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Mode, size, and location of foreign direct investments and industry markups

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Abstract

Several studies find that inward foreign direct investment (FDI) raises host industries' competition and productivity using aggregate FDI measures: the monetary flows or the change in the industries' foreign production share. Yet FDI flows are composed of many individual, heterogeneous investments. Reflecting this heterogeneity, I ask how the average traits of the individual investments that constitute the FDI flow further affect the host. While the results show that inward FDI does heighten competition for US manufacturing industries in 1987–1991, price–cost markups fall even more when foreign investments locate further away from incumbent industry, which is consistent with endogenous location choice.

JEL classification: F23; L11

Keywords: Foreign direct investment; Competition; Location choice; Entry mode

1. Introduction

Inward and outward flows of foreign direct investment increased more than three times between 1980 and 1990. As a result, nations' economies have become increasingly intertwined. However, questions remain about how foreign direct investment (FDI) influences the economies of both source and host nations. While numerous researchers find that FDI increases host industry productivity, few studies examine FDI's effect upon host industry competition.[1] In one of the few studies, Caves (1974) finds a weak competition relationship;

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[1] Some studies indirectly examine competition by focusing on productivity. Increased productivity may result from a rise in competition that forces marginal incumbents to exit and encourages remaining firms to improve their efficiency.

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in Canadian manufacturing industries, average firm profits are lower when foreign-owned firms account for a greater production share.

While these studies use measures of foreign presence to explain FDI's effect, research into firm-level FDI topics suggests other potentially important traits of FDI flows. Coughlin et al. (1991) and Head et al. (1995) show that foreign investments choose locations in the US, based on state characteristics like presence of related industry and unionized workers. Blonigen (1997) shows that foreign firms are more likely to acquire US targets with real dollar depreciation in bilateral exchange rates. Shaver (1998) shows that unobserved heterogeneity affects foreign firms' entry mode choice and subsequent performance. These and other related studies demonstrate that foreign investments vary substantially in their chosen entry mode, location, and other traits. Since, multiple heterogeneous investments compose an inflow of FDI, we can gain insight into how FDI affects industry competition by incorporating these other traits.

Therefore, in this paper, I ask how foreign investment entry mode, investment size, and geographic location alters FDI's expected positive effect upon host industry competition. To test FDI's expected relationship to competition, I use price–cost markup, the ratio of price over marginal cost, to measure industry competitiveness. Certain foreign investment traits should increase competition more, indicated by greater decrease in price–cost markup. While closely related to the more traditional price–cost margin, the methodology for measuring markup overcomes some recognized difficulties with margin's operationalization. Since markup, my dependent variable, is an industry-level measure, I aggregate information on individual investment transactions' mode, size, and location into average industry-level measures. These average measures indicate for example, how far on average did foreign investments locate from incumbent firms?

My empirical setting is United States manufacturing industries from 1987 through 1991. This is a rich environment for testing FDI's effects for two reasons. First, the US received just over half of the world's total flows in the 1980s. Second, comprehensive FDI data for individual inward investments is available for the US, but not for other nations. Using this information, I construct measures for the three average FDI traits in each industry-year: "mode" indicates the portion that is new facilities — greenfield investments; "size" is the investments' value relative to the average establishment size; and "distance" is investments' linear distance to existing industry.

While one result is unexpected, others are consistent with prior research. The traditional measure of industry-level FDI, percent of sales from foreign-owned affiliates, has a positive and significant effect on industry competition — markup falls, which parallels past studies. While "mode" and "size" are insignificant, I find that "distance" is significant and including these three traits almost triples the adjusted R-squared. While, hypothesizing that foreign investments located closer to incumbents will decrease industry price–cost markup more, I unexpectedly find that price–cost markup decreases more when foreign investments locate further away. One explanation is that weak firms locate close to incumbents to capture any positive externalities, while stronger firms prefer more distant locations. These distant locations have lower input costs that allow these distantly located foreign firms to set their prices commensurately lower; in turn incumbents have to meet these lower prices, which reduces industry markups.

I proceed as follows: first, I review literature on FDI's link to host industry competition. Next, I suggest how these three traits of foreign investments affect host industry price–cost markup. I then describe the data for the empirical test. The results of the test and a discussion of the results follow. Finally, I conclude with further possible improvements.

2. FDI and increase of host industry competition

Researchers generally argue and find that FDI increases both host industry competition and productivity. For FDI to positively influence the host industry, Caves (1971) identifies a key assumption: investing foreign firms are generally superior competitors to incumbent firms by virtue of their stock of intangible assets — accumulated managerial, process, or product skills. Several studies including Baldwin and Gorecki (1991), Liu (1993) and Baldwin (1995) show that entrants tend to be more productive than incumbents. Further, Globerman et al. (1994) and Howenstine and Zeile (1994) show that foreign firms especially tend to be more productive than domestic firms. Another assumption behind FDI's positive influence is that the host industry firms are mature enough to meet the foreign firms' competitive challenge (Caves, 1974: p. 184). If relatively nascent, incumbents will be unable to reduce inefficiency, borrow technology, or otherwise catch-up.

With these two assumptions met, foreign investments raise competition by overcoming entry barriers, competing for factor inputs and customers, and reducing the market power of entrenched firms. Market power typically accrues in industries with high entry barriers, which foreign firms are well suited to overcome, since they have established intangible stocks (Caves, 1996). For example in a technologically advanced industry, when R&D spending is needed to differentiate and develop new products, foreign firms often have already established technological stocks from activities in other nations.

For productivity, Caves argues that FDI increases productivity by raising competition and transferring technology from foreign firms to incumbents. Competition forces marginal firms to exit which aids allocative efficiency and forces remaining firms to improve their own internal firm efficiency to ensure their continued survival. Technology transfer can lead to increased productivity as incumbents apply new knowledge obtained directly or indirectly from foreign firms.

Empirical tests support FDI's positive influence. Studies focusing specifically on FDI and competition are few. Using cross-sectional regressions, Caves shows that increasing foreign presence, which is measured as the percent sales from foreign-owned firms, decreases domestic firms' profitability. Tests for productivity are more numerous. Early tests establish the overall positive relationship between FDI and labor productivity. Globerman (1979) uses industry aggregate data and Blomström and Persson (1983) use establishment level data to show that foreign-owned subsidiaries' production share in an industry relates positively to value-added per employee in Canada and Mexico.

More recent studies seek evidence for technology transfer from foreign to local firms, often find little significant effect, and conclude that observed productivity gains result from heightened competition. For Mexico, Blomström (1986) finds that more modern sectors are closer to best practices in industries with greater foreign presence. Using firm-level data for Morocco from the late 1980s, Haddad and Harrison (1993) find that greater foreign presence reduces dispersion in productivity among local firms, because the firms converge towards best practices. For Mexico in the 1970s, Kokko (1994) finds that local establishments' productivity level significantly lags in industries that use complex technologies and have a high foreign share of production — large technology gaps together with high foreign ownership inhibit knowledge spillovers to local firms. Overall, prior empirical research strongly supports FDI's positive influence on productivity, which indirectly supports FDI's positive influence upon competition.

3. FDI traits and host industry competition

While establishing that inward FDI increases host industry competition, existing research treats inward FDI as a uniform flow. Yet, the flow is composed of many different investments and is therefore inherently heterogeneous. By introducing traits of the FDI flow that reflect this heterogeneity, we might better understand FDI's link to industry competition. I suggest that the investment traits of mode, size, and location will influence prices and costs industry-wide and will further explain FDI's relationship to industry competition.

These three traits have received substantial prior attention as dependent variables, which suggests that they might in turn be important independent variables for explaining FDI's effect upon the host industry. Researchers have explored how parent firm characteristics and host industry conditions determine these traits. For example, Kogut and Chang (1991) show for Japanese FDI into the US that greater difference between home and host nation industry R&D intensity encourages greenfield investments but not acquisitions or joint-ventures. Thus, these three traits also indirectly capture parent firm characteristics like nation of origin, international experience, and differences between home and host nations.

How might these FDI traits affect prices and costs? Price–cost markup will be more strongly affected when these traits increase competitors' reaction. Competitive reaction is needed for industry conditions to change. In basic industrial organization economic frameworks, a firm maximizes profits by setting price or output while anticipating the other firm's actions. Each firm reacting to the other moves these decision variables to equilibrium. Equilibrium is reached because each firm necessarily reacts to the other. However, outside of a two player game framework, an industry will have many participants and not all participants will readily react to others. What then determines who will react to whom? Within an industry population Chen et al. (1992) argue that reaction between firms is more likely and will be faster when participants are more aware of each other.

How does incumbents' awareness relate to FDI traits? I suggest that incumbents will be more aware of closer, larger, greenfield investments. This greater awareness will reduce industry price–cost markup; price will move closer to marginal cost.

Physically proximate investments should decrease industry markup more than distant investments by increasing costs and decreasing prices. When the supply of inputs is localized, they face non-trivial transportation costs, which means their supply will be relatively inelastic. Even with increased factor return rates, the supply of factors will not readily increase. For example, labor must be obtained locally and labor supply will respond slowly to change in wage rates, since people have to relocate. More competitors increase factor demand, which raises costs. Similarly, if customers are localized, proximate competitors will decrease prices. Demand will be relatively fixed and as more numerous competitors shift the aggregate supply curve outwards, price will decrease. By competing for localized customers and suppliers, proximate competitors will also increase incumbents' awareness. Incumbents will be able to identify specific competitors who are responsible for price and cost changes.

Potential exists for the opposite outcome, that distant investments may decrease price–cost markup more than proximate investments, if we consider two explanations. First, Aitken and Harrison (1999) argue that FDI has both positive and negative influences. By introducing additional competitors, FDI harms incumbents' productivity by reducing their output, spreading their fixed costs across fewer units. This movement back-up the average cost curve increases costs, which compresses markups. In contrast, if FDI transfers useful technology to incumbents, the cost curve may shift affording lower per unit costs, which widens markups. Since, technology transfer is enhanced by proximity — through the hiring and firing of each other's workers, chance meetings between scientists, and demonstration of previously unknown technologies — proximately located FDI may have lessened downward pressure on industry markups than distant FDI.

The second explanation builds upon technology transfers and similar spillovers. Shaver and Flyer (2000) suggest that multinationals differ in how much they contribute to agglomeration economies. Examples of agglomeration benefits include Rivera-Batiz and Rivera-Batiz (1990) who argue that the presence of manufacturing FDI causes supporting industries to specialize, which increases manufacturing industries' productivity. Also Aitken et al. (1997) find that local firms are more likely to export when multinationals export, which suggests information spillovers. Given these gains from agglomerating, Shaver and Flyer suggest that those multinationals that contribute more to and gain less from these economies tend to locate their subsidiaries far from incumbent firms. This decision to locate distantly may suggest greater competitiveness since agglomeration benefits are unwanted. If stronger multinationals do locate distantly and incumbents recognize this, then distant investments might drop markup more.

The effect of heterogeneous strength and potential technology transfer is in addition to the main effect of proximity increasing costs and decreasing prices. Given the simplicity of the main effects arguments, I expect them to dominate, which suggests the following hypothesis.

Hypothesis 1. The closer the average investment in an FDI flow locates to incumbent industry, the more host industry price–cost markup will decrease.

For investment mode, greenfield investments should decrease price–cost markup more than other modes. First, while a greenfield investment may eventually cause competitors to reduce their capacity, industry output capacity initially grows. Increased capacity should lower price. In comparison, an acquisition does not initially alter industry output capacity. In addition, capacity increase means that demand for inputs will also grow, which may increase costs. With the decrease in price and increase in costs, price–cost markup will shrink.

Another consideration is that stronger parent firms might pursue greenfield investments and stronger firms should affect competition more. Given that greater ownership increases both risk and return for the parent, Gomes-Casseres (1989) argues that more capable parents will pursue higher ownership modes. Gatignon and Anderson (1988) show that parents with more international experience choose higher ownership modes. For acquisitions versus greenfield investments, Hennart and Park (1993) and Andersson and Svensson (1994) show that parents with more available resources and greater technical skills are more likely to enter by greenfield.

Also, greenfield investments may be more visible than other modes. Foreign acquisitions and new facilities often receive greater public attention than minority investments. And between acquisitions and greenfield investments, greenfield investment's visibility to managers of other firms may be greater because of the increased output capacity. These expectations suggest the following hypothesis.

Hypothesis 2. The greater the portion of greenfield investments in an FDI flow, the more host industry price–cost markup will decrease.

Finally, for investment size, while many small investments will have the same cumulative dollar value as fewer large investments, a FDI flow of fewer larger investments should raise industry competition more. From classical oligopoly theory, we know that larger firms influence industry profit margins more than smaller firms do. In a setting, where industry price is determined by aggregate output, each firm maximizes its profits by adjusting its output. In adjusting its output each firm anticipates how competitors will in turn respond with their own output adjustments; this anticipation is the firm's conjectural variation. Solving the maximization problem, an individual firm's price–cost margin is a function of its market share, the price elasticity of demand, and the conjectural variation (see for example Waterson, 1984: pp. 19–20; or Tirole, 1988: pp. 218–219).

At an industry-level, this means an industry's price–cost margin is then a function of the Herfindahl index, the price elasticity of demand, and the weighted sum of conjectural variations. The other variables held constant, a larger change to the Herfindahl index is associated with a larger change to the industry price–cost margin. While several large foreign investments might have the same dollar value of investment as numerous smaller investments, the index will change more with the introduction of several larger foreign firms. Thus, industry price–cost markup will respond more to fewer large foreign investments than to more numerous small foreign investments. Competitors should also be more aware that large foreign investments have greater potential to alter industry profitability. These expectations suggest that:

Hypothesis 3. The larger the average investment's value in an FDI flow, the more host industry price–cost markup will decrease.

4. Data

The empirical setting is US manufacturing for 1987 through 1991 inclusive, at the four-digit standard industrial classification (SIC) level. Estimating industry price–cost markup, price divided by marginal cost, requires individual firm or establishment data for outputs and inputs. Since, this disaggregated information is unavailable from census data, I use firm data from the Standard and Poor's Compustat tapes. As price approaches marginal cost, markup decreases towards 1.0, which indicates increasing competition. I am able to estimate markup for 171 four-digit SIC manufacturing industries that account for 56.5 percent of the total manufacturing output of US manufacturing industries.[2] Pooling across the 5 years of 1987 through 1991 yields some initial 855 industry-year observations.

The number of observations used for analysis is reduced in three ways. First, instead of levels, I am investigating change in levels, which reduces my panel from 5 to 4 years. Second, to examine change in a focal year, I use 1 year lags. Lagged data from before 1987 for some independent variables is unavailable, which further shortens the set of years examined. Third, the intersection between the set of dependent variable and independent variables is small, which drastically reduces the number of observations. The intersection is only about 40 four-digit SIC industries, which limits the starting panel to under 200 observations.

4.1. Industry competition: price–cost markup estimation

The dependent variable is year-over-year change in the industry-level of price–cost markup, D_MKUP. I obtain change from estimated yearly levels. Estimating yearly price–cost markup levels relies on knowing a firm's sales and input costs; the input costs multiplied by a 'price–cost markup' must be equal to its sales. The main equation for estimating price–cost markup is shown below and is similar to those used by Hall (1988), Levinsohn (1993), and Kang (1995). The line-by-line derivation is in Appendix A.

$$\mathrm{d}q_{it} = \left(\frac{p_t}{\mathrm{MC}_t}\right)[\alpha_{it}^{L}\,\mathrm{d}l_{it} + \alpha_{it}^{M}\,\mathrm{d}m_{it} + \alpha_{it}^{K}\,\mathrm{d}k_{it}] + f_{it}(\lambda_t + \mu_{it})$$

The intuition behind the equation is that change in output (sales revenues) is explained by change in the cost of inputs multiplied by the markup. Subscripts 'i' and 't', index firms and years. The q_{it}, l_{it}, m_{it}, and k_{it}, respectively represent log transformations of output, labor input, material inputs, and capital inputs. These inputs are weighted by their factor cost shares, α_{it}^{L}, α_{it}^{M}, and α_{it}^{K}. There is a two part error term for time related exogenous shocks, λ_t; and firm random effects, μ_{it}. A term for firm-specific fixed-effects is not needed because the specification is first-differenced, which is mathematically equivalent.

Sales revenues will be greater than input costs if an industry is not perfectly competitive. When the change in value of output is high in comparison to the cost of inputs, then firms must be receiving greater pricing for their output. Using this relationship and variation in the output and input quantities of individual firms composing an industry, I obtain a point estimate of p/MC.

Price–cost markup (p/MC) is closely related to price–cost margin ($p - \mathrm{MC}/p$), a historically more common measure. Following recent research, I use markup instead of margin. As discussed by other researchers notably Domowitz et al. (1988), measuring price–cost margin is problematic because price and marginal cost are not directly available. Typically, when

[2] From comparing the output from these 171 industries to that from all 450 four-digit SIC industries in the 1987 Benchmark survey of manufactures.

using Census data, researchers substitute revenues for price and total cost for marginal cost. This essentially multiplies the margin by quantity, but may over or understate the true margin because the researcher has to decide which variable and fixed costs to include in total cost. Price–cost markup sidesteps this issue by mathematically isolating the joint ratio of price divided by marginal cost in an equation form that is readily estimated econometrically at the industry-level using variation in individual firm inputs and output. In contrast with price–cost margins, the researcher does not have to decide which costs to include or exclude, but includes as many inputs as possible and the variation in the data across firms econometrically indicates how each input stock contributes to output. This is subject to the assumption that firms adjust their use across input stocks to maximize profits; firms will substitute away from an input as it becomes relatively more expensive.

Estimating industry markup requires three sets of firm-level information: (i) percent change in output, (ii) percent change in factor inputs, and (iii) factor cost shares. Percent change in a firm output is the difference in sales between 2 years of reporting divided by the focal year's sales. Before differencing, I standardize nominal values of sales by deflating with the appropriate industry-year's producer price index.

Change in factor inputs is the difference between years scaled by the factor's stock in the focal year. Labor is the number of employees. Firm-level labor-hour data would be more accurate, but is unavailable. Capital is the nominal reported value of net plant, property, and equipment (PPE). I do not deflate net PPE because, as a running stock measure taken from accounting data, net PPE is already deflated by each category of capital; accounting standards indicate how much each individual category should be deflated before it is aggregated into the reported value of net PPE. Material is cost of goods sold (CGS) minus annual labor expense and capital depreciation, which I subtract to prevent double-counting change in inputs since they are already reflected by change in number of employees and net-PPE. I then standardize this material cost estimate using annual consumer price index. [3]

I also need each inputs' cost share — the fraction of expense accounted for by a given input. Together these fractions will sum to one or less. The simplest cost share is α_{it}^{M}, which is the estimated material cost (CGS less labor and capital depreciation expense) divided by sales. For α_{it}^{L} and α_{it}^{K}, the quantities of factors used by a firm are multiplied by a factor rental rate and then divided by sales. Optimally, capital and labor factor rental rates are firm and year specific. For firm-year wage rates, I use wage expense divided by number of employees, both from Compustat. Since, wage expense reporting is intermittent on Compustat, I substitute industry average wage rates when firm-year specific rates are unavailable. [4] Capital's rental rate, or the cost of capital, is a function of the risk-free rate,

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[3] I also tried deflating the material cost estimate (CGS minus wage and capital depreciation expense) by industry-specific input price indexes, but price–cost markup estimates are qualitatively the same. I constructed the industry input price deflators by knowing what percentage of inputs came from which other industries and what the price deflators were for these input industries. Percentage of inputs comes from Input–Output tables (1987 Benchmark study, US Department of Commerce — Bureau of Economic Analysis). Producer Price Indexes come from the US Department of Commerce — Bureau of Labor Statistics. I employ the CPI because industry specific PPIs are unavailable for all the years of my data set.

[4] For 'estimated annual wage expense', I used year-by-year industry average wage expenses from the Annual Survey of Manufactures which reports industry aggregated values for the number of employees and total wage expense.

r_f, the market return rate, r_m, and the particular firm's B, beta; $r = r_f + B(r_m - r_f)$. I obtain firms' yearly betas from the Center for Research in Stock Prices (CRSP) data tapes for the New York and American stock exchanges.[5] Yearly risk-free rates were the return rate of 20 year treasury bills.

With these several data series merged, I follow Levinsohn and Kang by pooling all firm-year observations from 1985 to 1991 (about 11,000 observations) and including year dummy variables, and then estimate price–cost markup.[6] For each industry in the data, this procedure provides a point estimate for price–cost markup in 1985 while the year dummies capture the yearly deviations for 1986 through 1991.

For the 171 four-digit SIC industries, the estimation results in an across industry average markup of 1.0825 with a standard deviation of 0.2298 in 1985. Price exceeds marginal cost by 8.25 percent. The average of subsequent yearly offsets after 1985 was approximately 0.1 percent overall, the estimates behave as expected: the 1985 average is above but not greatly above 1.0 and subsequent yearly changes are small. Several industries have estimated 1985 markup levels that are below 1.0. The industries typically have relatively large increases in net PPE or estimated material costs without similar large increases in sales, which may reflect severe and persistent price competition or firms adjusting inputs in anticipation of yet unobserved shifts in industry demand.

4.2. Independent variables

For change in FDI, I use year-over-year change in percent of industry sales accounted for by foreign affiliates from the Bureau of Economic Analysis "Foreign Direct Investment in the United States: Establishment Data for Manufacturing".[7] Using the reports from 1987 through 1991, I first-differenced these percentages between years for my measure of change in FDI, D_PFSALE. While change in percent sales from foreign affiliates is not exactly change in foreign investment, rather both change in foreign investment plus any expansion or contraction of sales from existing foreign establishments, the two certainly

[5] If a Compustat firm was missing from the New York stock exchange and American stock exchange, CRSP tapes, I substituted a four-digit SIC level industry average cost of capital. If a four-digit level average was not available or based upon only a single observation, the 3-digit level average was used. I find little qualitative difference between using either firm-specific or industry average cost of capital, therefore I used 3-digit SIC industry averages in all subsequent analyses to retain the maximum number of observations.

[6] I exclude anything listed as an "ADR — American Depository Receipt" since these are not ongoing entities operating in the US, but just equity shares of foreign firms available on US exchanges.

When estimating markup, I also use two rules to reject potential outliers that would bias price–cost markup estimates. First, I reject any firm-year observation that recorded more than a 100 percent increase or 50 percent decrease in output or any factor input. I expect such large shifts indicate shocks such as impending shutdown or a recent merger, or indicate a reporting error. Second, using each observation's Cook's-*D* statistic, I reject any firm-year observation that extremely increased or decreased the industry's price–cost markup estimate. I am interested in representative industry estimates and want to exclude any individual observations that largely skew the estimates. The Cook's-*D* statistic reports an individual observation's leverage, or how much including the focal observation changes the estimate. I used a Cook's-*D* cutoff value of 3.0, which is standard for outlier analysis. These two steps eliminate some 5 percent of observations, leaving 11,223 firm-year observations.

[7] The Department of Commerce classifies any establishment with greater than 10 percent foreign ownership as 'foreign'. Though, this threshold of 10 percent seems very low, Graham and Krugman (1989) show that on average foreign parents in the US controlled 80.2 percent of an affiliate's equity.

are strongly linked. Examining their correlation using 1987 "benchmark year" data from the Bureau of Economic Analysis, which reports both percent sales from foreign affiliates and percent of industry establishments that are foreign-owned, the correlation for the 450 reported industries between foreign sales and foreign ownership is 0.800 and highly significant. This suggests that foreign ownership accounts for a major portion of percent sales from foreign affiliates and that change in FDI should commensurately change percent sales from foreign affiliates.

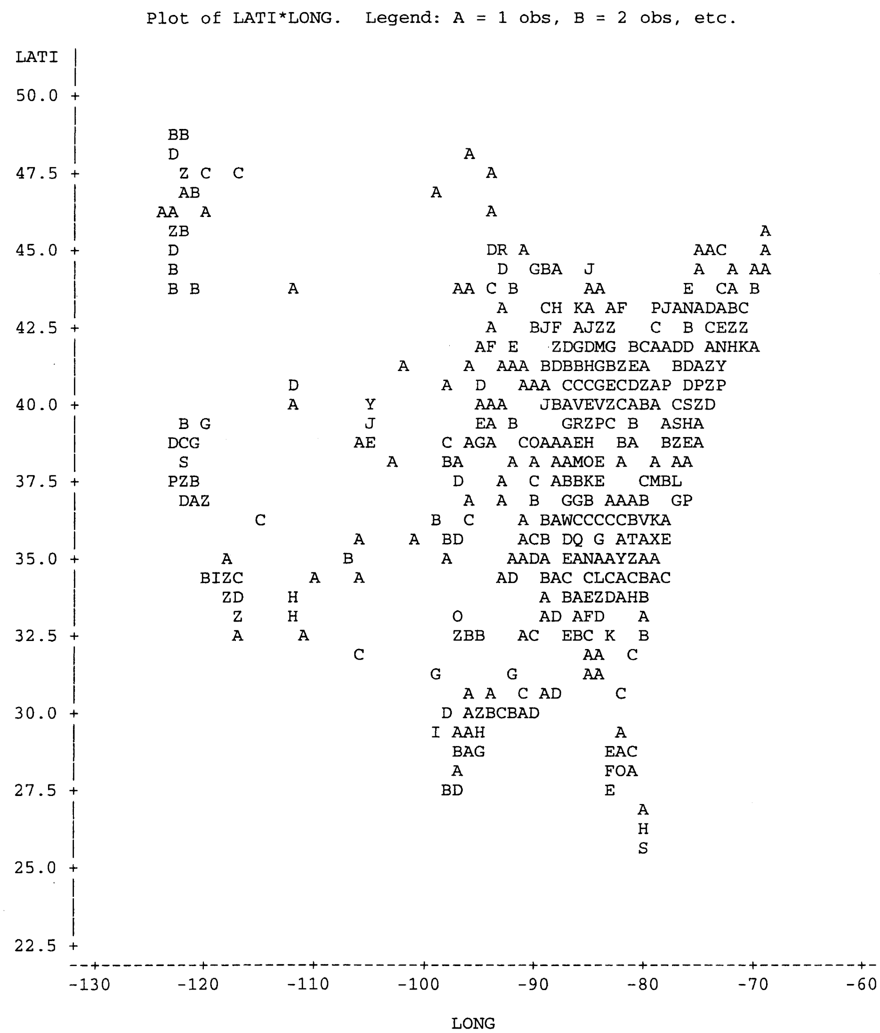
For traits of individual foreign investments, I use "Foreign Direct Investment in the United States, (various years) Annual Transactions" from the International Trade Administration (ITA) of the Department of Commerce, which tracks investments in the United States made by foreign entities. I use the reports from 1987 through 1991 that list 2897 total FDI transactions into US manufacturing industries. While by no means exhaustive, the ITA uses a wide range of public sources to assemble the annual list. This is the same data source used by Hennart and Park (1993), Blonigen (1997), Shaver (1998), and others. For each investment, the ITA lists the mode of entry, transaction value, country of origin, four-digit SIC industry, location by city and state, and ultimate foreign owner.

Using the ITA data, I construct the three average foreign investment traits — MODE, SIZE, and DIST for each industry-year. These averages are composed from only a hand-full of investments: on average only 2.6 investments per industry-year for the 450 manufacturing industries across 5 years.

MODE is the industry-year average of whether foreign firms entered via greenfield or by acquisition. The ITA data groups investments into seven mode classifications: acquisition/merger, equity increase, joint venture, new plant, other, plant expansion, and real estate. I code any investment that adds physical capacity as a greenfield investment; either 'new plant' or 'plant expansion' as '1'. I code acquisition/merger as '0'. I treat joint ventures as missing values since they may either be greenfield investments or acquisitions. I leave the remaining three classifications as missing values. Of the 2897 investments, 31.0 percent are greenfield investments, 45.3 percent mergers and acquisitions, 8.5 percent joint ventures, and 15.2 percent the other three classifications. I then obtain four-digit SIC industry averages, while using the investment's reported value as a weighting factor. MODE indicates the value-weighted fraction of investments, that were via greenfield for each industry-year.

SIZE is the industry-year average of foreign investments' declared value in 1991 dollars. Reported values are modified in two ways. First, I standardize the nominal reported values across years with the consumers' price index (CPI) so all values are in 1991 dollars. Secondly, I scale each value by the corresponding four-digit SIC industry establishment size, which is the average asset size taken from the 1987 Census of Manufactures. This scaling acknowledges that each industry could have different optimal establishment sizes, and so a high reported value may be typical for that particular industry. I then obtain averages for each four-digit SIC industry in each year. SIZE indicates the average investment value relative to existing establishments for each industry-year.

DIST is the industry-year average of where foreign investments locate relative to incumbents. Using longitude and latitudes, I calculate Euclidean distances between individual investments and the centroids of incumbent industry clusters. I then average investments' distances from these clusters' centroids for each industry-year.



NOTE: 17 obs had missing values. 688 obs hidden. 7 obs out of range.

Fig. 1. Location of manufacturing FDI transactions, 1987–1991. Investments in Hawaii and Alaska are suppressed for better viewing. Investment information taken from International Trade Administration-Department of Commerce Foreign Direct Investment in the US-Annual Transactions.

First, I convert city, state locations of individual investments into longitudes and latitudes.[8] The geographic locations of these 2897 FDI transactions are shown as Fig. 1.

Second, I determine the location of incumbent industry using data from Lotus "OneSource/CD-Private and Public Profiles", which provides thousands of publicly and

[8] I use 'places.txt' from the Census Bureau that provides the longitude and latitude of any city or town in the United States. The file is very exhaustive, including towns with populations of even less than 50 people.

privately owned firms across 450 four-digit SIC manufacturing industries. While by no means exhaustive, OneSource is a sampling-frame that provides a large sample, and I assume this sample is generally representative of both the location and size distribution of US manufacturing.[9] I convert city and state of individual firms into longitudes and latitudes. A plot of these 55,886 firms is shown as Fig. 2.

Third, using the OneSource data, I obtain nine geographic clusters and associated centroids (center point of cluster) for each industry. Nine clusters capture most of the variation in longitude and latitude per industry; the average pseudo R-squared is 96 percent.[10] I use nine centroids for two reasons: (1) to standardize incumbents' location across industries — each is identified by nine geographic centers instead of a varying number of observations and (2) to observe if the OneSource data makes sense, which is difficult with sometimes hundreds of observations per industry. Nine clusters capture most variation, while allowing easy observation of the data's location face-validity. For example, Fig. 3 below shows an example of this clustering process for SIC 3714 — "automotive components, new". The numerals are located at the corresponding clusters' centroid.

As we would expect, the largest cluster's centroid is located near Detroit, Michigan. The plot also suggests smaller cluster centroids near New Jersey, Southern California, and Kansas City. I similarly plot and examine other industries.

Fourth, I compute an individual investment's location to its nine associated industry centroids, which is the sum of these nine distances, each weighted by the cluster's economic output — the cluster's fraction of industry sales. Finally, DIST is the average of individual investments' locations for each four-digit SIC industry-year, with the investment's reported value as a weighting factor. Thus, higher values of DIST indicate that on average investments located further away in a particular industry-year.

Along with DIST, I include an industry's geographic spread, GEO_SPRD, as a control variable. Geographic spread may affect industry markup change, with more spread industries responding more slowly assuming that greater distance reduces economic interaction. GEO_SPRD is the sum of distances from the industry's one overall centroid to the nine clusters' centroids, weighted by each clusters' economic output in 1987. Larger values indicate higher spread. For example, SIC 3714 shown in Fig. 3 above has a very low GEO_SPRD. GEO_SPRD and DIST are inherently negatively correlated; if the industry is very spread, locating distantly is difficult. Based upon the 1 year of Lotus/OneSource industry location data, GEO_SPRD is time invariant.

I include two other control variables. First is change in imports (D_IMP), which is year-over-year change in import market share. I take the first-differenced of annual import market share, which is the value of imports divided by the value of industry shipments. Imports come from the Department of Commerce: Bureau of Census "Trade and Employment"

[9] Published since 1991, the earliest version available was the 1st quarter of 1993. Using reported founding dates, I include only those firms that existed in and before 1987. Firms that exited between 1987 and 1993 are missing. I assume that these missing firms do not significantly change the location and size distribution of US manufacturing.

[10] To investigate the results' sensitivity to the number of clusters, I increase the number from 9 to 99 per industry. The results reported later are identical. In addition, instead of specifically setting the number of clusters to nine, I also let the data indicate how many clusters exist per industry to explain 95 percent or more of the variation in location. With a threshold R-squared of 95 percent an average of 8.01 clusters are needed. I discuss these sensitivity analyses in more depth later.

NOTE: 42893 obs hidden.

Fig. 2. Location of manufacturing firms in the continental US. Firms in Hawaii and Alaska are suppressed for better viewing. Firms' locations, sizes, and SIC industry classifications are taken from Lotus OneSource/CD-private and public profiles database.

data series; and industry shipments comes from the Annual Survey of Manufactures. Second is change in industry demand (D_DMD), which is the year-over-year difference of annual aggregate industry demand, which is value of industry shipments plus value of imports after standardizing into 1991 dollars.

Descriptive statistics for the above variables are shown in Table 1. I limit the descriptive statistics to include only those observations that are actually used in subsequent regression analysis.

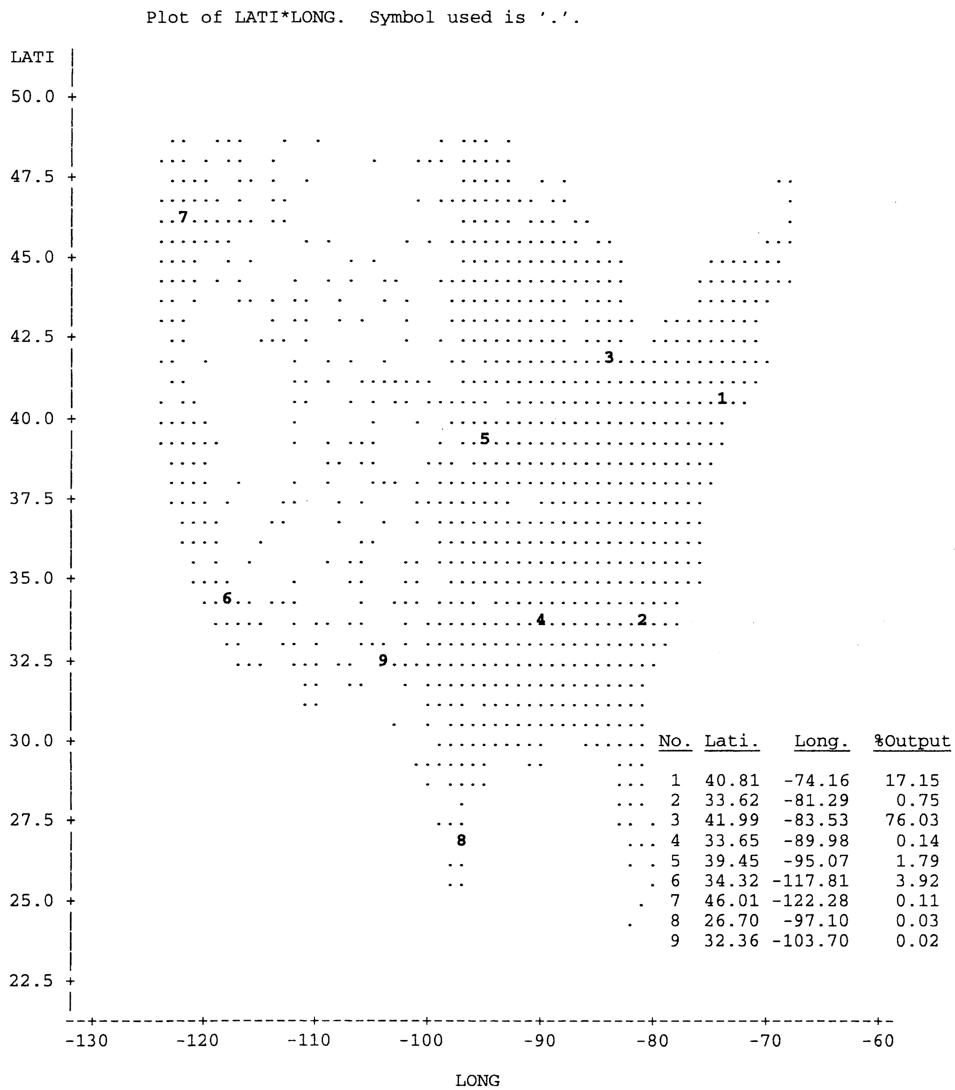


Fig. 3. Location of industry clusters for SIC 3714 — new automotive parts. Firms in Hawaii and Alaska are suppressed for better viewing. Note legend that lists the associated percent of economic output for each cluster. The largest cluster, 3, is located near Detroit, Michigan.

5. Results and discussion

I regress change in industry price–cost markup (D_MKUP) on 1 year lagged values of change in foreign presence (D_PFSALE$_{-1}$), the three average industry-year traits of foreign investments (MODE$_{-1}$, SIZE$_{-1}$, DIST$_{-1}$), and the control variables (GEO_SPRD,

Table 1
Descriptive statistics

	1	2	3	4	5	6	7	8
Correlations (correlation, significance, and number of pair-wise cases)								
1 D_MARKUP	1.000	−0.161	−0.110	−0.017	−0.146	−0.017	−0.097	0.05
	0.00	0.03	0.14	0.82	0.10	0.85	0.28	0.53
	178	178	178	178	126	126	129	178
2 D_PFSALE (lagged 1 year)	−0.161	1.000	−0.174	−0.131	0.106	0.316	−0.043	−0.08
	0.03	0.00	0.02	0.08	0.24	0.00	0.63	0.28
	178	178	178	178	126	126	129	178
3 D_IMP (lagged 1 year)	−0.110	−0.174	1.000	−0.003	−0.191	0.025	0.045	0.07
	0.14	0.02	0.00	0.97	0.03	0.78	0.61	0.32
	178	178	178	178	126	126	129	178
4 D_DMD (lagged 1 year)	−0.017	−0.131	−0.003	1.000	−0.122	0.061	−0.006	0.12
	0.82	0.08	0.97	0.00	0.17	0.50	0.95	0.10
	178	178	178	178	126	126	129	178
5 DIST (lagged 1 year)	−0.146	0.106	−0.191	−0.122	1.000	−0.173	0.188	−0.37
	0.10	0.24	0.03	0.17	0.00	0.05	0.04	0.00
	126	126	126	126	126	126	126	126
6 SIZE (lagged 1 year)	−0.017	0.316	0.025	0.061	−0.173	1.000	−0.291	0.09
	0.85	0.00	0.78	0.50	0.05	0.00	0.00	0.30
	126	126	126	126	126	126	126	126
7 MODE (lagged 1 year)	−0.097	−0.043	0.045	−0.006	0.188	−0.291	1.000	−0.385
	0.28	0.63	0.61	0.95	0.04	0.00	0.00	0.00
	129	129	129	129	126	126	129	129
8 GEO_SPRD	0.047	−0.081	0.074	0.124	−0.375	0.093	−0.385	1.000
	0.53	0.28	0.32	0.10	0.00	0.30	0.00	0.00
	178	178	178	178	126	126	129	178
Summary statistics								
Cases	178	178	178	178	126	126	129	178
Mean	0.00	1.81	−2.83	0.96	19.03	40.65	0.36	10.41
Standard deviation	0.05	3.62	36.11	7.48	14.63	92.23	0.44	4.73

D_IMP_{-1} and D_DMD_{-1}). Since, the data is across industries and across time, I try two-way fixed and random-effect models, but find industry effects are insignificant as a group. The *F*-statistic from jointly testing the industry fixed-effects is not significantly different from zero, which may result from the dependent variable being first-differences and the shortness of panel across time — the regression is closer to cross-sectional than time-series. Thus, I use only one-way, year-effect specifications.

The fixed-effect results are in Table 2. I report only the fixed-effect results since Hausman tests indicate that the fixed and random-effect coefficient estimates are not significantly different from each other, and since the random-effects estimates are almost identical. If they were significantly different, then the fixed-effect estimates would be preferred since they remain unbiased under less restrictive assumptions (random-effects assume that the error components are uncorrelated with all independent variables).

Column 1 presents a baseline model that relates change in price–cost markup to D_PFSALE$_{-1}$, D_IMP$_{-1}$, and D_DMD$_{-1}$. Column 2 introduces the average industry-year FDI flow traits of MODE$_{-1}$, SIZE$_{-1}$, and DIST$_{-1}$ plus the geographic control variable, GEO_SPRD. Column 3 additionally scales DIST$_{-1}$ by GEO_SPRD, which acknowledges that DIST$_{-1}$ is dependent upon how spread the industry is. Finally, column 4 interacts MODE$_{-1}$ and DIST$_{-1}$.

The baseline model in column 1 is consistent with prior research showing that increased inward FDI (D_PFSALE$_{-1}$) significantly decreases industry price–cost markup (D_MARKUP); more FDI raises competition for the host industry. The coefficient attracted by D_PFSALES$_{-1}$ suggests that a 10 percent increase in sales from foreign-owned affiliates would subsequently be correlated with a 0.0246 or 2.46 percent decrease in industry price markup, where the mean price–cost markup in the sample was 8.25 percent. These results are substantially stronger than Caves (1974) initial findings that FDI decreases average industry profitability. Likely, this strength stems from markup being more tightly linked to competition and the larger number of observations available.

Also consistent with prior "imports as market discipline" findings is that greater import competition (D_IMP$_{-1}$) decreases price–cost markup. For demand, while change in demand (D_DMD$_{-1}$) has no significant influence, the generally positive coefficient estimates across columns are consistent with greater demand leading to larger price–cost markups. Overall, this data behaves similarly to others that have been used for empirical tests.

Interestingly, the coefficient attracted by D_PFSALE$_{-1}$ is about 10 times larger than the coefficient attracted by D_IMP$_{-1}$ suggesting that FDI might be a stronger disciplining force than imports. Values for both D_PFSALE$_{-1}$ and D_IMP$_{-1}$ are dollars of sales scaled by total value of industry shipments, and therefore their coefficient estimates can be directly compared. This greater suggested discipline strength may stem from investing foreign firms competing to obtain inputs and to sell output. The foreign firm accompanies its goods and services abroad and then vies with incumbents for quality inputs and suppliers as well as for customers. By competing for factor inputs and customers, FDI's influence upon host industry competition might be more intense.

Turning to our variables of interest, we see in column 2 of the three average industry-year FDI traits that only DIST$_{-1}$ is significant. The attracted coefficient is negative, rather than the expected positive. This negative coefficient suggests that competition rises more when foreign investments locate further away from incumbents; price–cost markup decreases more. This negative direction and significance persists in column 3, when we include DIST$_{-1}$ scaled by GEO_SPRD. This scaling is included since values of DIST$_{-1}$ are dependent upon how spread the industry is. DIST$_{-1}$'s main-effect stays significantly negative while DIST$_{-1}$/GEO_SPRD is positive and significant. Multiplying these coefficient estimates by average values for DIST$_{-1}$ and GEO_SPRD, the combined outcome remains negative.

Table 2
FDI heterogeneity and change to host industry price markup[ab]

	Dependent variable: D_MARKUP, change in price markup			
	(1)	(2)	(3)	(4)
D_PFSALE	−2.4608 (1.1421)**	−2.9031 (1.3943)**	−2.4600 (1.3985)*	−2.8634 (1.4080)**
D_IMP	−0.2116 (0.1115)*	−0.2571 (0.1073)**	−0.2817 (0.1069)***	−0.2511 (0.1102)**
D_DMD	−0.1433 (0.5606)	0.6515 (0.6533)	0.7434 (0.6479)	0.6292 (0.6613)
MODE		−5.5429 (11.3592)	−6.9798 (11.2590)	−1.7581 (18.2958)
SIZE		0.0190 (0.0531)	0.0089 (0.0528)	0.0207 (0.0538)
DIST		−0.5598 (0.3343)*	−1.2308 (0.4838)**	−0.4574 (0.5124)
GEO_SPRD		−0.4919 (1.0843)	0.1544 (1.1250)	−0.4867 (1.0888)
DIST/GEO_SPRD			1.6621 (0.8750)*	
MODE* DIST				−0.1870 (0.7067)
n	178	126	126	126
R-squared	0.059	0.153	0.179	0.154
Adjusted *R*-squared	0.031	0.088	0.108	0.080
F-statistic	1.81*	2.21**	2.38**	2.00**
Degree of freedom	6	10	11	11
Joint tests				
$F(1, 116)$		0.24		
Pr(MODE + SIZE = 0)		0.63		
$F(1, 116)$		0.29		
Pr(MODE + SIZE + DIST = 0)		0.59		

[a] Positive coefficients indicate increases in price markup, price markup is the ratio of price over marginal cost. Results are for one-way (year) fixed effect models since two-way models show that industry effects are non-significant. Values reported are original estimates multiplied by 1000. All independent variables are lagged 1 year from the dependent variable, except GEO_SPRD, which is time invariant.

[b] Standard errors in parentheses; * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

The other two traits are not significant. While average investment entry mode (MODE_{-1}) is negative as expected and average investment size (SIZE_{-1}) is positive, the opposite of expectations, *t*-tests indicate that both are far from individually significant. Since, size and mode are highly correlated, greenfield sites are on average smaller than acquisitions; I jointly test SIZE_{-1} and MODE_{-1} by asking whether they sum to zero. This *F*-test is at the bottom of column 2 and is not significant. Since the correlation among all three traits is high, I also jointly test whether all three traits sum to zero. This test is also not significant.

As a final check, I interact MODE_{-1} with DIST_{-1} in column 4. Potentially, DIST_{-1}'s effect in columns 2 and 3 originates with distant greenfield investments driving heightened competition, and I include this interaction to identify this potential explanation. The interaction term's coefficient estimate is non-significant. A similar non-significance results when SIZE_{-1} and DIST_{-1} are interacted, which is not reported for space considerations. Overall, average investment size and entry mode do not significantly affect price–cost markup, at least in the short-run using 1 year lagged independent variables. Potentially the effects of size and entry mode heterogeneity require more time to manifest. For example, while acquisitions may become operational more quickly on average than greenfield investments, both may require several years to be fully operational. Unfortunately the shortness of my data set prevents including additional lags for the independent variables.

Returning to DIST_{-1}, this negative effect of average investment location is substantial. Using the mean plus one standard deviation for DIST_{-1} ($19.03 + 14.63 = 33.66^{\circ}$ of longitude/latitude) times the coefficient estimate of $-5.60\mathrm{E}{-04}$, a relatively distant investment flow decreases price–cost markup by 0.019 or 1.9 percent, where the mean price–cost markup in the sample was 8.25 percent.[11] A similar change to markup occurs using coefficient estimates in column 3 and the mean value of GEO_SPRD. Beyond investment location's economic influence, including DIST_{-1} also provides a large increase in adjusted *R*-square over the benchmark model. While the benchmark model explains 3 percent of variation, upwards of 9 percent variation is explained by including the three investment traits.

What explains this unexpected finding of more distant investments increasing host industry competition more? As raised earlier, proximate FDI may transfer useful technology to incumbents that offsets the downward price and upward cost pressure that compresses industry markup. While this study's findings are consistent with this explanation, when testing for such technology transfer in Venezuela, Aitken and Harrison find little evidence; they introduce both national and regional level FDI measures and find that the regional level FDI does not attract the expected positive, significant coefficient. With little evidence for technology transfer in Venezuela, such technology transfer from FDI to the incumbents populating US industries seems similarly unlikely.

Alternately, the investment's location choice might signal the multinationals' relative strength. Stronger multinationals may choose subsidiary locations further from incumbent industry. Incumbents recognize the arrival of stronger multinationals regardless of where they locate and respond accordingly, which then causes industry-wide price–cost markup to decrease.

[11] A degree of latitude is approximately 68.7 mile at the equator, so 33.66° of longitude/latitude is 2312 mile or about the distance from Detroit to San Diego.

Another explanation might be that incumbents are stuck in non-optimal, high cost locations. Overtime, established locations become crowded as new entrants agglomerate. Greater demand for inputs increases incumbents' costs. Incumbents face higher costs, but not high enough to warrant moving. In contrast, some multinationals choose less crowded locations with lower associated costs. Coughlin, Terza, and Arromdee show that foreign investment into the US is drawn to states with lower labor costs and higher unemployment. These lower costs allow multinationals to set lower prices which incumbents have to meet, which reduces industry average price–cost margins. These lower cost locations are likely more distant from established industry.

To evaluate these possible explanations, I test the determinants of investment location choice: what causes firms to invest distantly or proximately. The dependent variable is INV_DIST, the distance in degrees longitude/latitude that an investment falls from incumbent industry (DIST is the industry weighted average of these individual values). The raw values are scaled by GEO_SPRD, since some industries are inherently more geographically spread than others are. I regress INV_DIST on parent firm and investment transaction characteristics.[12] I include parent firm characteristic typically used by other researchers: parent firm size as indicated by total assets (P_ASSETS), profitability as indicated by return on assets (P_ROA), and a dummy variable for whether the investment and parent are in the same industry — a horizontal expansion (SAME_SIC).[13] I also include the particular transactions' size (INV_SIZE), the declared value standardized to 1991 dollars and scaled by the average establishment size for the particular industry (SIZE is the industry average of these individual values). Since the dataset is pooled over several years, I include year as well as four-digit SIC industry dummies. The results are shown in Table 3, column 1.

The number of observations is greatly reduced by missing data for SAME_SIC, since the ITA does not report many investment transactions' SIC. Looking at column 1, we see no variables are significantly different from zero. If most independent variables were significant — if larger, more profitable firms conducting large, horizontal expansions located distantly, we might conclude that stronger firms locate more distantly.

To investigate further, I examine the investments' nation of origin. Nation of origin proxies for the likelihood of technology transfer since substantial productivity differences existed between nations during the study period. For example, Baily and Gersbach (1995)

[12] To obtain foreign parent firm characteristics, requires linking the International Trade Administration data on FDI Investment Transactions to Compustat: GlobalVantage. This is inherently problematic since the ITA only identifies the foreign parent by name and not by Standard and Poor's CUSIP numbers. Therefore, linking these two data sets requires matching by name. Matching by name is also problematic since the two series use different naming conventions. For example "HONDA MOTOR CO." in the ITA data will not match "HONDA MOTOR CO LTD" in the Global Vantage data. To match I use a FORTRAN program that breaks each name into its component strings: For example "HONDA MOTOR CO." Becomes "HONDA", "MOTOR", and "COMPANY". After removing punctuation and expanding common abbreviations, the program then matches these component substrings while weighting matches by the position of a substring in the original string (up weight in 1st and 2nd position), contiguity of substring matches (up weighted), and commonness of substrings ("COMPANY" is worth less than "HONDA"). For the initial 2897 inward FDI transactions for 1987–1991, I am able to match 2042 transactions to foreign parent firm financial data. Privately held foreign firms undoubtedly account for many of these unmatched FDI transactions.

[13] P_ASSET and P_INCOME are 3 year averages to eliminate any potential yearly fluctuations. The years are t, $t-1$, and $t-2$ where t is the year that the investment transaction occurs.

Table 3
Determinants of FDI transaction location choice[ab]

	Dependent variable: INV_DIST, distance an investment locates from existing industry in degrees longitude/latitude		
	(1)	(2)	(3)[c]
P_ASSETS	0.0059 (0.0042)	0.0024 (0.0044)	0.0024 (0.0045)
P_ROA	0.5757 (0.6269)	0.5720 (0.6254)	0.5714 (0.6265)
SAME_SIC	2.4868 (2.6491)	2.5938 (2.6434)	2.6059 (2.6511)
INV_SIZE	−0.0028 (0.0042)	−0.0023 (0.0042)	−0.0023 (0.0042)
JAPANESE		6.0192 (2.7335)**	5.9676 (2.9811)**
GERMAN			1.0531 (4.9517)
DUTCH			−1.0870 (7.5271)
CANADIAN			−1.7580 (5.6572)
Year dummies	Included	Included	Included
Parent Ind. Dummies	Included	Included	Included
n	1026	1026	1026
R-squared	0.252	0.256	0.256
Adjusted R-squared	0.075	0.079	0.076
F-statistic	1.42***	1.44***	1.41***
Degree of freedom	197	198	201

[a] Positive coefficients indicate an investment transaction locates a greater linear distances from existing industry. Results are for two-way (industry and year) fixed effect models. Parent variables are 3 year averages for the investment year less 2 years.

[b] Standard errors in parentheses; * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

[c] Since British account for most investments after the Japanese, British firms are used as the base-case in column 3, therefore no British dummy is included.

find that the Japanese manufacturing labor productivity was higher than the US, while German productivity was lower.[14] This suggests that benefits for incumbent industry through technology transfer from FDI would more likely accrue if Japanese FDI located more proximately.

For the study period of 1987–1991, many investments originated from Japan: 1312 of the 2897 transactions. Therefore, I include a dummy variable for Japan and repeat the prior test. The results are shown in Table 3, column 2. The Japanese dummy variable is significant and relatively large. The coefficient estimate of 6.02 suggests that Japanese FDI on average located 413 mile (6.02×68.7 mile per degree of longitude/latitude) farther away than other nations' FDI. In column 3, I repeat the test while including country dummies for the other developed nations responsible for the majority of other investment transactions into the US.[15] While others are not significantly different from zero, the coefficient on the

[14] Bailey and Gersbach's data is for 1990. Fig. 1 of Baily and Gersbach (1995: p. 314) shows higher Japanese labor productivity in most manufacturing industries, including autos, car parts, steel, metal working, and consumer electronics; or industries typical of outward Japanese FDI. This figure also shows that German labor productivity is consistently lower than the US across all industries investigated.

[15] No dummy for British investments is included, since I use British investments as the base-level: no dummy = British investment. I use the British as the base-case since after the Japanese, the British account for the most FDI (409 transactions). Therefore, the included nation dummies indicate location choice relative to British FDI.

Japanese dummy remains significantly positive and of similar magnitude. Since, proximity is crucial for technology transfer, Japanese FDI locating more distantly suggests that benefits through technology transfer for US industry were less likely.

The finding that Japanese FDI locates distantly raises another question. Does the observed decrease in markup result from FDI located distantly or just FDI that is Japanese? To address this I repeat the regression reported in Table 2, column 3 while also including 1 year lagged values for the fraction of investments that originate from Japan (FRA_JPN) and FRA_JPN interacted with D_PFSALE (change in FDI — percent foreign sales).[16] FRA_JPN and FRA_JPN $\times$ D_PFSALE both attract coefficients that are not significantly different from zero, while all other coefficient estimates remain unaffected.

Overall, US industry markups respond to distantly located FDI and Japanese FDI on average located more distantly. Whether the Japanese firms were or were not stronger competitors, industry markups likely decreased since incumbent firms perceived the Japanese firms as important competitive threats.

5.1. Checks

Before settling on the above results, let me address several possible criticisms. First, is whether price–cost markup is an appropriate measure for industry competition. Does markup reflect something other than competition? Price–cost markup (p/MC) is clearly a linear transformation of the price–cost margin/Lerner index ($p - \mathrm{MC}/p$), a more widely accepted measure of competition.

A second criticism is whether markup estimated with Compustat data represents industry-wide competition or only that experienced among large, publicly held firms in the industries. To determine when the Compustat firms compose a majority of the industry, I sum and compare Compustat firms' reported nominal sales in each industry-year to the corresponding nominal value of shipments from the Annual Survey of Manufactures. On average across the study years, when Compustat firms represented <33 percent of an industry's output, I removed all years' observations for that industry from the data set.[17] This procedure eliminated about 40 percent of original industries from data set. I then repeated the regressions shown in Table 2. These results are very similar.

Another concern is that DIST, the continuous measure of the average distance from foreign investments to incumbent industry, is an uncommon measure in FDI research. Most FDI research explores location choice using state boundaries and discrete choice models by asking whether certain state factors encouraged investment (Coughlin et al., 1991; Head et al., 1995). While convenient, state classifications may be too coarse for my purposes, since states were not defined with economic output in mind. While activity in Kansas City,

[16] I calculate FRA_JPN two ways. First, using the count of Japanese FDI transactions divided by the count of all FDI transactions in each industry-year. Second, by using the portion of investment value that is Japanese. Either way, the results are qualitatively similar.

[17] I use a 33 percent cutoff based upon oligopoly theory. In a Stackleberg leader–follower model, the leader holds two-thirds of the market and can manipulate the follower's profits. In this setting, conservatively idealizing all Compustat firms as a single player and all unobserved firms as the other player, the Compustat player will become a follower when its market share is one-third. When the Compustat player is a follower, it's profitability and its price–cost markup will not represent the overall industry's average.

Kansas and in Kansas City, Missouri fall in different states, they are certainly in close physical proximity. The DIST measure explicitly allows clusters to emerge based upon location of economic output and not be restricted by state boundaries.

Why use nine clusters? An industry may have several geographic centers. Looking at automotive manufacturing, while suppliers are heavily concentrated in Michigan and Ohio, other smaller concentrations exist in California and the East Coast. Multiple concentrations suggest multiple clusters. Nine clusters capture most of the longitude/latitude variation; 96 percent across the 450 four-digit SIC industries. Checking the results' sensitivity, I increase the number of clusters from 9 to 99 per industry, which has a pseudo R-squared of 99.98 percent. I recalculate DIST using the 99 corresponding centroids and repeat the tests shown in Table 2. The reported results are totally unaffected by the increase.

A final geographic concern is my use of a grid system of absolute longitudes and latitudes to determine physical distances, while the physical length of a degree of longitude varies depending upon the latitude. A degree of longitude is some 20 percent shorter in Acadia, Maine than in Everglades, Florida. To address this, I re-scale longitudes so that 1° of longitude regardless of how far north or south is the same physical length as a degree of latitude. This re-scaling has inherent difficulties that stem from flattening a three-dimensional surface into its two-dimensional projection. Basically, I multiplied absolute values of longitude by a scaling factor so that all degrees of longitude were the same length. [18] With this re-scaled data, I then repeated the regressions shown in Table 2. The results are totally unaffected by the re-scaling.

6. Conclusions

Extant research finds that inward FDI raises competition in the host industry. Increased FDI is associated with decreases industry average profitability and increased productivity. While prior research explains FDI's effect using measures of foreign presence such as an industry's foreign production share or amount of monetary flow, a flow of FDI is composed of many individual foreign investments and is therefore inherently heterogeneous. I introduce several traits to reflect this heterogeneity, to further explain FDI's overall positive relationship to host industry competition. Specifically, I suggest that certain traits of FDI flow will heighten competition. Using data on the individual FDI transactions, I constructed industry-year averages for entry mode, relative size, and location. A flow is a certain percentage greenfield investments versus acquisitions; is composed of fewer large versus more numerous small investments; and is located closer to or further away from incumbent industry.

Examining US manufacturing industries between 1987 and 1991, I find that increases in foreign presence significantly decrease the industry's price–cost markup, the ratio of price divided by marginal cost. Decreased price–cost markup is synonymous with increased competition; firms' price approaches their marginal cost. While consistent with prior findings

[18] The re-scaling factor is given by the following equation: re-scale $= 1.018685$ — $(0.002257 \times \text{latitude})$ — $(0.000103 \times \text{latitude}^2)$. The formula comes from assuming a second order polynomial, and regressing the length of a degree of longitude at a given latitude on latitude. The 19 data points, providing the length for a degree of longitude at 5° latitude increments, came from The Economist Intelligence Unit's Desk Reference: How to Calculate and Measure Just About Anything.

of FDI raising competition, these results are much stronger likely due to markup's strong link to competition and the greater number of observations used here over prior studies.

The new result is that price–cost markup decreases significantly more when investments locate on average further away from incumbent industry. This is counter to proximate investments driving markup down more by directly competing for localized inputs. This unexpected result is consistent with two explanations. First, FDI both positively and negatively affects the host industry. By introducing additional competitors, FDI compresses markups; but this compression may be offset if technology transfer from FDI reduces incumbents' costs. Since, technology transfer is enhanced by proximity, closely located FDI might compress industry markups less than distant FDI. Second, stronger foreign firms might purposefully locate distantly to prevent aiding competitors through technology spillovers. By locating far away, strong foreign firms might slow technology spillovers to local competitors and reduce contributions to agglomeration externalities.

Further investigation finds that on average Japanese FDI chose to locate significantly further away. Due to their higher productivity during this period, the Japanese are the most likely source of technology transfer to US industry. The finding that Japanese FDI located more distantly suggests that technology transfer to US industry was minimal. Overall, US industry markups respond to distantly located FDI which happened to originate predominantly from Japan. Whether the Japanese firms were or were not stronger competitors, industry markups likely decreased since incumbent firms perceived the Japanese firms as important competitive threats.

These findings have implications for both managers and policy makers. For policy makers, the findings reinforce expectations that FDI positively influences the host. Greater foreign presence raises competition. Past research establishes that heightened competition leads to enhanced productivity, with society obtaining more output for less input. The drop in price–cost markup may increase consumer surplus. Further, policy makers do not necessarily have to encourage certain types of foreign investment. At least initially, many smaller investments appear to have the same benefit as few larger ones and "de nouveau" investments have the same benefit as acquisitions of existing establishments.

For firm managers, the findings suggest that investing foreign firms indicate their relative strength through their location choice. The managers of incumbent firms should worry about foreigners that establish themselves far away. Similarly, the managers of investing foreign firms should recognize that the host industry responds not only to their arrival but also to their location choice. While a foreign firm may hope to slow incumbent competitors benefiting from agglomeration economies by locating more distantly, the host industry responds strongly and quickly. A relatively more distant FDI flow (mean plus standard deviation for the sample) causes a 1.9 percent decrease on an average starting markup of 8.25 percent, which occurs using independent variables that are only 1 year lags.

Several caveats should be noted given the study context of US manufacturing industries from 1987 through 1991. First, US manufacturing industries are relatively more mature than industries in the rest of the world, and therefore likely to respond faster to foreign investments. Second, the US has adequate infrastructure both near to and far from incumbent industry. Distant infrastructure may be lacking in less developed nations, which may force most foreign firms to locate close to existing industry. In such a setting, an investment flow's average location likely would explain little additional variation.

Given these caveats, this analysis shows that average industry-year traits constructed from the individual investments composing the FDI inflow are statistically and economically significant for explaining change in price–cost markup. These traits capture some of the inherent heterogeneity of the inward FDI flow. The counter-intuitive finding of competition rising more when foreign investments locate further from incumbents highlights the importance of strategic interactions among foreign and local firms for industry outcomes. Future investigation might focus on further determinants of location choice and technology transfer. Under what conditions do "stronger" multinationals locate further away? Under what conditions does significant technology transfer occur between foreign investments and incumbent industry?

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Appendix A. Price–cost markup estimation

To estimate price–cost markup, I follow Levinsohn (1993) and Kang (1995). Underlying the method are two main relationships: (1) a general multi-factor production function and (2) firm-level profit maximization.

Let output be a function of ϕ — a firm-specific productivity multiplier and f — the production technology. The production technology uses several inputs, including capital, labor, and materials — K_{it}, L_{it}, and M_{it}, respectively, where i refers to an individual firm and t refers to the period (in this case year). This production function is shown as Eq. (A.1).

$$Q_{it} = \phi_{it} f(K_{it} L_{it} M_{it}) \tag{A.1}$$

We obtain an expression for Δq_{it} from a first-order Taylor-Series expansion of Eq. (A.1). Dividing the expansion by Q yields Eq. (A.2).

$$\frac{\Delta Q_{it}}{Q} = \phi_{it}\left[\frac{\Delta f_{it}}{\Delta K_{it}}\frac{\Delta K_{it}}{Q} + \frac{\Delta f_{it}}{\Delta L_{it}}\frac{\Delta L_{it}}{Q} + \frac{\Delta f_{it}}{\Delta M_{it}}\frac{\Delta M_{it}}{Q}\right] + \Delta\phi_{it} f_{it} \tag{A.2}$$

Introducing profit maximization, the basic firm profit relationship (revenues minus input costs) to be maximized is shown as Eq. (A.3).

$$\pi_{it} = p_t Q_{it} - \sum_j w_{it} L_{it} - r_{it} K_{it} \tag{A.3}$$

Assuming the firm is a price taker, it then maximizes with respect to any decision variables including Q_{it}, K_{it}, L_{it}, M_{it}. For example, differentiating Eq. (A.3) with respect to L_{it} and setting the result equal to zero yields Eq. (A.4):

$$p_t \frac{\partial Q_{it}}{\partial L_{it}} + \frac{\partial p_t}{\partial L_{it}} Q_{it} - w_{it} = 0 \tag{A.4}$$

Define the following identities: market share, $s_{it} = Q_{it}/Q_t$; conjectural variation, $\theta_{it} = \partial Q_t/\partial Q_{it}$; elasticity of demand, $\eta_t = (Q_t/p_t)(\partial p_t/\partial Q_t)$.Rearranging (A.4), we are left with the below, which is a condition of profit maximization.

$$\frac{\partial Q_{it}}{\partial L_{it}}[1 + s_{it}\theta_{it}\eta_t] = \frac{w_{it}}{p_t} \tag{A.5}$$

This equation can be rearranged and rewritten in terms of ∂f using the $\partial Q_{it}/\partial L_{jit} = \phi_{it}(\partial f_{it}/\partial L_{jit})$. Analogous equations are obtained by differentiating with respect to other inputs.

Eq. (A.3) also is maximized with respect to quantity, q_{it}. For notational simplicity, when maximizing let the sum of input costs be know simply as total costs. Differentiating with respect to q_{it} yields:

$$\frac{\partial \pi_{it}}{\partial Q_{it}} = p_t + \frac{\partial p_t}{\partial Q_{it}} Q_{it} - \mathrm{MC}_{it} = 0$$

Rearranging and again replacing terms with identities for market share, conjectual variation, and elasticity of demand yields Eq. (A.6):

$$[1 + s_{it}\theta_{it}\eta_t]^{-1} = \frac{p_t}{\mathrm{MC}_{it}} \tag{A.6}$$

Eq. (A.5) for all inputs and Eq. (A.6) are substituted into Eq. (A.2), which yields Eq. (A.7).

$$\frac{\Delta Q_{it}}{Q_{it}} = \left(\frac{p_t}{\mathrm{MC}_{it}}\right)\left[\frac{r_{it}K_{it}}{p_t Q_{it}}\frac{\Delta K_{it}}{K_{it}} + \frac{w_{it}L_{it}}{p_t Q_{it}}\frac{\Delta L_{it}}{L_{it}} + \frac{c_{it}M_{it}}{p_t Q_{it}}\frac{\Delta M_{it}}{M_{it}}\right] + \Delta\phi_{it} f_{it} \tag{A.7}$$

Defining $r_{it}K_{it}/p_t Q_{it}$, $wL_{it}/p_t Q_{it}$, and $c_{it}M_{it}/p_t Q_{it}$ as the cost share of capital, labor, and materials α_{it}^K, α_{it}^L, and α_{it}^M Eq. (A.7) becomes Eq. (A.8). Under constant returns to scale these three shares would add to one (times the inverse of price–cost markup). I do not constrain returns to scale to any particular value but allow scale to vary industry by industry.

$$\frac{\Delta Q_{it}}{Q_{it}} = \left(\frac{p_t}{\mathrm{MC}_t}\right)\left[\alpha_{it}^L\frac{\Delta L_{it}}{L_{it}} + \alpha_{it}^M\frac{\Delta M_{it}}{M_{it}} + \alpha_{it}^K\frac{\Delta K_{it}}{K_{it}}\right] + \Delta\phi_{it} f_{it} \tag{A.8}$$

Another change is dropping the firm-specific subscript from marginal cost. Maintaining a firm-specific price–cost markup results in an estimation with negative remaining degrees of freedom. Assuming all firms in an industry charging the same price–cost markup is commonly assumed. Levinsohn (1993: p. 15) provides a detailed discussion.

Finally, an expression for $\Delta\phi_{it}$ is needed. Assume a firm's productivity multiplier is composed of three elements. First, a firm-specific fixed-effects (which we do not need consider here because the specification is first-differenced); second, a time related exogenous shocks, λ_t; and finally a firm random effect, μ_{it}. With this error term specification Eq. (A.9) then becomes:

$$\frac{\Delta Q_{it}}{Q_{it}} = \left(\frac{p_t}{\mathrm{MC}_t}\right)\left[\alpha_{it}^L\frac{\Delta L_{it}}{L_{it}} + \alpha_{it}^M\frac{\Delta M_{it}}{M_{it}} + \alpha_{it}^K\frac{\Delta K_{it}}{K_{it}}\right] + f_{it}(\lambda_t + \mu_{it}) \tag{A.9}$$

Or rewritten in terms of natural logs this becomes Eq. (A.10).

$$\mathrm{d}q_{it} = \left(\frac{p_t}{\mathrm{MC}_t}\right)[\alpha_{it}^{L}\,\mathrm{d}l_{it} + \alpha_{it}^{M}\,\mathrm{d}m_{it} + \alpha_{it}^{K}\,\mathrm{d}k_{it}] + f_{it}(\lambda_t + \mu_{it}) \tag{A.10}$$

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