hypothesis 1 that the random effects model in column 3 provides.

In order to check the robustness of the random-effects results, column 4 in Table 6A reports a regression using GEE (General Estimating Equation) for panel data (Liang and Zeger, 1986). The GEE estimator is asymptotically equivalent to a weighted-GLS estimator provided by the random effects estimator (Greene, 1993). In the context of this paper, GEE holds certain methodological appeals. GEE uses a quasi-likelihood approach, where repeated observations from the same subject are assumed to be independent. A particularly useful feature of the GEE approach for random effects specifications is that it does not require the observations for all subjects have the same correlation structure. Instead, GEE allows us to specify the within-group correlation structures as well as to assume robust standard errors. Assuming robust standard errors, we find both *(GroupShare)* and *(GroupShare)*^{2} again are statistically significant; *TRCA* reaches its peak when the sector share of groups is 59%.

From the regressions in Tables 5A and 6A, the hypothesis of an inverted-U relationship between the sector share of groups and *TRCA* is robust for the Korean data across diverse statistical techniques. It appears that *TRCA* reaches its peak when the sector share of groups in Korea is about 60% to 75%. When we analyze these results in light of the sector share of groups presented in Table 2A, our results seem sensible. *Electronic products* and *Transportation equipment* have 70% of their total sales coming from firms that belong to business groups. From Table 1(A), we observe that the *Electronics* and

Transportation equipment sectors have some of the highest values for *TRCA* innovation measure. Thus, the results in these two tables provide robust evidence of an inverted-U relationship between group structure and innovation.

Table 6B provides the panel data results for Taiwan. The results are similar to the Korea analyses. Again, the poor performance of the fixed effects model in column 1 of Table 6B is plausible given the inter-temporal consistency of *GroupShare*. Approximately 80% of the variance in *GroupShare* in Table 3B appear to be cross-sectional, suggesting both between sector as well as the random-effects models should outperform the fixed effects model. The subsequent models, however, provide significant support for hypothesis 1. The lower significance of the coefficient of $(GroupShare)^2$ in random-effects GLS model (column 3) relative to the GEE model (column 4) might be driven by heteroscedasticity and/or autocorrelation, which would inflate the standard errors. The random-effects GLS model does not account for possible autocorrelation or hetroscedasticity, while the random-effects GEE model does. This may explain why the GEE model performs the best for both Korea and Taiwan.

3.5. Sensitivity analyses

Sensitivity analyses find robust results for the inverted-U impact of group share on innovation.

Pure non-parametric regression

In the context of our analysis, nonparametric treatment of the hypothesized nonlinearity between group structure and innovation helps check the parametric results. Non-parametric estimation techniques allow the data to determine the shape of the functional form without *a priori* constraints. These techniques are useful for building and checking parametric models, as well as for data description. Two techniques that are particularly useful for exploratory analysis are nearest-neighbor non-parametric regression (kernel and localized linear regression) and spline regression (linear spline and cubic spline).

The kernel estimation technique uses a formula called a kernel to weight nearby observations. One way of computing weights is to use localized linear (or polynomial) regressions. Rather than a weighted mean, a localized linear regression estimate is computed in every neighborhood (Cleveland, 1979). Given our hypothesis of an inverted-U relation between group-structure and innovation, localized linear regression has particularly attractive features. Instead of estimating the mean at every point, the curve is approximated by estimating a tangent at every point. Local regressions are attractive because if the points lie on a line or polynomial, the line or polynomial will be reproduced (Altman, 1992: 179).

Figures 1A and 1B use localized linear regression to demonstrate the non-linearity between a sector's share of business groups and the sector's innovative performance (measured by *TRCA*) for Korea and Taiwan. In each figure, the horizontal axis represents *GroupShare* and the vertical axis represents *TRCA*. We observe that *TRCA* for Korea approaches its peak when the sector share of groups is approximately 70%, consistent with the earlier parametric regression analyses. For Taiwan, the threshold is when *GroupShare* is approximately 25%, again consistent with the parametric analyses. This result is robust across band-widths of 0.4, 0.6, and 0.8 (a band-width of 0.4 means that 40% of the data are used in smoothing). Overall, this nonparametric approach provides results that are consistent with the parametric regression results and with the postulated non-linearity between *TRCA* and the sector share of groups.

Semiparametric regression

Pure nonparametric estimation techniques such as the localized linear regressions are subject to certain problems. As suggested by McFadden (1985), the assumption of zero asymptotic efficiency relative to estimates of a correct parametric model suggests that precise and comprehensive picture requires extensive data. In this context, 39 observations might be too few to justify pure nonparametric estimation but, as long as the entity of interest is the shape of the function, nonparametric methods can describe the data, even when the sample size is modest (Robinson, 1988).

Semiparametric models compromise between pure parametric and pure nonparametric estimation techniques. Semiparametric models contain both parametric and nonparametric components, reflecting what has been learned from theory and experience, and what is unknown. The semiparametric approach allows one to nonparametrically estimate the Group Share-TRCA relationship, while controlling for sector-specific characteristics that are assumed to be parametrically related to TRCA across sectors.[8] Consistent with the parametric and non-parametric results, we found a quadratic relationship between TRCA and GroupShare in both Korea and Taiwan using the semiparametric estimation procedure.

Results excluding petroleum and electronics

We conducted two sensitivity analyses concerning particular sectors, petroleum and electronics. First, the inverted-U might depend on having the petroleum industry in the sample. The sector has a high group market share and low innovation, which pulls the curve down (Figure 1A). The petroleum industry might be an outlier because most countries in the world have heavy government involvement in petroleum, while in Korea, groups take up the role of government. Moreover, this is a sector that might have little patenting because of the nature of the industry. When we drop the petroleum industry from the analysis, though, we find continued support for the inverted-U effects, although with somewhat lower significance in Korea. Second, as we observe in Figure 1, with the exception of the electronic/electrical products sector, TRCAs in period III seem to be smaller than the TRCAs in periods I or II within the same sector. Therefore, we conducted sensitivity analyses in which we dropped the electronics/electrical industry, finding a robust inverted-U for both Korea and Taiwan. Thus, the inverted-U evidence does not seem to be determined by either petroleum or electronics.

Are entry barriers to the domestic market relevant?

The inverted-U hypothesis assumes that group structure provides an indicator of entry barriers. Since many of the Korean and Taiwanese firms face global competition, we need to ask how meaningful domestic entry barriers are for technological innovation. In case of Korea, one might argue that, even though many of the sectors are export oriented, a substantial portion of their sales comes from the Korean domestic market, where various types of entry barriers continue to shield them from external competition.

Nonetheless, a recent report prepared by the McKinsey Global Institute argues that domestic competition is the dominant factor, noting that "The most important driver for productivity growth is intense competition, notably with global best practice [domestic] companies. Although many Korean companies feel that they are subject to intense competition both in Korea and export markets, they were in fact relatively protected, especially from foreign best practice companies, by the prevailing regulatory environment" (McKinsey Global Institute, 1998). In the manufacturing sectors, for example, explicit or implicit (e.g., no access to distribution channels) barriers to imports of manufactured goods and FDI effectively kept foreign companies out of the Korean markets. The automotive industry provides an example. In the late 1980s, import tariffs of up to 50% protected the Korean auto industry. As part of the GATT and WTO process, these tariffs declined to 10% in 1996, but non-tariff barriers continue to limit the penetration of imported cars. In 1998, imported cars still accounted for less than 1% of the Korean domestic market. Examples of non-tariff barriers include an outright ban on importing cars assembled in Japan, limitations on the size and ownership of dealer networks, advertising restrictions, and tax audits of foreign car owners. Thus, even though globalization has intensified, entry barriers to domestic markets still played an important role in the competitive intensity of these sectors during the study period.

Primarily, then, this is an empirical question that may be tackled by controlling for variation in export intensities across sectors. As sensitivity analysis, therefore, we added export intensity as a control variable. We found results that remained materially equivalent to those that we report.

Is the inverted-U relation driven by technology characteristics?

Following the work of Pavitt (1984), empirical studies sometime differentiates industries with different technological features. For instance, scale-intensive sectors such as automobiles, chemicals, and steel involve high capital intensity, wide economies of scale, and incremental innovation. Science-based sectors, on the other hand, include industries such as biotechnology, semiconductors, telecommunications, and aerospace — industries involve product innovations with broad scope for spillovers. If groups patent primarily in scale-intensive sectors, while independent firms patent mainly in science-based sectors, failure to control for such technology characteristics may contribute to the inverted-U relation. When we examine the profiles of Korean patent assignees, however, we observe that groups patent actively across science-based as well as scale-based industries. In 1996, for instance, 86% of the Korean patents in telecommunications, 85% of the patents in semiconductors, and 61% of the patents in biotechnology went to groups (although only 38% of the patents in chemicals and 29% of the patents in pharmaceuticals went to groups). Thus, groups are active across a broad gamut of technology classes, suggesting that the inverted-U relation does not rely on technology characteristics.

4. Discussion & Conclusions

We argue that business groups in emerging economies play dual roles towards innovation. While groups limit innovation by creating entry barriers for non-group members, they contribute to innovation by providing institutional infrastructures. Using data from Korea and Taiwan, we find robust evidence of an inverted-U relationship between the sector share of groups and the sector's innovative performance.

One key difference between Korea and Taiwan appears to be the relatively lower threshold level for group share in Taiwan than for Korea. While the optimal group share for Korea is approximately 60% to 75%, the threshold is approximately 25% to 30% for Taiwan, with the variations arising in different estimation techniques. This result is plausible when we consider the differences in competitive landscapes between these two countries. While the industrial landscape in Korea prevented the small and medium sized enterprises (SME) from entering the market, government in Taiwan explicitly promoted SMEs.

An alternative explanation of the quadratic link between the sector share of groups and *TRCA* could be that group share acts only as a proxy for entry barriers, rather than as a combination of entry barriers and institutional infrastructure, and the non-linearity in the relationship between group share and innovation captures a non-linearity in the relation between entry barriers and innovation. The theory and evidence on technological innovation suggest a threshold concept of the most favorable climate for rapid technological change (Scherer and Ross, 1990: 660). The early game theoretic treatment by Scherer (1967) predicted that rivalry, approximated by lower concentration indices, invigorates R&D spending up to a point, but that too atomistic a market structure discourages R&D by causing would-be innovators to capture an insufficient share of the payoffs from the innovation. More recent decision theoretic models (Kamien and Schwartz, 1982: 105-145) are consistent with Scherer's hypothesis that an intermediate market structure is often the one in which innovative activity is the greatest. In this paper, however, group share remains statistically significant when we include both group share and the concentration ratio together in the regression equation. Moreover, we do not find a significant inverted-U relationship between C5 and innovation for either Korea or Taiwan (Tables 5A and 5B). Thus, the results suggest that both the infrastructure and entry barrier arguments affected innovation in the two countries.

The study has policy implications. Confronted with the recent economic crisis in Asia, groups are under great pressure to restructure. The IMF demands more transparent accounting practices as a condition for bailout. This demand might make it harder to transfer funds internally by way of loans, debt guarantees, equity participation, and transfer pricing. Despite the recent anti-group rhetoric in Asia, the policy implication of the inverted-U curve is the following: as long as groups can add value by providing institutions that do not exist in developing countries, it may not be desirable to break them into independent companies, at least as long as market institutions remain weak. Instead, governments in emerging economies should promote rivalry and dissemination of new ideas, encouraging the groups to be more innovative. As countries such as Korea and Taiwan approach their technological frontiers, the role of groups in enhancing dynamic efficiency is as important as, if not more important than, their role in providing second-best solutions to market imperfections. However, it is important to recognize that groups contribute less as market imperfections decline.

Finally, technological specialization of countries in particular sectors arises from many different factors rooted in the structure of their economies. Given the widespread presence of business groups in developing economies, our focus is on the role of business groups. However, we recognize that there are other factors that may also influence a country's comparative advantage in certain fields. These include sectoral specialization in industrial production and trade, the existence of certain natural resources and a domestic industry based on their exploitation, and particular structures of national demand and consumer tastes that may lead to particular technological developments. Government industrial and technology policies focusing national resources in specific technological fields may also result in a country's relative specialization in these areas (Nelson, 1993).

Endnotes

[1] The SIC classification only imperfectly matches industry assignment with underlying technologies (Scherer, 1983, Griliches, 1990). Although the CHI database also uses the International Patent Classification (IPC) to class patents, we use the SIC classification rather than the IPC because our explanatory variables match more accurately with the SIC and because the IPC-USPOC mapping used by the CHI Research also required arbitrary judgments, according to CHI Research personnel.

[2] Both patents and R&D expenditure data are common indicators of innovation, with strengths and weaknesses (Griliches, 1990). The absence of uniform accounting standard as well as unavailability of R&D expenditure data makes the R&D data analysis impractical in the context of cross-country comparison of developing countries. On the other hand, patenting data may fail to capture the cumulative and incremental aspect of learning. Critics of patent data further argue that many technological developments in Asia are not patented, making patents a less reliable source for measuring relative technological competence (Amsden and Hikino, 1994). Finally, the extent of foreign patenting has been historically quite small for developing countries. However, over the past two decades, the increasing number of patents granted to firms in Korea and Taiwan allows meaningful analysis. For example, the number of US patents granted to Korea rose from a total of 43 patents during 1975-1979 to 11,366 patents during 1995-1999. Similarly, the number of US patents granted to Taiwan rose from 176 patents during 1975-1979 to 12,366 patents during 1995-1999.

[3] We added the 1995 data for Korea owing to data availability, for comparison to Taiwan in 1994. Group share has sufficient year-to-year stickiness that the one year difference provides a reasonable comparison.

[4] For Korea, we have group share data for 1983, 1989, and 1995, so that our patent data for Korea divide into three periods: Period I [1983-1985], Period II [1989-1992] and period III [1994-1996]. Although the Feenstra data includes 1989 group share information for Korea, we lacked similar information for Taiwan.

[5] The assumption behind the use of the concentration ratio as a measure of market structure is that firms in a more concentrated industry possess more monopoly power than in a less concentrated industry (Kamien and Schwartz, 1986: 85). But with efficient capital markets, market power is neither a necessary nor sufficient condition for generating financial resources (Teece, 1996). We note that our data are more aggregated than in other studies, which makes it harder to discern the effects of *C5* on *TRCA*.

[6] A high debt to equity ratio might not limit a firm's access to new debt. Theories of capital structure suggest that, if a large fraction of a firm's assets are tangible, then assets should serve as collateral, diminishing the risk of lender suffering the agency cost of debt, such as risk shifting (Rajan and Zingales, 1995). Assets should also retain more value if they are subject to

liquidation. Therefore, the greater the proportion of tangible assets on the balance sheet, the more willing should the lender be to supply new loans. However, in emerging economies, government intervention, information asymmetries, and lack of transparency imply that creditors may have to pay more attention to a firm's intangible resources, such as management's reputation, its access to connections, and its competitiveness. Under these circumstances, a firm's debt to equity ratio may reflect the firm's access to intangible resources for which external transactions face market failures. Thus, a high debt to equity ratio might not limit a firm's access to new debt. Anecdotal evidence from the Asian financial crisis points out that in some cases, the banks in developing nations continued to provide the highly leveraged business groups with new credit.

[7] We recognize that current group share may be a function of past innovation and may in turn affect future innovation. In that case, the OLS estimates will be asymptotically biased. One way to solve this problem is to find an appropriate instrumental variable for group share. While the lagged *TRCA* variable might be used as one such instrument, its use as an explanatory variable would require dropping one period of observations, leaving only 26 observations. Moreover, although the OLS estimates may be biased, techniques that address the endogeneity problem (e.g., two-stage least squares, indirect least squares) are also biased in small samples (Kennedy, 1998: 163). Indeed, Monte Carlo studies have shown that, for small samples, OLS estimates tend to have the minimum variance among all the estimators.

[8] For the semiparametric methodology, see Robinson (1988) and Aw and Batra (1998). Given a data set $[(y_i, x_i, z_i), i = 1,\ldots\ldots, n]$, the semiparametric model takes the following functional form:

$$y = x'\beta + m(z) + \varepsilon,$$

where, y is a n x 1 vector representing the dependent variable, the index of TRCA; y is assumed to be a linear function of x, a (n x k) matrix of sector characteristics, such as C5, Current Ratio, Debt Ratio, Export Intensity, and Sector Dummies. The nonparametric component, *GroupShare*, is represented by a (n x 1) vector z. We assume that ε is distributed with mean zero and finite variance. In addition $E(\varepsilon|z, x) = 0$ and m is unknown function of z. Estimation proceeds, first, by fitting y and x nonparametrically as a function of z. Secondly, the resulting residualized y is regressed on residualized x to obtain β_{OLS}. Finally, m(z) is obtained by fitting y-x β_{OLS} nonparametrically with z.

REFERENCES

Acs, Zoltan J. and David B. Audretsch (1988) "Innovation in large and Small Firms: An Empirical Analysis," American Economic Review, Vol. 78, pp. 678-90.

Afuah, Allan (2000). "Do your *Co-opetitors'* Capabilities Matter in the Face of a Technological Change?" Strategic Management Journal, 21, pp. 387-404.

Aghion, Philippe and Peter Howitt (1992) "A Model of Growth Through Creative Destruction," Econometrica, March, 1992, Vol. 60, No. 2, pp. 323-51.

Aguilar, F. J. and D-S. Cho (1985a) "Daewoo Group," Case Study 9-385-014, Harvard Business School Case Services, Boston, Massachusetts.

Aguilar, F. J. and D-S. Cho (1985b) "Goldstar Co., Ltd.," Case Study 9-385-264, Harvard Business School Case Services, Boston, Massachusetts.

Altman, N. S. (1992) "An Introduction to Kernel and Nearest Neighbor Nonparametric Regression," American Statistician, Vol. 46, No. 3, pp. 175-185.

Amsden, Alice and Takashi Hikino (1994) "Project Execution Capability, Organizational Know-How and Conglomerate Corporate Growth in Late Industrialization," Industrial and Corporate Change, pp. 111-148.

Amsden, Alice H. (1989) Asia's Next Giant: South Korea and Late Industrialization, Oxford University Press.

Angelmar, R. (1985) "Market Structure and Research Intensity in High Technological-Opportunity Industries," Journal of Industrial Economics, 34, 69-79

Archibugi, Daniele and Mario Pianta (1992) The Technological Specialization of Advanced Countries, Kluwer Academic Publishers.

Aw, B.-Y. and G. Batra (1998) "Firm Size and the Pattern of Diversification" International Journal of Industrial Organization, May. 1998.

Bain, Joe S. (1956) Barriers to New Competition: Their Character and Consequences in Manufacturing Industries, Harvard University Press.

Berger, Philip G. & Eli Ofek (1995) "Diversification's effect on firm value," Journal of Financial Economics, 37: 39-65.

Bernheim, B Douglas & Michael D Whinston (1990) Multimarket contact and collusive behavior. RAND Journal of Economics, 21: 1-26.

Caves, R. and M. Uekusa (1976) Industrial Organization in Japan, Brookings Institution, Washington, DC.

Chandler, A. D. Jr. (1990) Sccale and Scope: The Dynamics of Industrial Capitalism. Harvard University Press, Cambridge, Massachusetts.

Chang, Sea Jin, and Jaebum Hong (1998) "Economic Performance of the Korean Business Groups: Intra-group Resource Sharing and Internal Business Transaction," author's manuscript.

Chang, Sea Jin, and Unghwan Choi (1988) "Strategy, Structure, and Performance of Korean Business Groups: A Transactions Cost Approach," Journal of Industrial Economics, December.

Chesbrough, H.W, and David J. Teece (1996) "When is Virtual Virtuous: Organizing for Innovation," Harvard Business Review, January-February.

Cho, Dong Sung (1989) "Diversification Strategy of Korean Firms," in Kae H. Chung and Hak Chong Lee edited, Korean Managerial Dynamics, Praeger Publishers, New York. pp. 99-113.

Claessens, S., S. Djankov, and L. Lang (2000) "The Separation of Ownership and Control in East Asian Corporations," Journal of Financial Economics**,** Vol. 58

Cleveland, W. S. (1979) "Robust Locally Weighted Regression and Smoothing Scatterplots," Journal of American Statistical Association, Vol. 74, pp. 829-836.

Comanor, W.S. (1964) “Market Structure, Product Differentiation, and Industrial Research, Quarterly Journal of Economics, Vol. 81, pp. 639-57.

Feenstra, Robert (1997) “Business Groups in South Korea and Taiwan: A Comparison and Database,” Working Paper Series, Institute of Governmental Affairs, University California, Davis.

Fisman, Raymond, and Tarun Khanna (1998) Facilitating Development: The Role of Business Groups, Harvard Business School Working Paper.

Geroski, P. A. (1991) “Entry and the Rate of Innovation,” Economics of Innovation and New Technology, Vol. 1, pp. 203-14

Ghemawat, Pankaj, and Robert E. Kennedy (1998) “Competitive Policy Shocks and Industrial Structure: The Case of Polish Manufacturing,” Harvard Business School Working Paper.

Ghemawat, Pankaj, and T. Khanna (1998) “The Nature of Diversified Groups: A Research Design and Two Case Studies,” Journal of Industrial Economics, XLVI(1): 35-62.

Granovetter, M. (1994) “Business Groups,” Chapter 18, in N.J. Smelser and R. Sweberg (ed.) Handbook of Economic Sociology, Princeton University Press, Princeton, New Jersey.

Greene, William H. (1993) Econometric Analysis, Paper 16. Macmillan Publishing Company.

Griliches, Z. (1990) “Patent Statistics As Economic Indicators: A Survey,” Journal of Economic Literature, Vol. 28, pp. 1661-1797.

Griliches, Z. (ed.) (1984) R&D, Patents and Productivity, University of Chicago Press, Chicago.

Hardle, Wolfgang (1990) Applied Nonparametric Regression, New York: Cambridge University Press.

Henderson, Rebecca; Cockburn, Iain (1996) “Scale, Scope, and Spillovers: The Determinants of Research Productivity in Drug Discovery,” Rand Journal of Economics. Vol. 27 (1). p 32-59.

Hikino, Takashi, and Alice H. Amsden (1994) “Staying Behind, Stumbling Back, Sneaking Up, Soaring ahead: Late Industrialization in Historical perspective,” Convergence of Productivity: Cross-National Studies and Historical Evidence (Edited by William J. Baumol, Richard R. Nelson, and Edward N. Wolff), Oxford University Press.

Himmelberg, Charles and Bruce Petersen (1994) “R&D and Internal Finance: A Panel Study of Small Firms in High-Tech Industries,” Review of Economics and Statistics, Vol. 76, pp. 38-51.

Hirshleifer, Jack (1973) “Where Are We in the Theory of Information,” The American Economic Review, Vol. 63, pp. 31-39.

Hobday, Michael (1995) Innovation in East Asia, Hants, England: Edward Elgar Publishing Ltd.

Jacquemin, A. P., and C.H. Berry (1979) “Entropy Measures of Diversification and Corporate Growth,” Journal of Industrial Economics, Vol. 27, pp. 359-69.

Jewkes, John, David Stawers, and Richard Stillerman (1970) The Sources of Invention, New York: W. W. Norton.

Johnston, J. (1991) Econometric Methods, New York: McGraw Hill.

Jung, K. H. (1989) “Business Government Relations in Korea,” in K. H. Chung and H. C. Lee (eds.) Korean Managerial Dynamics, New York, Praeger, pp. 11-26.

Jung, K. H. (1991) Diversification and Industrial Competitiveness, Korea Economic Research Institute, Seoul.

Kamien, Morton I., and Nancy L. Schwartz (1982) Market Structure and Innovation, Paper 3, Cambridge University Press.

Kang, Myung Hyun (1996) The Korean Business Conglomerates, Institute of East Asian Studies, University of California, Berkeley.

Kennedy, Peter (1998) A Guide to Econometrics, Papers 14, 19, The MIT Press.

Khanna, Tarun and J. W. Rivkin (2001) "Estimating the Performance Effects of Networks in Emerging Markets," Strategic Management Journal, Vol. 22, No. 1

Khanna, Tarun and Krishna Palepu (1997) "Why Focused Strategies May be Wrong for Emerging Markets," Harvard Business Review (75:4).

Khanna, Tarun and Krishna Palepu (1999) "Policy Shocks, Market Intermediaries, and Corporate Strategy," Journal of Economics and Management Strategy, 2(1): 270-310.

Khanna, Tarun and Krishna Palepu (2000) "Emerging Market Business Groups, Foreign Investors, and Corporate Governence," Concentrated Corporate Ownership, edited by Randall Morck, University of Chicago Press.

Kim, Linsu (1998) From Imitation to Innovation: Dynamics of Korea's Technological Learning, Harvard Business School press, Boston.

Kortum, Sam and Josh Lerner (2001) "Does Venture Capital Affect Innovation," Rand Journal of Economics.

Leff, Nathaniel (1978) "Industrial Organization and Entrepreneurship in Developing Countries: The Economic Groups," Economic Development and Cultural Change, Vol. 26, July, pp. 661-75

Leff, Nathaniel (1979) "Enterprenurship and Economic Development: The Problem Revisited," Journal of Economic Literature, Vol. 17, pp. 46-64.

Lemelin, A. (1982) "Relatedness in the Patterns of Interindustry Diversification," Review of Economics and Statistics, Vol. 44, pp. 646-57.

Lerner, Joshua (1996) Discussion on "Microeconomic Policy and Technological Change," by Edwin Mansfield, Technology and Growth, Federal Reserves Bank of Boston, Conference Series No. 40

Liang, K. Y. and Zeger, S. L. (1986) Longitudinal Data Analysis Using Generalized Linear Models," Biometrika, Vol. 73.

Lincoln, J., M. Gerlach, and C. Ahmadjian (1996) "Keiretsu Networks and Corporate Performance in Japan," American Sociological Review, Vol. 61, pp. 67-88.

MacDonald, James, M. (1985) "R&D and the Direction of Diversification, "Review of Economics and Statistics," Vol. 67, pp. 583-590.

Mansfield, Edwin (1996) "Microeconomic Policy and Technological Change," Technology and Growth, Federal Reserves Bank of Boston, Conference Series No. 40

McKinsey Global Institute (1998) Productivity-led Growth for Korea.

Methé, David, Will Mitchell, and Anand Swaminathan (1997) "The Role Of Established Firms As The Sources Of Major Innovations In The Telecommunication And Medical Equipment Industries". Industrial and Corporate Change, 5, Second Special Issue on Telecommunications Policy and Strategy, 1997.

Mokyr Joel (1994) "Cardwell's Law and the Political Economy of Technological Progress," Research Policy, Vol. 23, pp. 561-574.

Montgomery, Cynthia A. and S. Hariharan (1991) "Diversified Expansion by Large Established Firms," Journal of Economic Behavior and Organization, Vol. 15, pp. 71-89.

Nakatani, I. (1984) "The Economic Role of Financial corporate Groupings," in M. Aoki (ed.), The Economic Analysis of the Japanese Firm, North Holland, New York.

Nelson, Richard R. (1959) "The Simple Economics of Basic Scientific Research," Journal of Political Economy, Vol. 67, pp. 297-306.

Nelson, Richard R. (ed.) (1993). National Innovation Systems: A Comparative Analysis. Oxford University Press, New York.

Ravenscraft, David J., and F. M. Scherer (1987) Mergers, Sell-offs, and Economic Efficiency, The Brookings Institution, Washington D.C.

Reddy, N. Morhan, Liming Zhao (1990) International technology transfer: A review, Research Policy, 19, 285-307.

Reinganum, Jennifer R. (1989) "The Timing of Innovation: Research, Development, and Diffusion," In Richard Schmalensee and Robert D. Willig, eds., Handbook of Industrial Organization, Vol. 1, Chapter 14.

Robinson, P. M. (1988) "Semiparametric Econometrics," Journal of Applied Econometrics, Vol. 3, pp. 35-51.

Rumelt, R. P. (1982) "Diversification Strategy and Profitability," Strategic Management Journal, Vol. 3, pp. 359-369.

Scherer, F. M. (1965) "Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions," American Economic Review, Vol. 55, pp. 1097-1125.

Scherer, F. M. (1967) "Research and Development Resource Allocation Under Rivalry," Quarterly Journal of Economics, Vol. 81, pp. 359-95.

Scherer, F. M. (1980) Industrial Market Structure and Economic Performance, Boston: Houghton Mifflin, Second edition.

Scherer, F. M. (1983) "The Propensity to Patent," International Journal of Industrial Organization, Vol. 1, pp. 107-128.

Scherer, F. M. and David Ross (1990) Industrial Market Structure and Economic Performance, Boston: Houghton Mifflin, Third edition.

Servaes Henri (1996) "The value of diversification during the conglomerate merger wave" Journal of Finance, 51, 227-252

Silverman, B. W. (1984) "Spline Smoothing: The Equivalent Variable Kernel Method," Annals of Statistics, Vol. 12, No. 3, pp. 898-916.

Toulan, Omar N. (2001) "The impact of market liberalization on firm vertical scope" Strategic Management Journal (forthcoming).

Teece, David J. (1996): "Firm Organization, Industrial structure, and Technological Innovation," Journal of Economic Behavior and Organization, Vol. 31, pp. 193-224.

Von Hippel, Eric (1994) "Sticky Information and the Locus of Problem Solving," Implications for Innovation," Management Science, Vol. 40, No. 4, April.

Wegman, Edward, and Ian Wright (1983): "Spline in Statistics," Journal of the American Statistical Association, Vol. 78, Number 382, pp. 351-364.

Weitzman, Martin (1998) "Recombinant Growth," Quarterly Journal Of Economics

Williamson, Oliver E. (1967) "Hierarchical Control and Optimum Firm Size," Journal of Political Economy, Vol. 75, pp. 123-38.

Williamson, Oliver, E. (1985) The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting, Free Press, New York.

Weinstein, D. and Y. Yafeh (1995) "Collusive or Competitive? An Empirical Investigation of Keiretsu Behavior," Journal of Industrial Economics, Vol. 43, pp. 359-376.

Table 1A. Profiles of Relative Sector Specialization in Technology Korea

Industry Sector	TRCA Period I (1983-85)	TRCA Period II (1989-92)	TRCA Period III (1994-96)
Electronic/ Electrical products	0.95	1.91	2.31
Machinery	0.73	0.76	0.69
Transportation equipment	2.56	1.22	0.67
Precision instruments	0.97	0.54	0.53
Chemical materials	1.61	0.55	0.42
Chemical products	0.85	0.37	0.40
Rubber and plastic products	0.79	0.80	0.43
Non-metallic mineral products	1.63	0.52	0.50
Primary metals	0.91	1.56	0.92
Metal products	1.43	0.77	0.52
Petroleum and coal	0.44	0.00	0.01
Food and beverages	0.00	0.54	0.35
Textiles and apparel	1.25	0.41	0.67

Table 1B. Profiles of Relative Sector Specialization in Technology (Taiwan)

Industry Sector	TRCA Period I (1983-85)	TRCA Period II (1986-88)	TRCA Period III (1994-96)
Electronic/ Electrical products	0.93	27.43	38.98
Machinery	1.14	26.15	28.13
Transportation equipment	1.60	7.28	7.62
Precision instruments	0.76	11.15	10.98
Chemical materials	0.41	1.30	2.11
Chemical products	0.16	0.56	0.91
Rubber and plastic products	1.06	5.49	6.53
Non-metallic mineral products	1.02	1.63	1.88
Primary metals	0.52	0.42	0.67
Metal products	2.26	28.46	21.98
Petroleum and coal	0.24	0.06	0.07
Food and beverages	0.28	0.24	0.10
Textiles and apparel	0.46	0.13	0.35

Note: TRCA = Technology Revealed Comparative Advantage. TRCA for country *i* in sector *j* is equal to the ratio of country *i*'s share of total world patents in sector *j* to country *i*'s share of total world patents. The higher the value of the TRCA index, the relatively stronger the country is in that sector.

Source: Calculation based on CHI Research data

Table 2A. Sector Shares Of Groups In Korea

Industry Sector	Group-share 1983	Group-share 1989	Group-share 1995
Electronic/ Electrical products	50.90	64.30	80.21
Machinery	34.90	33.90	79.46
Transportation equipment	79.00	80.40	85.47
Precision instruments	14.00	11.10	11.10
Chemical materials	54.30	37.50	35.00
Chemical products	24.00	26.90	31.34
Rubber and plastic products	76.80	12.10	37.00
Non-metallic mineral products	44.60	28.00	60.00
Primary metals	28.00	34.30	45.00
Metal products	26.70	25.80	31.78
Petroleum and coal	91.90	100.0	100.00
Food and beverages	33.70	23.80	30.00
Textiles and apparel	38.40	32.50	20.00

Source: Calculation based on Feenstra database and the *Business Korea Yearbook*,1997

Table 2B. Sector Shares of Groups in Taiwan

Industry Sector	Group-share 1983	Group-share 1986	Group-share 1994
Electronic/ Electrical products	22.70	23.55	24.40
Machinery	3.60	7.95	12.30
Transportation equipment	23.60	29.25	34.90
Precision instruments	10.70	5.41	0.12
Chemical materials	42.40	38.85	35.30
Chemical products	8.40	5.30	2.20
Rubber and plastic products	13.00	7.10	1.20
Non-metallic mineral products	47.60	42.60	37.60
Primary metals	7.80	5.30	2.80
Metal products	6.00	14.25	22.50
Petroleum and coal	0.00	2.13	4.25
Food and beverages	26.30	20.10	13.90
Textiles and apparel	50.70	48.00	45.30

Source: Calculation based on Feenstra database

Table 3A. Summary of The Panel Data For Korea

Variable		Mean	Standard Deviation	Minimum	Maximum
TRCA	*Overall*	0.811	0.534	0.000	2.190
	Between-sectors		0.389	0.156	1.670
	Within-sectors		0.377	-0.777	0.829
GroupShare	*Overall*	44.92 (%)	25.231	11.100	100.000
	Between-sectors		23.592	12.066	97.000
	Within-sectors		10.4558	-23.930	31.660
Number	*Overall*	11.92	3.436	5	21
	Between-sectors		3.064	7	18
	Within-sectors		1.706	7.92	15.92
C5	*Overall*	62.60(%)	20.4	18.1	99.0
	Between-sectors		17.3	37.9	97.0
	Within-sectors		11.5	-13.8	21.1
Debt/ Equity	*Overall*	351.58(%)	271.603	83.256	1258.424
	Between-sectors		201.801	187.917	894.911
	Within-sectors		187.584	-470.76	705.092
Current Ratio	*Overall*	120.84(%)	29.632	43.527	210.279
	Between-sectors		25.431	80.232	169.446
	Within-sectors		16.290	-37.730	40.830
	Within-sectors		8.621	-7.479	19.082

Table 3B. Summary of The Panel Data For Taiwan

Variable		Mean	Standard Deviation	Minimum	Maximum
TRCA	*Overall*	6.191	10.261	0.0601	38.975
	Between-sectors		7.997	0.125	22.444
	Within-sectors		6.686	-15.325	22.722
GroupShare	*Overall*	19.21 (%)	15.994	0.000	50.700
	Between-sectors		15.941	2.125	48.000
	Within-sectors		3.881	10.964	27.464
Number	*Overall*	10.69	2.811	7	17
	Between-sectors		2.806	7.333	16.66
	Within-sectors		0.662	9.358	12.025
C5	*Overall*	27.92 (%)	18.578	0.012	71.670
	Between-sectors		14.642	0.215	57.417
	Within-sectors		11.918	- 0.264	51.498
Debt/ Equity	*Overall*	211.00(%)	52.522	100.00	383.40
	Between-sectors		37.708	153.47	281.43
	Within-sectors		37.570	133.239	312.96
Current Ratio	*Overall*	132.38(%)	29.334	100.10	218.30
	Between-sectors		24.421	111.866	199.13
	Within-sectors		17.189	84.953	169.753
	Within-sectors		1.101	0.716	05.103

Table 4A. Correlation Matrix for Korea

	TRCA	*GroupShare*	*Number*	*C5*	*Current Ratio*	*Debt/Equity*	*ROS*
TRCA	1.00						
GroupShare	0.32*	1.00					
GroupNumber	0.18	-0.16	1.00				
C5	0.06	0.36*	0.13	1.00			
Current Ratio	0.12	-0.25	0.03	-0.07	1.00		
Debt/Equity	-0.20	-0.29	0.17	-0.09	0.47*	1.00	
ROS	-0.13	0.07	-0.15	-0.04	-0.85*	-0.42*	1.00

Note: * indicates significance at 5% significance level.

Table 4B. Correlation Matrix for Taiwan

	TRCA	*GroupShare*	*Number*	*C5*	*Current Ratio*	*Debt/Equity*	*ROS*
TRCA	1.00						
GroupShare	-0.07	1.00					
GroupNumber	0.06	0.14	1.00				
C5	-0.25	0.31	-0.01	1.00			
Current Ratio	0.08	-0.09	0.21	-0.40*	1.00		
Debt/Equity	-0.10	-0.31	-0.22	-0.05	-0.31*	1.00	
ROS	-0.22	0.12	0.17	0.55*	0.05	-0.22	1.00

Note: * indicates significance at 5% significance level.

Table 5A. OLS Regression Results on the Pooled Data for Korea (Dependent variable: TRCA)

Independent variables	(1)	(2)	(3)
Constant	-.218	-.028	.046
	(-0.686)	(-.067)	(-.053)
GroupShare	.043	.036	
	(3.109)**	(2.045)**	
(GroupShare)^2	-.0003	-.0002	
	(-2.758)**	(-1.531)**	
Number of groups	-.015	-.010	.003
	(-0.657)	(-.386)	(.131)
C5		-.385	2.204
		(-.689)	(0.856)*
C5-square			-1.99
			(-0.996)
Current-Ratio	.003	.003	-.003
	(3.188)**	(2.921)**	(2.348)**
Debt/Equity	-.0005	-.0005	-.0006
	(-2.532)**	(-2.349)**	(-2.781)**
Electrical (v. Traditional)	.569	.653	.577
	(2.330)**	(2.099)**	(1.831)*
Metals (v. Traditional)	.088	.213	.121
	(.339)	(.629)	(.509)
Chemicals (v. Traditional)	-.312	-.202	-.183
	(-1.451)	(-.674)	(-.969)
Machinery (v. Traditional)	-.230	-.090	-.065
	(-1.122)	(-.300)	(-.339)
Cases (R-square)	39 (.53)	39 (.54)	39 (.39)
GroupShare when TRCA is at peak	72%	72%	

Table 5B. OLS Regression Results on the Pooled Data for Taiwan (Dependent variable: TRCA)

Independent variables	(1)	(2)	(3)
Constant	-2.72	-.854	-.537
	(-0.166)	(-0.053)	(-.031)
GroupShare	.703	0.743	
	(2.151)**	(2.154)**	
(GroupShare)^2	-.013	-.013	
	(-2.201)**	(-2.184)**	
Number of groups	-.900	-.790	-.422
	(-1.534)	(-1.273)	(-.746)
C5		-0.066	-.213
		(-1.047)	(-0.737)
C5-square			0.002
			(704)
Current-Ratio	.126	.107	.090
	(1.503)	(1.306)	(1.127)
Debt/Equity	-.030	-.025	-.005
	(-1.098)	(-.143)	(-.143)
Electrical (v. Traditional)	11.86	18.85	18.857
	(1.204)	(1.940)*	(1.940)*
Metals (v. Traditional)	7.07	7.23	7.239
	(.1.506)	(1.203)	(1.203)
Chemicals (v. Traditional)	-4.52	-2.24	-2.242
	(-1.776)*	(-.897)	(-.897)
Machinery (v. Traditional)	-22.04	17.76	17.76
	(3.082)**	(2.095)**	(2.095)**
Cases (R-square)	39 (.56)	39 (0.57)	39 (0.48)
GroupShare when TRCA is at peak	27%	29%	

* p<.10, ** p<.05 (t-stats in parentheses)

Table 6A. Panel Data Regression Results For Korea (Dependent variable: TRCA)

Independent variables	1. Fixed-effects (within) OLS	2. Between-sector OLS	3. Random-effects WGLS	4. Random-effects GEE, robust
Constant	.778	-.652	-.218	-.403
	(1.018)	(.633)	(-.561)	(-3.372)**
GroupShare	.003	.024	.043	.047
	(.119)	(1.012)	(2.879)**	(6.010)**
(GroupShare)^2	-.00002	-.0002	-.0004	-.0004
	(.171)	(-1.056)	(-2.496)**	(-5.213)**
Number of groups	-.045	-.028	-.015	.004
	(-.871)	(1.077)	(-.625)	(.324)
Current-Ratio	.003	.005	.004	.003
	(1.097)	(1.966)**	(2.776)**	(2.977)**
Debt/Equity	-.0002	-.0009	-.0005	-.0007
	(-.497)	(-3.572)**	(-2.026)**	(-6.057)**
Electrical		.364	.569	.475
		(2.234)**	(2.631)**	(6.357)**
Metals		-.050	.088	-.036
		(-.328)	(.374)	(-.368)
Chemicals		-.161	-.312	-.354
		(-1.558)	(-1.386)	(-4.904)**
Machinery		-.302	-.230	-.403
		(-1.558)	(-.771)	(-3.372)**
Cases	39	39	39	39
R-square	.28 (within)	.96 (between)	.50 (overall)	
GroupShare with TRCA at peak	75%	60%	72%	59%

Table 6B. Panel Data Regression Results For Taiwan (Dependent variable: TRCA)

Independent variables	1. Fixed-effects (within) OLS	2. Between-sector OLS	3. Random-effects WGLS	4. Random-effects GEE, robust
Constant	-36.788	33.562	-9.440	9.368
	(-1.022)	(1.001)	(-.655)	(.529)
GroupShare	.460	1.070	.603	.895
	(1.022)	(1.962)**	(1.688)*	(2.179)**
(GroupShare)^2	.006	-.020	-.011	-0.017
	(.541)	(-1.876)*	(-1.429)	(-2.212)**
Number of groups	2.835	-1.715	-.510	-1.398
	(1.737)*	(-1.733)*	(-0.607)	(-2.790)**
Current-Ratio	0.266	-.0008	.141	0.096
	(3.952)**	(-.004)	(2.150)**	(.936)
Debt/Equity	-0.007	-0.099	-024	-0.050
	(-0.287)	(-1.548)	(-.860)	(-1.488)
Electrical		9.320	12.800	10.220
		(1.184)	(1.921)*	(2.538)**
Metals		7.577	8.104	6.472
		(1.508)	(1.560)	(1.392)
Chemicals		-4.055	-4.957	-4.237
		(-0.882)	(-1.042)	(-2.198)**
Machinery		29.156	19.683	25.569
		(3.381)**	(2.319)**	(5.736)**
Cases.	39	39	39	39
R-square	0.42 (within)	0.91 (between)	0.55 (overall)	
GroupShare with TRCA at peak	38%	27%	27%	24%

* p<.10, ** p<.05 (t-stats in parentheses)

FIGURE 1A - KOREA

Locally weighted scatterplot smoothing of the relationship between Group Share and TRCA

(Band-width =0.4)

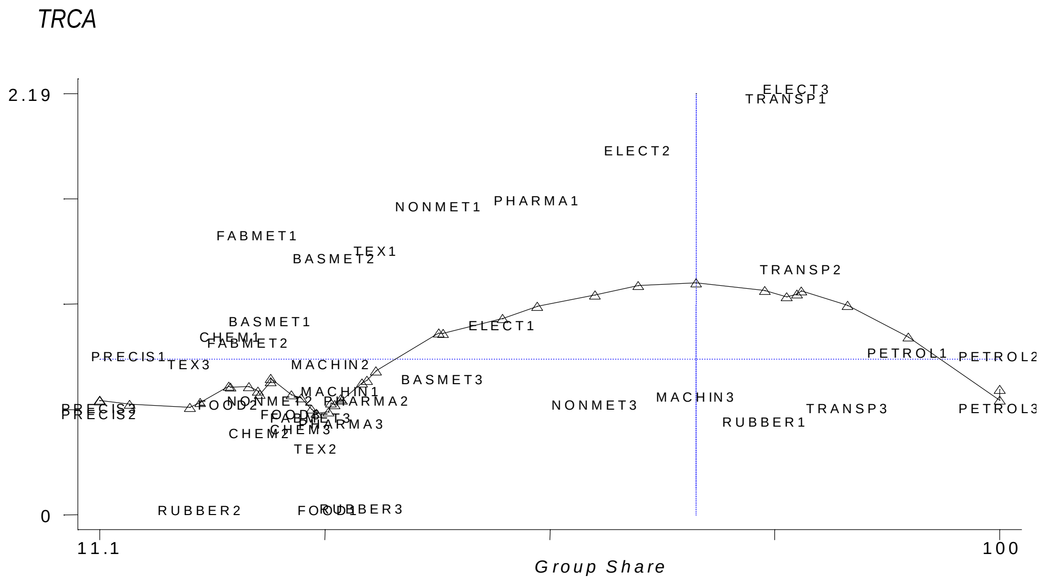
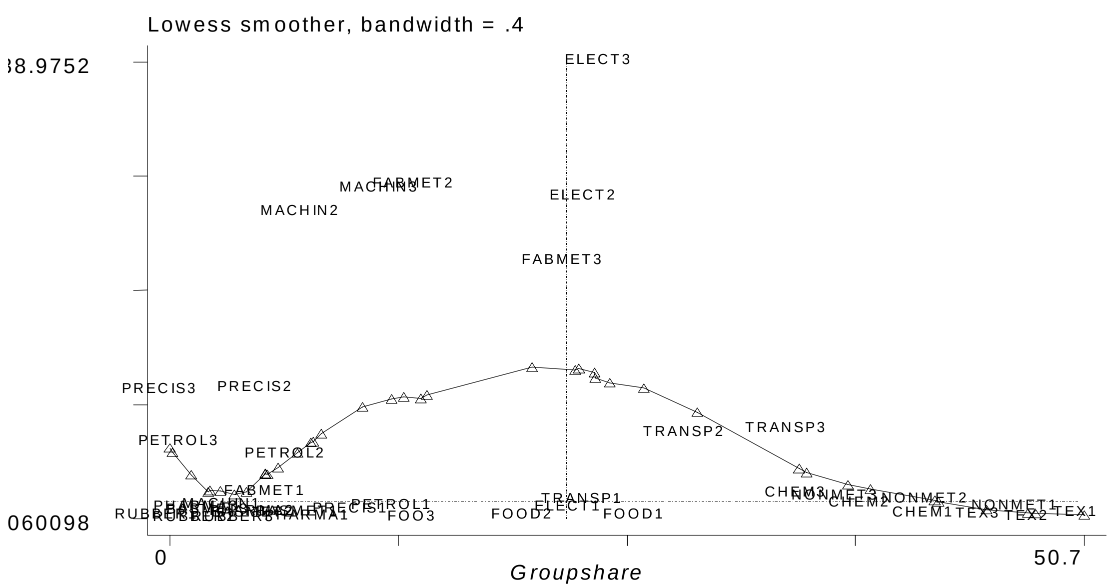


FIGURE 1B - Taiwan

Locally weighted scatterplot smoothing of the relationship between Group Share and TRCA

(Band-width =0.4)



Legend

FOOD = Food and beverages; TEX=Textiles and apparels; PHARMA = Chemical products; CHEM = Chemical materials; RUBBER = Rubber and plastics; PETROL= Petroleum and coal; NONMET= Nonmetallic mineral products; BASMET= Primary metals; FABMET= Metal products MACHIN = Machinery; ELECT= Electronics/electrical; TRANSP =Transportation equipment; PRECIS = Precision instruments

Note: The numerals stand for time periods. For instance, ELECT3 indicates TRCA for *ELECT* in period III