Essays on Foreign Direct Investment, Capital Flows and Exchange Rates

by

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To my Parents and Grandparents for always believing in me.

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CHAPTER I

Introduction

This dissertation studies the relationship between foreign direct investment, firm performance and the exchange rate. The first two chapters evaluate the performance of firms that have undergone mergers and acquisitions (M&A). Chapter 2 evaluates the differences in post-acquisition performance of target firms based on the geographic origin of the acquiring firm. Chapter 3 specifically focuses on the group of developing country firm acquirers and assesses their impact on U.S. target firms. Chapter 4 examines the relationship between cross-border M&A and the exchange rate. The setting for this research is the United States from 1980 until 2008, a period that captures vast capital inflows into the U.S., particularly in the form of foreign direct investment.

Acquiring firms from different parts of the world vary in productivity and factor endowments. Chapter 2 will test the hypothesis that these underlying heterogeneities have consequences for target selection, implementation of M&As, and, therefore, post-acquisition target performance. Although existing studies have shown performance improvements in foreign-acquired firms compared with domestically owned firms, little is known about differences in performance within the group of acquired firms. The empirical analysis uses new data on a comprehensive sample of public U.S. firms acquired during 1979–2006. The comparison is complicated by selection issues and missing counterfactuals, since at any given point in time a target firm experiences only one of three options–it is acquired by either (1) a domestic firm, (2) an industrial country firm, or (3) a developing country firm. To solve this problem, I use propensity score matching to construct a comparison group of domestically acquired target firms that is similar on a set of given observables to the group of targets acquired by industrial country firms or developing country firms. The findings suggest that target firms are subject to significantly different restructuring processes depending on the nationality of the acquiring firm. Whereas industrial country acquirers increase profits in their targets by increasing revenues, developing country acquirers are more likely to reduce the labor costs of target firms.

Chapter 3 examines the recent upsurge in foreign acquisitions of U.S. firms, specifically focusing on acquisitions made by firms located in emerging markets. Neoclassical theory predicts that, on net, capital should flow from countries that are capital-abundant to countries that are capital-scarce. Yet increasingly emerging market firms are acquiring assets in developed countries. Co-authors Anusha Chari, Kathryn Dominguez and I use transaction-specific acquisition data and firm-level accounting data in order to evaluate the post-acquisition performance of publicly traded U.S. firms that have been acquired by firms from emerging markets over the period 1980–2007. Our empirical methodology uses a difference-in-differences approach combined with propensity score matching to create an appropriate control group of non-acquired firms. The results suggest that emerging country acquirers tend to choose U.S. targets that are larger in size (measured as sales, total assets and employment), relative to matched non-acquired U.S. firms before the acquisition year. In the years following the acquisition, sales and employment decline while profitability rises suggesting significant restructuring of the target firms.

In the fourth chapter of the dissertation, I study a potential determinant of foreign direct investment. Theoretical and empirical studies of foreign direct investment have generated mixed support for a link between exchange rates and FDI. Previous empirical work, however, lacks the detail and data quality that satisfy the stringent assumptions of the theoretical models. I use transaction-specific data on foreign acquisitions of U.S. targets during

1979–2008 to examine the relationship between the relative value of the U.S. dollar and the price and number of cross-border acquisitions. Using a model proposed by Froot and Stein, I test the implications of the theory. In the model, informational imperfections make external financing more costly than internal financing, thereby, forcing investors to use part of their wealth to finance a project. Assuming that all things are equal between foreign and domestic investors, a depreciation of the U.S. dollar leads to an increase in the wealth position of foreign acquirers relative to domestic acquirers. This in turn allows foreign entrepreneurs to bid higher on U.S. assets relative to domestic entrepreneurs and hence leads to higher inflows of foreign direct investment in the aggregate. I utilize data true to the model's underlying assumptions, using acquisitions by private acquirers and controlling for the wealth position of the acquiring firm. Using an aggregate measure of foreign direct investment as was done in Froot and Stein, the value of the dollar is not significantly correlated with foreign direct investment for the extended period of 1979 – 2008. Using appropriate data of private acquiring firm investment inflows, however, a depreciating dollar is significantly correlated with an increase in acquisition foreign direct investment consistent with the model's prediction.

CHAPTER II

Does the Country of Origin of the Acquiring Firm Impact Performance?

2.1 Introduction

Over the past decade, U.S. firms have increasingly been targets of acquisition by firms from all over the world. The geographic composition of these cross-border acquirers has shifted over time. This paper aims to examine whether this trend has influenced the post-acquisition performance of U.S. target firms. Historically, almost all mergers and acquisitions (M&As) have taken place among firms in the United States and Europe.[1] In recent years, however, an increasing number of developing country firms have entered the global M&A market as both acquirers and targets.[2] Acquiring firms from different parts of the world vary in productivity and factor endowments. This paper will test the hypothesis that these underlying heterogeneities have consequences for target selection, implementation of M&As, and, therefore, post-acquisition target performance. Although existing studies have shown performance improvements in foreign-acquired firms compared with domestically owned firms, little is known about differences in performance within the group of acquired

[1] Brakman, Garretsen, and van Marrewijk (2006) provide a comprehensive overview of the geographical distribution of M&As using the entire SDC Thompson database.

[2] Source: Citigroup.

firms. Estimating the effects of foreign acquisition on target performance by different acquirers contributes to our general understanding of the ways in which firms realize gains from M&As.

This paper uses a newly-constructed data set to examine whether the post-acquisition performance of U.S. target firms differs when the buyer is either a U.S. domestic firm, an industrial country firm, or a developing country firm.[3] I assemble a comprehensive sample of acquired U.S. public firms by linking daily M&A transaction information from SDC Thompson to each target firm's financial statement in Compustat. The United States provides a particularly suitable setting in which to study M&As given its role as the world's most sought after target country, with a combined value of cross-border and domestic M&A deals of $1.47 trillion.[4]

When comparing the impact of domestic and foreign acquisitions on U.S. target firm performance, one would ideally compare the performance of a target firm that is acquired by a domestic firm with the performance of the same target had it been acquired by a non-U.S. industrial country firm or a developing country firm.[5] At any given point in time a target firm experiences only one of three options – it is acquired by either (1) a domestic firm, (2) an industrial country firm, or (3) a developing country firm – so that the desired counterfactual is not observable and creates a missing data problem. To solve this problem, I use propensity score matching to construct a comparison group of domestically acquired target firms that is similar on a set of given observables to the group of targets acquired by industrial country firms or developing country firms. In evaluating the target firm performance after the acquisition, I use measures of profits, sales, and employment as outcome variables.

I find that over a period of five years following acquisition, targets acquired by industrial country firms and developing country firms exhibit higher average profits compared with

[3]See Appendix A.1 for a full list of countries in the sample.

[4]Source: SDC Thompson Financial.

[5]The same can be said of comparisons between target firms that are acquired by industrial country firms and by developing country firms.

acquisitions by U.S. firms–by ten and six percentage points, respectively. The data show that compared with domestic acquisitions, sales also tend to increase in industrial country firm acquisitions–by over 28 percentage points, whereas sales decline by 29 percentage points for targets acquired by developing country firms. Finally, whereas industrial country firm acquisitions lead to an increase in employment of 17 percentage points in their targets, targets of developing country firm acquisitions reduce their total number of employees by 18 percentage points.

In previous studies no distinction was made between acquisitions made by developing and industrial country firms. Thus, it would not have been possible to identify the opposite restructuring effects on the target firms. The results based on this combined group of acquirers are explained in more detail in a later chapter.

Several sensitivity analyses are performed to assess the validity of the findings. I first show that the results are robust to different propensity score specifications. Additionally, to corroborate my findings that change in ownership leads to change in performance, I use a small sample of announced deals that were subsequently withdrawn during the course of the sample period. Using this sample of failed transactions, I find no differences in target performance between domestic withdrawn and foreign withdrawn deals. This result based on withdrawn deals supports my main findings: only targets that undergo actual acquisition by foreign firms improve their performance compared with those that are acquired by U.S. firms; targeted firms from withdrawn deals do not show similar effects. To illustrate the importance of controlling for selection and creating appropriate comparison groups, I redo the analysis without propensity score matching and show that the results are substantially different. Lastly, I perform robustness checks on various subsamples of the data to make sure that the results are not specific to one particular feature of the data.

This paper makes three main contributions. First, it provides some of the first findings on the effects of acquirer country heterogeneity on post-acquisition performance. It expands on the recent body of trade literature that assesses the causal link between foreign ownership and firm performance by differentiating between acquirer countries of origin. The majority of these previous studies focus on foreign M&As into developing countries.[6] These papers generally assume that foreign acquirers of developing country targets are more productive on average and should therefore lead to an improvement in the target's performance. These previous studies do not differentiate between the country of origin of the acquiring firms, since the comparison is conducted only between foreign-acquired and non-foreign-acquired firms. Therefore, any performance differences caused by the various types of acquirers could be masked. By considering only acquired public U.S. M&A targets in this study, I reformulate the question as follows: given that a firm is acquired, does it matter what the country of origin of the acquirer is? Analyzing the data with this new focus allows a potential target firm and its stakeholders to anticipate possible post-acquisition effects based on the acquirer country of origin.

Second, this paper extends and tests the predictions based on models from New Trade Theory. The seminal work by Helpman, Melitz, and Yeaple (HMY) in 2004 suggests that firms that invest abroad come from the upper part of the productivity distribution of firms in their country of origin.[7] This paper extends HMY's predictions in two ways. First, it adds a cross-country dimension to HMY's original acquirer productivity ordering. Second, it tests the hypothesis that the heterogeneity in acquirer productivity levels translates into differences in target post-acquisition performance.

Finally, examining the impacts of foreign and domestic acquisitions on target firms also has important policy implications. The U.S. government has sometimes taken a hostile attitude toward foreign acquirers of U.S. target firms.[8] Foreign investments tend to cause anxiety for national security reasons, such as when China's attempt to acquire the U.S. oil company Unocal in 2005 was thwarted by Congress. Another source of concern about for-

[6]Exceptions are the cross-sectional studies of Doms and Jensen (1995), Harris and Ravenscraft (1991), and Swenson (1993) on U.S. firms, and panel analysis by Bertrand and Zitouna (2005) on French target firms as well as studies by Fukao et al. (2006) on Japanese manufacturing firms.

[7]I will refer to this paper as HMY henceforth.

[8]See the article "Love me, love me not" in the July 2008 issue of *The Economist*.

eign acquisitions is the potential loss of American jobs. Domestic M&A transactions do not provoke the same sort of concerns as their cross-border counterparts.[9] Understanding the impacts of cross-border M&As sheds light on whether these political concerns are validated by the post-acquisition economic performance of the different types of acquisitions.

I begin the paper with a brief overview of the existing literature in Section 2. Section 3 provides the theoretical background for why acquirer heterogeneity may lead to different target performance outcomes and provides predictions for where impacts might be the largest. The data sets employed in this study are discussed in Section 4. Section 5 outlines the details of the identification strategy using multiple treatment propensity score matching combined with a difference-in-differences estimator. Sections 6 and 7 present the empirical results and discuss the different ways in which gains are realized among the varying types of acquirers. Section 8 provides robustness checks, and Section 9 concludes with a discussion of the implications of these results for both future research on FDI and economic policy.

2.2 Related Literature

In the early empirical literature on foreign ownership and firm performance, studies relied mostly on cross-sectional analyses (Doms and Jensen 1995; Chhibber and Majumdar 1999). In these papers a test of whether foreign ownership matters is implemented by using a dummy variable indicating a firm's foreign status. The main problem with these cross-sectional studies is that causality and correlation are entangled. It might be the case that foreign firms pick exceptionally productive targets, making it difficult to disentangle the role played by foreign acquirers in improving the post-acquisition performance.

A more recent group of papers in international economics have conducted causal analyses (Petkova 2008, Arnold and Javorcik 2005, and Girma 2005). These papers focus

[9] For instance, Whirlpool's bid to buy Maytag was received with enthusiasm, while a potential buyout of the same company by a Chinese-owned firm was perceived with concern by both American politicians and media.

on ex-post performance changes in the target firm after foreign takeover. This literature has found mixed evidence on whether foreign-owned firms perform better than domestic-owned firms. To disentangle correlation from causality, these papers create a carefully selected group of non-acquired firms using a propensity score matching technique. The causal effect of foreign acquisition on firm productivity is identified by implementing a difference-in-differences matching estimator.

Essentially, previous studies have treated all foreign acquirers as homogeneous when exploring the question of whether foreign acquisition leads to higher productivity. In contrast, the present paper regroups acquired target firms by acquirer firm country of origin. This study asks the following: Are there differences in the target firm performance after the acquisitions? And if so, how do these effects differ within the group of all acquired firms? To answer this question, I also take into account the domestically acquired targets which are usually buried in the comparison group of all non-foreign-acquired targets in other studies. The next chapter explores in more detail the group of U.S. target firms that have been acquired by firms from emerging markets and compares them to U.S. firms that have not been acquired by that same group. Since domestic acquisitions play a dominant role, especially in the United States, previous papers might have overlooked important insights into M&As by not comparing domestic acquisitions directly with foreign acquisitions.

Domestic M&As and their resulting stock reactions around the announcement time, on the other hand, have been a focus of studies in the finance literature. This paper contributes to the existing finance literature by adding the international dimension of M&As and builds on the work by Harris and Ravenscraft (1991). These authors analyze stock return differences between domestically acquired and foreign-acquired U.S. target firms during 1970–1987 and find that foreign acquisitions are accompanied by higher target firm stock returns. Their study has several limitations. Stock price reactions might convey an overall sense of the wealth gain from the merger, but they do not shed light on the question of how the wealth gain comes about, and they also do not account for the selection problem discussed above. Moreover, information on M&A often leaks out several months in advance of announcement, potentially biasing reactions that are captured around announcement times.

This paper relies on firm-level accounting data and new empirical techniques to analyze the effects of M&As. Instead of stock prices, this paper focuses on the firm's financial data such as operating income and sales, which provide information on the actual restructuring process behind the merger that cannot be understood by analyzing the stock price alone. Furthermore, I employ a matching methodology that controls for selection issues. This study covers a period that spans several years before and after the merger in order to capture long-term effects as well as possible information leakages prior to acquisition. Lastly, I divide the foreign acquirers into industrial and developing country firms in order to allow for potential different effects on target post-acquisition performance relative to that of U.S. acquired firms.

2.3 Theoretical Background

Building on the Helpman, Melitz, and Yeaple (2004) model, I explore several ways in which different acquirer types affect targets' post-acquisition performance. HMY hypothesize that within a country and industry, firms that invest abroad have higher productivity levels than firms that participate only in the home market. I build the case that there is an ordering of productivity levels among U.S. domestic, industrial country firm (hereafter ICF), and developing country firm (hereafter DCF) acquirers. Next, I discuss the possible ways in which these cross-country differences in productivity are transferred to the targets. Finally, I explore reasons for why these effects on the post-acquisition performance of targets differ for different acquirers.

Based on HMY, I anticipate that ICF acquirers are more productive than U.S. domestic acquirers on average. To work through the intuition for this premise, consider first the

HMY model. In a given country, for a firm to participate in home production and sales, it is required to overcome a fixed cost of f_D units of output; home production and export sales, however, require a higher fixed cost of f_X. Finally, home and foreign production with sales catering to both markets require the largest fixed cost of f_I. Sales volume alone determines a firm's ability to recoup the associated fixed costs, and sales is solely an increasing function of the firm's productivity level. Thus, it emerges that increasing participation in international markets is a strictly monotonous function of a firm's productivity: low productivity firms serve only the home market, while better performers can afford to pay the additional fixed cost of expanding their market to foreign buyers through export. Finally, only the most productive firms end up establishing production plants in foreign markets, and thus engage in FDI. Based on country level productivity data,[10] U.S. and industrial country firms have similar productivity levels. I assume that their firm productivity distributions are also similar and that U.S. domestic acquirers are represented by the entire U.S. firm distribution. By investing in U.S. targets and thus engaging in the most costly form of international production, ICF acquirers must be more productive on average than domestic U.S. acquirers.

Extending HMY, I expect that the productivity levels of DCF acquirers should be below those of ICF acquirers but close to and potentially above those of U.S. domestic acquirers. On average, DCFs exhibit lower productivity levels than U.S. domestic firms and ICFs.[11] Using HMY, it follows that for a DCF to become a foreign acquirer, it must be situated at the upper part of its productivity distribution. A first glance at the acquisition data suggests that DCFs acquire targets in similar industries and price ranges as U.S. domestic firms and ICFs. This evidence indicates that in order for the DCFs to compete with bidders from the U.S. and other ICFs, the mean level of productivity among these acquiring DCFs must be near the overall productivity mean for both domestic and ICF acquirers. Since the ICFs

[10]The United Nations Industrial Development Organization (UNIDO) provides country-level productivity measures.

[11]Productivity levels in UNIDO are based on wage levels and hours worked.

start out at a much higher average productivity level, DCF acquirers are on average less productive than ICF acquirers. Given the lower threshold of domestic acquirers, however, it is likely that DCF acquirers surpass the average productivity level of domestic acquirers. The resulting productivity ordering of the acquirers by global origin is the following:

$$\overline{\tau}_{ICF}^{acq} \geq \overline{\tau}_{DCF}^{acq} \geq \overline{\tau}_{US}^{acq}$$

where $\overline{\tau}$ is the mean productivity level of the respective acquirers.

If indeed the acquiring firms transfer their productivity onto the target firms as has been shown in the literature, then given this productivity ordering among the acquirers, ICF acquisitions would lead to the biggest performance gain in the target firm, followed by DCF acquisitions, and lastly by U.S. domestic acquisitions. As mentioned in the literature section above, there is evidence that targets gain from foreign ownership. This gain in target post-acquisition performance may occur for several reasons. First, better management qualities of the acquiring firm are implemented in the target firm after the acquisition, thus enhancing performance in the target (Hymer 1976 and Dunning 1981). Second, synergy effects between the target and acquirer can arise as a result of the acquisition, such as integrating local market knowledge of the target with better managerial capabilities of the acquirer (Markusen 2000). Third, transfer of better technology from the parent to the target company can lead to lower costs and higher profits in the target as well (Dunning 1981). Due to the different productivity levels of the acquirers, positive gains in the targets depend on the skill levels of the acquirers. Since ICF acquirers have the best ability among the three, their acquisitions are expected to lead to the biggest performance gain in target firms, followed by those of DCFs, and lastly, by U.S. domestic acquisition, i.e.,

$$\overline{\tau}_{ICF}^{targ} \geq \overline{\tau}_{DCF}^{targ} \geq \overline{\tau}_{US}^{targ}$$

Although target firm-level productivity data is not available, I use measures such as sales and profits to assess post-acquisition performance. In the monopolistic competitive setting of the HMY model, higher productivity implies producing at lower marginal cost, which allows firms to charge lower prices, produce more output, and obtain both higher revenues and higher profits. Thus, profits and sales have the same ordering as productivity.[12]

Stepping away from the HMY model, there are other reasons besides productivity differences why acquirers from different types of countries can benefit from M&A. Developing countries are generally endowed with more unskilled labor than industrial countries. Therefore, DCFs are able to hire unskilled workers at comparatively lower wages than ICFs and U.S. firms.[13] It is reasonable then for acquirers from developing countries to outsource labor activities from the U.S. target back to the acquirer country of origin. For U.S. targets acquired by ICFs, this outsourcing of employment is not as likely, since wage differentials are virtually absent between the parent and target locations. I will use firm-level employment data to measure whether there are changes in the number of workers in the U.S. target firms that might be an indication of these outsourcing effects.

It is possible that M&As fail to create positive performance effects in the acquired targets. Acquirers might reap all the benefits of the M&A, while the targets do not gain from the deal. In particular, foreign acquirers could be targeting U.S. firms in order to gain access to technology, existing brand names, or network distributions, or simply to bypass tariffs.[14] These reasons would not necessarily result in gains for the target firms. Since the data set has no financial data for the acquirers, I am not able to measure their gains. Based on an extensive study of all public U.S. M&As, however, Andrade, Mitchell, and Stafford (2001) have found that on average, target firms experience significantly higher wealth gains around the time of deal announcements than do acquiring firms. These results

[12] Appendix A.2 provides more details on the HMY setup.

[13] Ashenfelter and Jurajda (2001) compare hourly real wage rates of workers in identical jobs in McDonald's restaurants across countries and find that wage rates in developing countries are lower than those in industrial countries by several magnitudes.

[14] Chari, Chen, and Dominguez (2008) explore in more detail the reason why developing country firms acquire U.S. targets.

are supported by Jensen and Ruback (1983) and Jarrell, Brickley, and Netter (1989).[15] This evidence suggests that target firms are likely to capture a significant portion of the gains available from M&A. Another reason why target firms may not experience an improvement in their post-acquisition performance could be that the acquirer lacks experience in successfully implementing a merger. Other explanations include insufficient regional knowledge by the acquirer and a significant cultural distance between acquirer and target (Harris and Robinson 2003). For the particular sample under consideration, these negative M&A effects on the target are not as relevant because all the targets are public firms that are listed on one of the major stock exchanges. Generally, it is safe to assume that mergers happen because both the bidder and the target firm hope to gain from the deal. Otherwise, the bidder can walk away. On the target side, since it is a public firm, its management and shareholders can reject inadequate offers. Furthermore, in order to remain publicly listed and be included in the data set, a firm must maintain a certain stock price as well as a minimum amount of earnings during a fiscal year.[16]

The differences in DCF, ICF, and domestic acquirers may be relevant to selection issues. Due to high levels of asymmetric information and possible lack of experience, DCFs are expected to pick targets that perform the worst among all three comparison groups, which could lead to a negative bias in the post-acquisition performance of a DCF-acquired target. Harris and Ravenscraft (1991) found that most foreign investors in their sample (which consisted almost exclusively of ICFs) tend to buy U.S. targets that are more research and development intensive compared with U.S. domestic acquirers. Since these more technology intensive targets tend to be more productive before the acquisition, the post-acquisition result of ICF-acquired targets would have a positive bias. Additional systematic differences in selection can stem from the year when the acquisition takes place and the state where the target firm is located, mainly because of tax considerations and state-specific incentive

[15] Harris and Ravenscraft (1991) provide a more extensive discussion of this observation.

[16] See more details on data attrition in the next section.

packages.[17] Thus, the empirical analysis should account for these selection issues, and in a later section I will go into more detail about my identification strategy for how to resolve them.

It is important to note that HMY's model is designed for horizontal FDI and firms in manufacturing. It is reasonable, however, to extend their setup to other industries and types of FDI. Productivity and performance are generally highly correlated. Extending their results beyond manufacturing, it can be inferred that in addition to technology, management ability is also an important factor in enhancing the performance of a company. Although the transfer of technology requires that the target and parent company are in the same industry (i.e., a horizontal merger), the transfer of management capabilities does not. In the data, horizontal mergers are the most prevalent form among cross-border M&As (Brakman, Garretsen, and van Marrewijk 2006).[18] Among all forms of M&As, horizontal mergers are the easiest to detect, but without detailed information on the acquirers, it is often impossible to identify the other types of M&As in the data.

It is worthwhile pointing out that the HMY setup is static and that acquirers differ in fixed levels of productivity. The transfer of technology from the parent firm to the target firm, however, is a dynamic process. Implementing an M&A and transferring managerial capabilities and technology from the acquirer to the target firm often involves integration processes that take at least several years.[19] Thus, it is necessary to conduct the empirical study on the target performance over an extended time period after the acquisition in order to capture potential changes.

[17] Froot and Stein (1991) and Chen (2008) have shown that the U.S. foreign exchange rate is highly correlated with a foreign buyer's decision to acquire a U.S. firm.

[18] Other forms of M&A include vertical mergers that have separate geographic locations for various stages of production, and hybrid forms such as "export-platform" FDI, where a firm might manufacture goods in a foreign subsidiary and sell the output primarily in third-country markets. Ekholm et al. (2003), Yeaple (2003), and Grossman, Helpman, and Szeidle (2004) provide models for various types of these FDIs.

[19] In the case of public target acquisitions, the integration process usually involves the board of directors along with important shareholders, top management, and consultants of the two companies involved in the merger. According to a 2006 issue of the *Harvard Business Review*, the effectiveness of the merger between Hewlett-Packard and Compaq (which was announced in 2001) still remains to be seen in the years to come.

2.4 Data Description

The data sample contains M&As involving all acquisitions of public U.S. target firms that were announced and completed between January 1, 1979, and December 31, 2006, and are reported by SDC Thompson Financial. The data include all public and private M&A transactions involving at least 5 percent ownership of a target company or transaction values exceeding $1 million. SDC collates information from over 200 English and foreign language news sources, SEC filings and the filings from its international counterparts, trade publications, news wire reports, and proprietary surveys of investment banks, law firms, and other advisory firms. For each transaction, the SDC database provides information about the date on which the transaction was announced and the date on which the transaction became effective. The database also provides some characteristics of the target and acquiring firms such as name, nation, industry sector, and primary North American Industry Classification System (NAICS) code. Many of the transactions contain transaction-specific information such as the percentage of shares acquired, the value of the transaction, the number of bidders, the method of payment, and whether the target firm is delisted as a result of acquisition.

Over the sample period 1979-2006, SDC reports a total of 2,074 M&A transactions between foreign firms and public U.S. targets and 22,971 between U.S. acquirers and U.S. public target firms (see Table 2.1). Out of the 2,074 foreign takeovers of public U.S. firms, 1,768 (85 percent) are undertaken by ICFs and the rest by DCFs. Out of the total number of foreign public acquisitions, only 68 transactions (61 of them by ICF) end up with the target firm being delisted in the year of the acquisition. Among U.S. domestically acquired firms, 1,357 target firms (5.9 percent) were delisted during the year of the acquisition. SDC also provides information on the number of bidders on each target firm. In my sample, 5 percent of each type of public acquisitions involved multiple bidders.

The summary statistics of the acquisitions are presented in Table 2.2. Among the ICF acquisitions, the top five acquirer nations make up about 75 percent of all ICF public acquisitions and the top five DCF acquirers make up 67 percent of all DCF public acquisitions. The top three industries for each type of acquisition are manufacturing, finance, and real estate. The fraction of majority acquisitions are similar for ICF and U.S. domestic public acquisitions (40 percent), but lower for DCF public acquisitions (25 percent).

The financial statement data for the U.S. target firms come from Compustat North America.[20] Financial data items are collected from a wide variety of sources including news wire services, news releases, shareholder reports, direct company contacts, and quarterly and annual documents filed with the Securities and Exchange Commission. In order to match the public U.S. target firms from SDC Thompson with the firms' financial statements in Compustat, several identifiers are used. SDC Thompson provides the CUSIP number, ticker symbol, target name, and target industry information for M&A transactions in its data set. The CUSIP Issuer Code, assigned by the CUSIP Services Bureau, identifies each company in Standard & Poor's Compustat software.[21] Using the CUSIP, ticker symbol, target name, and industry provided in SDC, each public U.S. target is matched by hand with the same firm listed in the Compustat database. During this process, some firms in SDC cannot be found in Compustat. The two main reasons are that (1) the firm has been delisted, or (2) the firm is not listed on a stock exchange that is covered by Compustat. As mentioned above, SDC indicates that 5 percent of each type of acquisition results in the delisting of a target firm in the year of the acquisition. If a firm is delisted in the years after the acquisition, Compustat will change the status of the firm from active to inactive. For ICF public acquisitions, U.S. public targets from 1,379 transactions (78 percent) were

[20]Compustat North America is compiled by Standard & Poor's and provides the annual and quarterly Income Statement, Balance Sheet, Statement of Cash Flows, and supplemental data items on over 24,000 publicly held companies in North America.

[21]The CUSIP is a six-character code consisting of numbers in the first three positions and either an alpha or numeric character in the fourth, fifth, and/or sixth positions. CUSIP numbers and target names can often change due to splits, mergers, and delistings and relistings. Furthermore, depending on what stock exchange a firm is listed on, the ticker symbol is generally not unique, and one firm can also have several ticker symbols. Thus, it takes several identifiers to make sure that the U.S. target firm from SDC is indeed linked to the correct one in Compustat.

matched into Compustat and 254 transactions (83 percent) were matched for DCF public acquisitions. Among U.S. domestic M&As, 16,499 transactions (72 percent) are matched into Compustat.

The availability of financial data in Compustat varies strongly by year and by variable. For instance, the employment variable is reported on a voluntary basis in Compustat, which leads to spottiness in the availability. Although individual variables might be available on their own, several variables have to be available for a given year to do the analysis. This collective lack of data shrinks the sample size. I correct for this problem by using multiple imputations for several missing variables. Table 2.3 lists the mean characteristics of acquired public U.S. firms based on Compustat by 2-digit NAICS codes. Log sales show similar means across different industries, whereas both return on asset and log employment vary across industries.

There are target firms that have been acquired more than once by both U.S. acquirers and foreign firms. Of the 18,132 completed deals for all three types of acquirers that are matched into Compustat, about 20 percent of target firms have been acquired more than once. I handle this type of acquisition in several ways. One method is to include only the first occurrence of a transaction of each target firm in the data set, and in the case of a target firm acquired by a U.S. firm and by either an ICF or DCF, the first acquisition is included in the data set only if the subsequent transaction is at least five years after the first transaction. In another method, all transactions are kept in the data set, and each transaction regardless of reoccurrence of the same target is regarded as a unique observation. A third method is to take out all targets that have been acquired multiple times. There are pros and cons to each way of handling the data. The first method has the advantage of a clearer interpretation of the result, namely how change in ownership affects target firm performance over the five years after acquisition. Especially for cases where the same firm is acquired multiple times within five years of the first acquisition, the results for the performance on the second acquisition would become hard to interpret. However, the second method has the virtue of using the maximum amount of data and not conditioning the data on an outcome. The last method is the most restrictive, and I use that sample only for robustness checks. For the main analysis, I conduct the study using the first method, thus resulting in an acquired target's showing up only once throughout the sample. I conduct the same study using data from the second and third methods as a robustness check.

2.5 Econometric Strategy

2.5.1 Evidence of Selection

In evaluating the effects of ownership on post-acquisition target performance, one has to take into account the possibility that superior target selection is the driving force behind performance rather than change in ownership. As discussed in the theoretical background section, information asymmetry – which puts foreign investors, especially the DCFs, at a disadvantage – is one of the reasons why such selection issues might arise. Other reasons for selection issues are exchange rates and the ICF's particular preference for choosing research and development intensive U.S. public targets. Lastly, state-specific factors such as tariff, tax, and incentive packages may also play a role in choosing target firms.

A simple analysis of pre-acquisition performance among foreign and domestic targets reveals strong evidence that before acquisition, potential foreign targets differ systematically from future domestic targets. There are three pairwise comparisons among the three acquirer types (U.S., ICF, DCF). For each acquirer type combination, e.g., DCF versus U.S., a performance measure based on the time period prior to acquisition year is regressed on a dummy variable that takes a value of zero if the target is acquired by a U.S. firm in year t. It takes a value of one if the firm is acquired by firms from developing countries in year t.[22] I also control for industry-, state- and year-fixed effects in the regression. The estimation results, presented in Table 2.4, demonstrate that future acquisition targets of

[22]The same analysis is repeated for the other pairs of comparisons, e.g., ICF vs. U.S. and ICF vs. DCF.

industrial countries are smaller, measured in terms of log sales, than future domestic U.S. acquired firms. Furthermore, the regression indicates that industrial-country-acquired firms have fewer employees and lower levels of operating income than domestic-acquired-firms prior to acquisition. The same relationship holds true when comparing DCF targets and U.S.-acquired targets. The comparison between the pre-acquisition performance of ICF targets relative to DCF targets reveals that the former tend to acquire bigger target firms (in terms of sales and employment) than do the latter. These significant differences in pre-acquisition target performance between the various acquirer types are a strong indication of selection. The analysis of the differences in post-acquisition performance between foreign and domestic targets will therefore need to take this selection into account.

2.5.2 Propensity Score Matching and Differences-in-Differences

In order to conduct a meaningful comparison of performance between U.S. public firms acquired by foreign investors and those acquired by domestic firms, it is necessary to create a missing counterfactual capturing the performance of the foreign-acquired firms had they been acquired by domestic firms. The prototypical model of the microeconometric evaluation literature that is applied in the international economics context assumes that a target firm can take on only two acquisition states. The case here is complicated by the fact that foreign acquirers are from different country groups-more specifically, industrial countries and developing countries. In previous studies, it is common to use binary choice models, since there are two acquisition states, e.g., foreign-acquired or not foreign-acquired. In this paper, there are more than two possible treatments for a target firm: (1) acquisition by a domestic firm, (2) acquisition by an ICF, and (3) acquisition by a DCF. Following the labor economics literature, I will refer to the different acquisition states of a potential target firm as *treatments* and the performance variables as *outcomes*. The three main outcome variables of interest are log sales, log employment, and profits–profits being operating income before depreciation (OIBD) scaled by total assets, also referred to as return on assets

(ROA). The reason to use these three measures as outcome variables is that they are all closely related to productivity. In the HMY model, sales and profits are correlated since both are determined solely by productivity. This correlation has been generally confirmed in the data (Bernard et al. 2005). In addition, studies also find that higher productivity firms employ more workers. For tractability and interpretation, it is assumed that each target firm receives only one of the above treatments, and the set of outcomes of three mutually exclusive states is denoted by $\{Y^{US}, Y^{ICF}, Y^{DCF}\}$. Therefore, for any target firm, only one component of $\{Y^{US}, Y^{ICF}, Y^{DCF}\}$ can be observed in the data. The remaining outcomes are counterfactuals. Participation in a particular treatment is indicated by the variable $S\varepsilon\{US, ICF, DCF\}$ and m and l can take on any state within S.

Given the multiple treatments, the analysis will focus on pairwise average treatment effects. Following Gerfin and Lechner (2002) and Imbens (2000), the pairwise average treatment effects of treatments m and l for the target firm in treatment m is:

$$\theta_0^{m,l} = E(Y^m - Y^l|S = m) = E(Y^m|S = m) - E(Y^l|S = m) \quad (1)$$

where $\theta_0^{m,l}$ denotes the expected effect for a target firm randomly drawn from the population of participants in treatment m.[23] In equation (1), $Y^m|S = m$ is readily observed for firms that have the acquisition status m, but the counterfactual $Y^l|S = m$ is not, creating a missing data problem. In social experiments, this problem is solved by applying random assignment, which guarantees that the potential outcomes are independent of the assignment mechanisms, i.e., $E(Y^l|S = m) = E(Y^l|S = l)$. In observational studies such as this one, selection is not random and the preceding equality does not hold. To overcome this issue, one may obtain data from a set of potential comparison units that are not necessarily drawn from the same population as the treated units, but that are similarly based on a set of observable characteristics X.

Propensity score matching alone eliminates differences between the treatment and con-

[23] If the target firms in acquisition status m and l differ in a way that is related to the distribution of attributes (or exogenous confounding variables) X, and if the treatment effects vary with X, then $\theta_0^{m,l} \neq \theta_0^{l,m}$, i.e., the treatment effects on the treated firms are not symmetric.

trol groups based on observable characteristics included in X_i. In addition to the observable characteristics, there might be other systematic differences between the two groups that are due to unobservables. The difference-in-differences matching (DDM) estimator alleviates this issue by eliminating unobservable time-invariant differences between the treatment and control groups. In particular, the performance outcome variable in a time period before the acquisition is subtracted from the outcome variable in a time period after the acquisition, resulting in the following pairwise average treatment effects of treatments m and l for the target firm in treatment m:

$$\begin{aligned}\theta_{DDM}^{m,l} &= E[(Y_{t+u}^{m} - Y_{t'}^{m}) - (Y_{t+u}^{l} - Y_{t'}^{l})|X_i, S = m] \\ &= E(Y_{t+u}^{m} - Y_{t'}^{m}|X_i, S = m) - E(Y_{t+u}^{l} - Y_{t'}^{l}|X_i, S = m), \quad (2)\end{aligned}$$

where t denotes the year of acquisition and u denotes the number of years after the acquisition year and t' denotes a time period before acquisition.

The framework above makes it clear that the average causal effect is generally not identified. Therefore, this lack of identification must be overcome by plausible assumptions. More intuitively, matching works well only if both the constructed comparison group (based on the set of X_i) and the treated firms have the same expected performance had they all received the same acquisition treatment. When using propensity score matching without difference-in-differences (DiD), this condition is generally known as the conditional independence assumption (CIA). However, when combining DiD with propensity score matching, this assumption leads to conditioning on both observable and time-invariant unobservables. It is known as the bias stability assumption (BSA) using the terminology of Heckman et al. (1997). This assumption states that conditional on observables X_i, the bias stays the same over different time periods before and after the implementation of the acquisition, so that differencing the differences between the treated and comparison units eliminates the bias. More specifically, the effect of treatment on the treated is identified if

$$E(Y_{t+u}^{m} - Y_{t'}^{m}|X_i, S = m) = E(Y_{t+u}^{m} - Y_{t'}^{m}|X_i, S = l). \quad (3)$$

The comparison group is created on the basis of observable plant characteristics. As emphasized above, the vector of control variables in X_i should include all factors that affect both treatment and outcome. As described in the theoretical background section, the three types of potential acquirers choose targets based on specific criteria that might be systematically different. All potential investors rely heavily on basic observable characteristics of firms, such as their age, size, employment, and machinery and equipment available. The level of a target firm's income and sales is an indication of its profitability and market power. As pointed out previously, ICF acquirers prefer more technology intensive industries, thus requiring the use of industry-fixed effects. By using year-fixed effects, I control for time dependent macro factors such as the exchange rate. Lastly, since targets are located in different states that might have state-specific factors affecting the acquisition status, such as tax benefits, state-fixed effects are also included.

Matching on all characteristics simultaneously creates an intractable dimensionality problem. In the case of binary treatments, Rosenbaum and Rubin (1983) showed that conditioning the outcome variable on X_i is not necessary; it is sufficient to condition on a scalar function of X_i, namely the acquisition status probability conditional on the attributes. This is the so-called balancing score property of the propensity score. For the case of multiple treatments Lechner (2001b) shows that some modified versions of the balancing score properties hold in this more general setting as well. More specifically, I denote the marginal probability of treatment j conditional on X as $P(S=j|X=x)=P^j(x)$. Lechner (2001a) shows that the following result holds for the effect of treatment m compared with treatment l on the target firms in treatment m:

$$\theta_{DDM}^{m,l} = E(Y_{t+u}^m - Y_{t'}^m | S=m) - E_{P^{l|ml}(X)}[E\{Y_{t+u}^l - Y_{t'}^l | P^{l|ml}(X), S=l\}|S=m], \quad (4)$$

$$\text{where } P^{l|ml}(x) = P^{l|ml}(S=l|S\varepsilon\{l,m\}, X=x) = \frac{P^l(x)}{P^l(x)+P^m(x)}. \quad (5)$$

The individual marginal probabilities $[P^{US}(x), P^{ICF}(x), P^{DCF}(x)]$ can be estimated in the multiple treatment case using multinomial logit or probit functions.[24] If the respective

[24]The robustness check section provides more information about multinomial discrete choice models.

probabilities $P^{l|ml}(x)$ are known or if a consistent estimator is available, the dimension of the estimation problem is reduced to 1. Alternatively, instead of conditioning on $P^{l|ml}(x)$, one could also condition on estimates of $P^{l}(x)$ and $P^{m}(x)$ jointly, and Lechner (2002) shows that $\theta_0^{m,l}$ is identified in this case as well.

As defined previously, u denotes the number of years after the acquisition year, and t' denotes a time period before acquisition. The pre-acquisition period is given by $t' = -1$, while the post-acquisition period, u, ranges from zero to five years. According to previous studies in the literature on foreign acquisitions, it generally takes at least two to three years to implement changes resulting from the acquisition and even longer to observe those effects. Therefore, I choose a five-year span following the acquisition in order to document possible changes in the target firms. The choice of the year preceding the acquisition as the base year of the DDM matching estimator might raise concerns about an "Ashenfelter Dip." This term is based on the finding in Ashenfelter (1978) that in job program evaluations, participants tend to suffer a temporary decline in earnings prior to enrolling in a program. In this data set of target firms, however, there is no visible decline in target firm performance in the year prior to acquisition.

In addition to the bias stability assumption, propensity score matching requires the common support condition that all target firms can actually participate in all states. There are several ways to define the common support, especially with three different treatment options. One way is to make sure that for any pairwise comparison it is sufficient that, for all values of X_i for which those treated firms have positive marginal probability, there are comparison observations as well. Alternatively, one could limit the common support to include only those targets that have a positive marginal probability of being acquired by all three types of acquirers. The second definition is more strict than the first, since it would exclude firms that have positive marginal probabilities for two out of three types of acquisitions, but not for all of them. I will use the less restrictive form of common support in the analysis, but use the alternative form as a robustness check.

There are various matching methods available. Each scheme involves the definition of a closeness criterion, a neighborhood, and the selection of an appropriate weighting function to assign to the set of comparison observations with each treated firm. The choice relies on the trade-off between variance and bias associated with each type of matching performed and the computational intensity allowed. In general, increasing the neighborhood or bandwidth to construct the comparison units will reduce the variance and increase the bias resulting from using on average more, but lower quality matches. It will also increase the computational burden. In this case, kernel matching is applied to the comparison group. More specifically, kernel matching assigns positive weight to comparison observations with propensity scores similar to that of each treated observation, where the weights decrease with the propensity score distance. Formally, the analysis that follows uses a Gaussian kernel weighting function:

$$W(P_i^{l|ml}(X), P_j^{l|ml}(X)) = \frac{G(\frac{P_j^{l|ml}(X) - P_i^{l|ml}(X)}{a_n})}{\sum_{k \varepsilon I_0} G(\frac{P_k^{l|ml}(X) - P_i^{l|ml}(X)}{a_n})}, (6)$$

where G is the Gaussian normal function $G(\alpha) = e^{\frac{\alpha^2}{2}}$ and a_n is a bandwidth parameter. The mean of the comparison group is calculated based on the weighting function in equation (6). The selection of this bandwidth parameter is based on the "leave one out" cross-validation method. For each comparison unit, I use a bandwidth under consideration and the other comparison units to construct an estimated expected value given that unit's propensity score. Then I calculate and square the distance between the actual outcome for that unit and the estimate. The bandwidth that minimizes the mean of the cumulated squared errors across observations is chosen. The cross-validation procedure and the resulting optimal bandwidth for each of the comparison groups and outcome variables are listed in the Appendix. I follow Plesca and Smith (2007) in the implementation of the bandwidth exercise.

2.5.3 Multiple Treatment Matching

For each pair of comparisons, I can run a binary logit to estimate the propensity scores and then proceed to matching. With three treatments, however, a better way is to use multinomial logits to estimate the propensity scores. This multiple treatment matching has several advantages. First, it allows me to estimate a number of parameters. There are a total of six different effects among the three types of treatment, $E[Y^m - Y^l]$, where $m, l = US, ICF, DCF$. The multiple treatment matching allows a comparison between the two effects of acquisition. The first one, $E[Y^m - Y^l | S = m]$, is the effect on the outcome of target firms that are acquired by firms of type m compared with that of the same firms had they been acquired by firms of type l. The second one, $E[Y^m - Y^l | S = l]$, is the effect on the outcome of target firms that are acquired by firms of type l compared with that of the same firms had they been acquired by firms of type m. Based on these different effects, it is possible to identify the type of acquirers that leads a given group of acquired firms achieve the highest performance. Another advantage of using multiple treatment propensity scores is that I can impose a support condition that is common to all analyses, as described above.[25]

2.5.4 Balancing Test

To assess how well the propensity score matching does at balancing the conditioning variables, I calculate the standardized differences (SDiff) for the covariates. More specifically, for each covariate, I take the average difference between the treated units and the matched (or reweighted) comparison units and normalize it by the pooled standard deviation of the covariate in the treated and comparison samples. Based on Rosenbaum and Rubin (1985), I calculate the following measure:

[25] A detailed matching protocol is provided in the Appendix.

$$SDiff(X_k) = 100\frac{\frac{1}{n_m}\sum_{i\varepsilon\{A_i=m\}} X_{ki} - \frac{1}{n_l}\sum_{j\varepsilon\{A_j=l\}} W(P_i, P_j)X_{kj}}{\sqrt{\frac{var_{i\varepsilon\{A_i=m\}}(X_{ki}) + var_{j\varepsilon\{A_j=l\}}(X_{kj})}{2}}},$$

where n_m is the number of firms with acquisition status m and n_l is the number of firms that experience acquisition status l. As noted in Smith and Todd (2005), there is no clear criterion for determining if a value of the standardized difference is too large. However, Rosenbaum and Rubin suggest that a value of 20 is large. As an illustration of how balancing works, Figure 2.1 depicts the distributions of the propensity scores for target firms that have been acquired by DCFs and ICFs, where the former is the treated and the latter is the comparison group. Before applying matching, the distributions of the two different groups are visibly far apart. After applying matching, however, the two distributions are almost lying on top of each other, indicating the similarity in the treated and comparison groups.

2.5.5 Testing the Bias Stability Assumption

In addition to testing for the balance among the covariates that are included in the multinomial logit estimation, I also test for balance for covariates that are not included. This test is related to one of the main criticisms of the matching procedure–namely, the non-testable nature of the BSA. Previous research has to rely on the quality and extensiveness of the data in order to satisfy the BSA. In this paper, however, the data provide a unique opportunity to apply a novel test of the BSA. A little over 20 percent of the firms in the sample are acquired multiple times, and 20 percent of those firms were acquired by both domestic and foreign firms. This information allows me to verify whether the important underlying BSA is violated in this context. Specifically, the BSA requires that given the set of observable characteristics in X, a target firm in the comparison group should have the same expected performance as the treated firm had it received the same treatment. A test of the BSA for the treated foreign-acquired firms and the comparison group of domestic-acquired firms would be to see whether the multiple acquisition information balances between the respective group of treated and comparison firms. If the BSA were to hold, then after matching along the set of observable X and taking into account time-invariant unobservables, the comparison group should not differ significantly from the treated group in this multiple-acquisition information variable.

2.6 Results

2.6.1 Propensity Score Estimates

The propensity scores are calculated by estimating a multinomial logit. Table 2.5 displays the mean derivatives using the set of covariates discussed in the theoretical section. The base outcome in the multinomial logit is set to U.S. domestically acquired target firms. For instance, as sales increase by one percent, it is 0.2 percentage points more likely for a target firm to be acquired by a developing firm. The only covariates that are significant are the industry-, state- and year-fixed effects, as predicted in Section 3. In fact, their joint tests of being zero is rejected at the one percent significance level. The low pseudo-R^2 value of about 0.1 is common for this type of cross-country study. As the pairwise balancing test results indicate in Tables 2.6, 2.7, and 2.8, some covariates that have significant differences in means between the treated and the comparison groups do not differ significantly after being matched along the set of observables. These balancing results are an indication that this approach is capable of grouping together relatively homogeneous firms.

As for the test of the BSA, Table 2.9 shows that before matching, the mean difference between the domestically acquired group of targets is significantly different from that of ICF-acquired targets (there are not enough observations with multiple acquisitions by domestic and DCF firms). After matching, however, the difference in means is not statistically different from zero. This result based on matching on covariates that are not included in the logit is a further indication of the validity of the BSA.

2.6.2 Matching Results Based on Sample of Completed Deals

The matching estimate indicates that on average ICF-acquired firms compared with U.S.-acquired public firms that have been matched on the set of observable covariates have significantly higher levels of profits following acquisition. More specifically, compared with the group of matched U.S. domestic firms, industrial-acquired U.S. public firms experience on average a 10-percentage-point increase in their profits in the three to five years following the acquisition relative to the year preceding the acquisition. For instance, if domestically acquired targets on average were to experience a 10 percent increase on their return on asset compared to the year before the acquisition, the ICF-acquired targets would experience an increase in their return on asset of 11 percent compared to the year before the acquisition. In addition, ICF-acquired firms also experience statistically significant increases in log sales relative to the year before acquisition and compared with the matched group of domestically acquired U.S. target firms. On average, this increase in sales is about 22 percentage points. This result suggests that on average ICF-acquired targets experience higher increases in sales, for example, if domestically acquired target firms were to increase their sales by $10 million from the year before the acquisition, the matched group of ICF-acquired firms would experience a $12.2 million increase in their sales relative to the year before the acquisition. Finally, when comparing ICF-acquired firms with U.S. domestically acquired target firms, the two groups do not differ significantly in terms of post-acquisition employment for the first four years after acquisition. In the fifth year, however, ICF-acquired firms show a 17-percentage-point employment increase compared with U.S. domestically acquired targets and relative to the year before acquisition. Difference-in-differences matching estimation results are presented in Tables 2.10a, 2.11a, and 2.12a and the effects are plotted in Figures 2.2, 2.3, and 2.4.

Developing country targets tend to perform better than U.S. domestically acquired firms in terms of profits, especially in the fourth and fifth year after the acquisition. The average increase in profits in those two years for DCF compared with U.S.-acquired firms and to the year prior to acquisition is about 5.5 percentage points. In contrast to the industrial-country-acquired firms, log sales decrease significantly for DCF-acquired firms in years one to four following acquisition. On average, log sales decrease by 25 percentage points during those four years when firms are acquired by DCFs compared with U.S.-acquired firms. Employment declines by 18 percentage points for DCF-acquired firms in the second year after acquisition when compared with U.S. domestically acquired firms. For instance, if the domestically selected targets were to increase sales by \$10 million over the course of the four years following acquisition, then the DCF-acquired targets would have had a decline of \$12.5 million over that same time period after the acquisition relative to the year before the acquisition.

Figures 2.2, 2.3, and 2.4 summarize the dynamics of the effects by pinning down their development over time starting with the acquisition year.[26] They present the pairwise effects for all types of acquisitions and their respective targets. For each of the three outcome variables–profits, log sales and log employment–each panel presents a different acquirer type that acts as the base case, and the depicted effects are in relation to the base case. A value larger than zero indicates that target firms by a particular acquirer type would show an increase in the performance value compared with an acquisition by the base type acquirer in question and relative to the year before acquisition. For instance, in Figure 2.2, considering the relative positions of the curves, compared with the base category of ICF-acquired targets, U.S.- and DCF-acquired targets show declines in profits. For log sales, Figure 2.3 shows that targets acquired by ICFs clearly increase sales compared with the other two groups of targets. Figure 2.4 reveals that DCF-acquired targets show significant declines in employment compared to those targets acquired by U.S. domestic firms and ICFs. There are no significant differences in employment between U.S.- and ICF-acquired targets. Overall, the findings suggest the following: ICF acquired target firms dominate in

[26] A colored version of those figures is available on my website: http://www-personal.umich.edu/~wenjiec.

profits and sales, while DCF acquired firms experience the largest employment decreases.

2.6.3 Matching Results Based on Sample with all Foreign Deals Combined

Instead of differentiating between acquiring firms from developing and industrialized countries, earlier studies have generally lumped the two groups of acquirers into one. The matching estimates (Table 2.13) based on targets acquired by all foreign firms compared to the group of targets bought by domestic acquirers indicates that foreign acquisitions lead to statistically significant increases in profits in years three and five after the acquisition relative to the targets acquired by U.S. domestic firms. The estimates on sales and employment are not statistically significant except for an increase in foreign-bought target sales in the year of the acquisition. The coefficients on the estimates are also much smaller than those when performing the analysis using separate groupings of targets bought by firms from developing countries and industrialized countries. Since the ICF acquisitions outweigh the DCF acquisitions in number, one might have expected that the combined results are more similar to the those when using only the group of ICF acquirers. The reason for the lack of statistical significance and the smaller magnitude of the coefficient estimates might be due to the fact that the two groups of acquirers have such opposing results on their own. As previous studies have combined these two types of acquirers, it would not have been possible to identify the opposite restructuring effects on the target firms.

2.6.4 Matching Results Based on Sample of Withdrawn Deals

Along with the list of all completed M&A transactions, SDC Thompson also provides information on announced deals that are withdrawn during the course of the sample period. Over the sample period of 1979 – 2006, ICFs withdrew 195 deals with US firms, and US firms withdrew 2,993 deals with other US companies. The number of failed acquisitions for DCFs that have financial statement data is only 18, and therefore, too small to conduct inference. Using this sample of failed ICF and US domestic transaction deals, I can test how domestically targeted firms compare with ICF targeted firms. If it is the change of foreign ownership that affects the target firm's post-acquisition performance relative to a change of domestic ownership, then after controlling for selection, one would expect no performance differences between ICF targeted firms and domestically targeted firms within the group of withdrawn deals. I use binary treatment propensity score matching to control for selection and compare the performance between withdrawn ICF targeted firms and withdrawn U.S. targeted firms. Results indicate that there are indeed no significant differences in their performances over a five-year period following the announcement date (Table 2.14). This finding contrasts with the results obtained in a comparison between ICF and domestic acquisitions where the deals are executed. Thus, this result is a strong indication that the differences in post-acquisition performance between actual ICF-acquired and domestic-acquired targets are caused by the respective changes in ownership status.

2.6.5 Simple Difference-in-Differences Results

To illustrate the importance of creating the appropriate comparison group in order to control for selection, I redo the analysis with a simple difference-in-differences (DiD) approach without propensity score matching. The underlying assumption is that the three different groups of acquirers are choosing their targets in the same pattern. Table 2.15 shows that the results based on the simple DiD estimates are substantially different from results obtained when controlling for selection by applying propensity score matching. In fact, without creating the appropriate control groups, one might draw the misleading conclusion that targets acquired by ICFs are the worst-performing among the three groups. Moreover, the employment effects for industrial acquisitions are reversed when using the simple DiD; it predicts that targets acquired by ICFs show significant employment decreases compared with those acquired by domestic firms. This result is opposite to the finding obtained when controlling for selection by creating appropriate comparison groups. Based on the pre-acquisition results in Table 2.4, on average, targets selected by U.S. domestic firms tend to be significantly larger in terms of sales and employment in years prior to the acquisition compared to targets selected by ICF, and persist to be statistically different along these dimensions after the acquisition without the appropriate comparison group. Similarly, the DCF selected targets exhibit statistically smaller sales than those picked by U.S. acquirers prior to acquisition, and this feature remains after the acquisition when not creating the appropriate control group. The employment decreases for DCF-acquired targets are exacerbated when using only simple DiD. This simple exercise highlights how studies that do not create appropriate comparison groups will yield potentially misleading results.

2.7 Discussion

The results in the study confirm the theoretical predictions. As expected, ICF-acquired target firms exhibit the highest performance among all three types of acquirers, followed by DCF-acquired firms. In particular, for ICF-acquired firms, the increase in profits, scaled by total assets, is accompanied by large increases in log sales. Furthermore, employment also increases, although changes are not statistically significant. These results strongly indicate that ICF acquirers increase profits through increased market share. A potential explanation of this result can be found by using the implications of the Helpman, Melitz, and Yeaple (2004) model. Within the HMY framework, foreign acquirers–i.e., ICF acquirers–have lower marginal costs due to their higher productivity levels; they therefore set prices lower. Lower prices in turn make them more competitive and more able to increase output and total revenue. These predicted output and revenue increases are reflected in the data by the jump in sales at target firms after acquisition. Within a few years, these sales increases translate into higher profits.

DCF-acquired firms also experience increases in profits compared with U.S.-acquired firms, but not in comparison with ICF-acquired firms. Target firms that are acquired by

DCFs suffer large decreases in sales as well as downsizing of workers compared with the other two types of acquired firms following M&A. The decreases in sales are somewhat puzzling at first glance. The productivity differences in the acquirers alone cannot explain this trend in the data, but there are maybe other factors at play.

As explained in the theoretical section above, DCF acquirers are likely to exploit the wage differences by outsourcing some of the work in the U.S. target firm back to the acquirer's home country. Thus, DCF-acquired targets are likely to suffer decreases in employment compared with domestically and ICF-acquired targets. Upon closer look, these seemingly contradictory findings can be explained as follows: When employment decreases in DCF-acquired targets, the firm itself gets smaller. Sales would go down, but profits as a percentage of assets would increase. ICFs, on the other hand, do not have the same wage differential advantage and are therefore not likely to change employment in the target firm post-acquisition compared with U.S.-acquired targets.

2.8 Robustness Checks

2.8.1 Multinomial Discrete Choice Model

So far, all results have been generated using the multinomial logit. One limitation of this approach is that it requires the strong assumption of independence of irrelevant alternatives (IIA), that the relative probabilities depend only on the two alternatives being compared.[27] An alternative multinomial discrete choice specification is the multinomial probit, which does not require the IIA. In fact, it does not impose any structure on the covariance matrix. The main problem with the multinomial probit comes with estimation. Using a maximum

[27]This condition results from the assumption that the error terms are identically and independently distributed across alternatives. In this paper, for example, the IIA would translate into the same relative probability either of being acquired by a U.S. firm or of being acquired by an ICF when the option of being acquired by a DCF becomes available. Although a Hausman test is sometimes used to check the validity of the IIA assumption, the power is often too small to support the assessment.

simulated likelihood implemented by the Geweke-Hajivassiliou-Keane algorithm, I impose exclusion restrictions to achieve convergence. Specifically, I assume that the covariances among domestically acquired targets are always zero, but non-zero among the events of being acquired by either developing country or industrial country firms. In other words, acquisitions among U.S. domestic firms are imposed to be random, but foreign acquisitions are allowed to be correlated with each other. The reasoning is that domestic and foreign acquisition decisions are inherently different and a target that might be of interest to an ICF might also be of interest to a DCF, whereas a target selected by a U.S. domestic firm might not necessarily attract the same interest by the two foreign types of acquirers. The results obtained from this set of multinomial probit propensity scores are similar to those for the multinomial logit. It is more computationally intensive to calculate the estimates using the multinomial probit due to its long convergence time.

2.8.2 Horizontal M&As

As mentioned in the theoretical section, the HMY model is specifically targeted toward horizontal M&As where the acquirer and target firms come from the same industries. Using a subsample of only horizontal M&As, where both target and acquirers have the same 6-digit NAICS codes, the matching estimates are close to those used for the whole sample. Table 2.16 shows that the subsample of horizontal M&As have matching estimates that are similar to those in the full sample in terms of magnitude and level of statistical significance.

2.8.3 Sample Without Target Firm Attrition

In the five years after acquisition, the sample size decreases from year to year by about 15 percent on average. Part of the attrition is due to the long period of investigation. In particular, firms acquired after 2001 do not have the full five-year period after the acquisition, since the current acquisition data is available only through December 2006. Another reason for the attrition that affects a smaller portion of the firms is delisting of the firm or even bankruptcy. Once the firm leaves Compustat it is not possible to track its financial statement data, and the reasons for delistings are generally not specified. Thus, an alternative way to analyze the data is to concentrate only on the sample of firms that are listed in Compustat for at least the five years following their acquisition. Table 2.17 presents the matching estimates using this sample without firm attrition, and the results are similar in magnitude to those using the whole sample. In fact, using this balanced sample of firms with no attrition, the matching estimates for all outcome variables are more statistically significant than the results obtained from the unbalanced sample.

Further robustness checks using the following samples can be found in the Appendix: majority or minority acquisitions, U.S. acquiring firms with and without foreign affiliations, and acquisitions where target firms are never acquired more than once throughout the sample period. The results remain qualitatively the same when using these various samples.

2.9 Conclusion

This paper measures the performance of U.S. target firms after acquisition by firms from a broad range of countries over a five year period. Using daily announced M&A information and firm-level financial statement data, I examine the post-acquisition performance of all U.S. public target firms over a twenty-eight-year period. In contrast to previous studies that lump all acquisitions by foreign firms together, I differentiate those acquisitions made by industrial country firms from those made by firms from developing countries. In order to control for non-random selection, I use multiple treatment propensity scores to match similar firms between comparison groups.

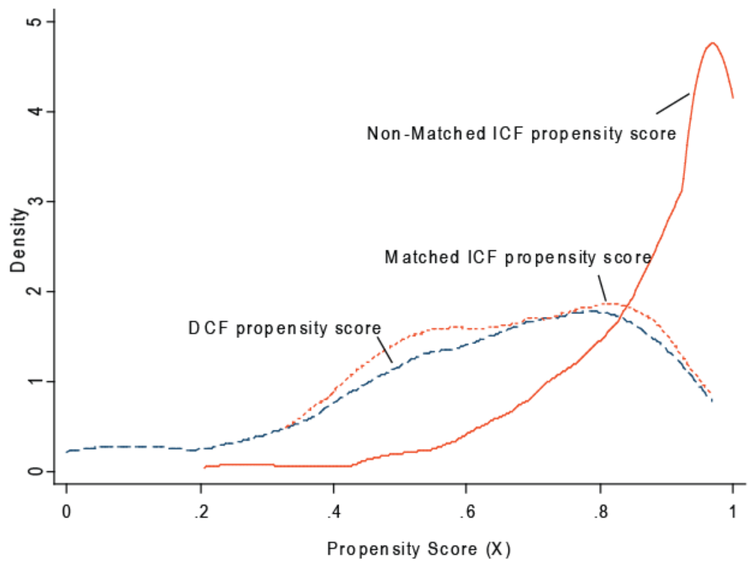
Consistent with the predictions of the Helpman, Melitz, and Yeaple (2004) model, targets acquired by firms from industrial countries exhibit the best post-acquisition performance. Targets acquired by non-U.S. firms from industrial countries experience an increase in profitability that is greater by 10 percentage points compared with targets acquired by domestic firms. This improvement in performance is driven by increases in sales. Acquirers from developing countries improve the post-acquisition performance of their targets by 6 percentage points more than U.S. domestic acquirers do. In contrast to acquisitions by non-U.S. industrial country firms, acquisitions by developing country firms tend to result in decreases in employment and sales in U.S. targets. These results are robust to different propensity score specifications as well as to sample classifications.

The study provides some of the first evidence that the acquirer's country of origin matters both for selection of targets and for post-acquisition performance. The findings also highlight how accounting for heterogeneity in acquirer types reveals different channels by which post-acquisition performance is improved. The use of multiple treatment propensity score matching and detailed firm level data in this paper provides a methodology for controlling possible selection issues that could be employed in other studies of acquisition types where selection is non-random. In fact, I show that when not controlling for selection, the estimation yields substantially different results that do not separate causality from correlation. Finally, even though an overall welfare assessment is not possible here due to the lack of data on the acquirers, the results suggest that U.S. public target firms benefit more from foreign acquisitions than from domestic M&As in terms of overall performance, with the largest improvements stemming from non-U.S. industrial country firms. At the same time, workers in U.S. public target firms that are acquired by developing country firms are more likely to lose their jobs.

These findings provide new insights into the workings and consequences of domestic and cross-border M&As. In particular, for governments that are devising policies toward FDI, these results suggest that not all types of foreign investments should be treated in the same way. By building on this paper's approach to differentiating acquirer types, future studies can use more detailed data on the acquirer firms to help evaluate the overall impact of M&A deals. For instance, do acquirers perform differently after purchasing target firms? Do revenue and employment also change differently in the acquirers depending on the type of target? The methodology in this paper allows for the study of the effect on acquirers by differentiating the types of targets. Specifically, it enables us to identify how post-acquisition performance changes when targets are located in different parts of the world. Complementing the results in this paper, such future studies will increase our general understanding of the effect of M&As on both acquirers and targets in a variety of locations around the globe.

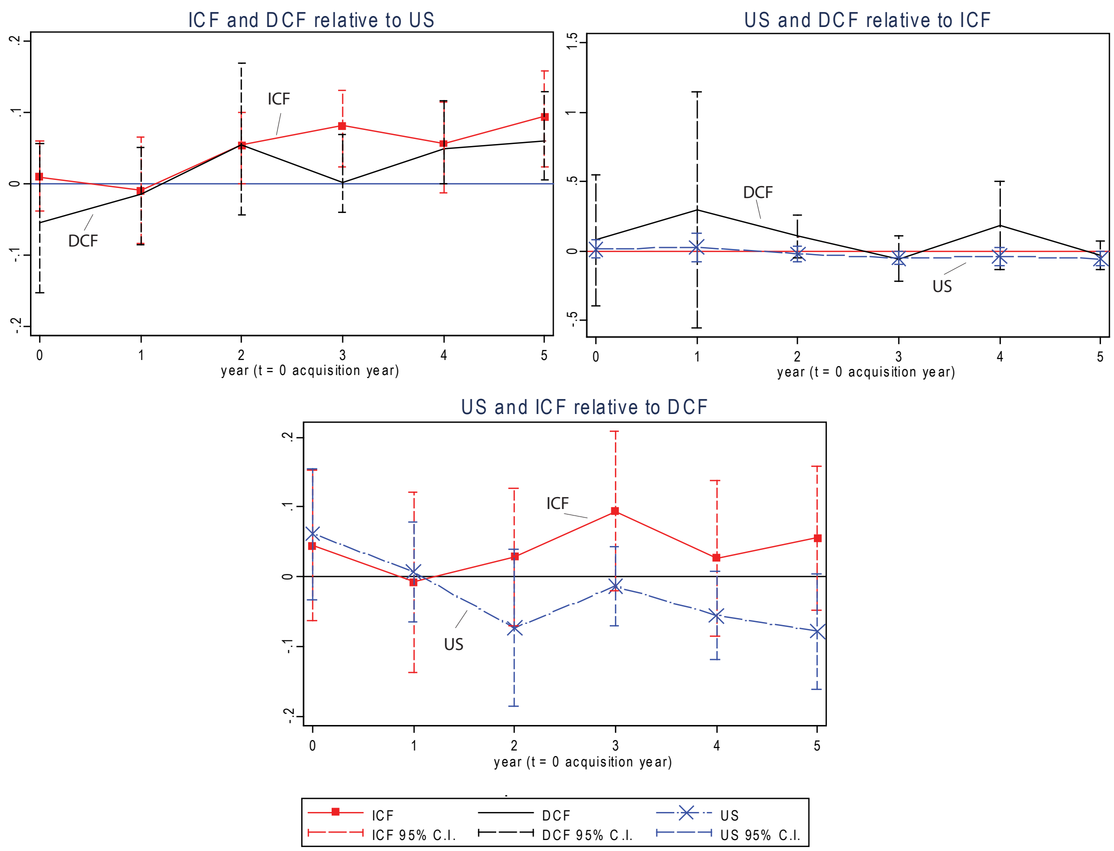
Figures and Tables

Figure 2.1: Balancing on Propensity Scores



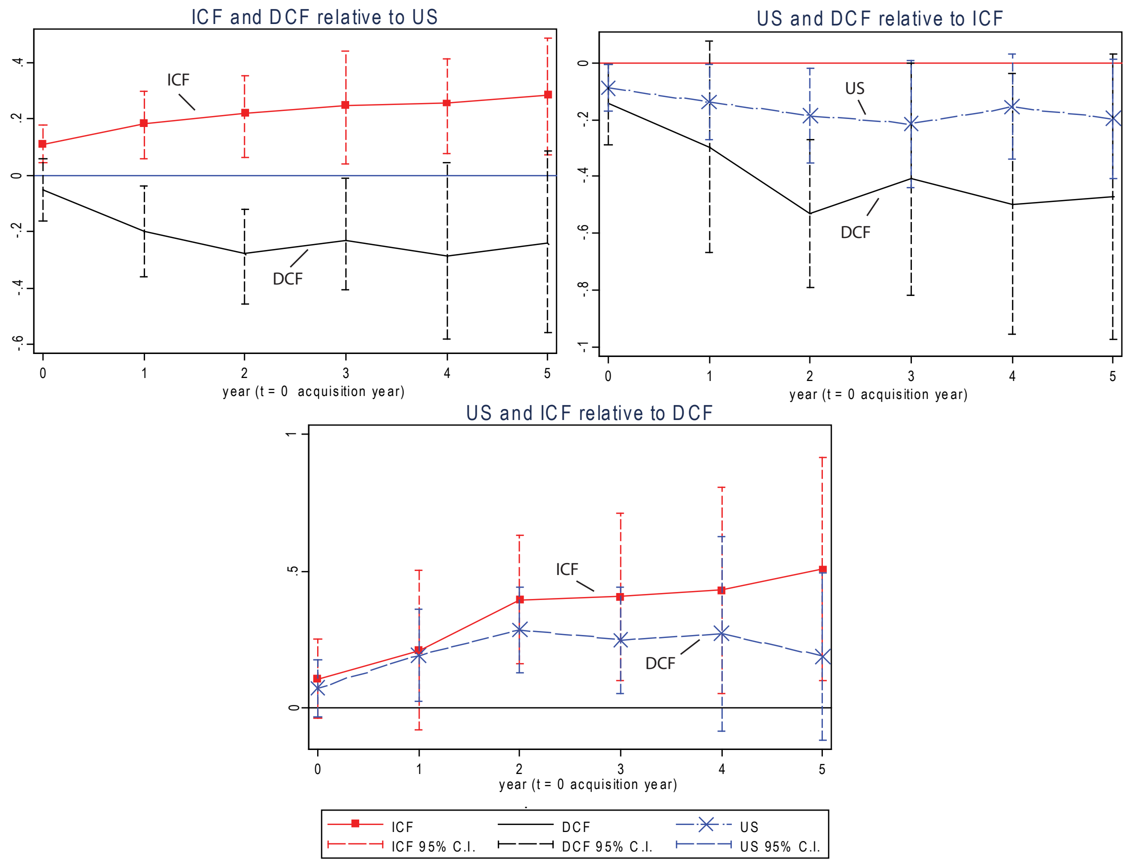
Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: Density of propensity scores before and after matching for comparison between U.S. target firms that have been acquired by developing country firms (DCF) and industrial country firms (ICF).

Figure 2.2: Dynamics of Average Effects on Profits (Operating Income/Total Assets)



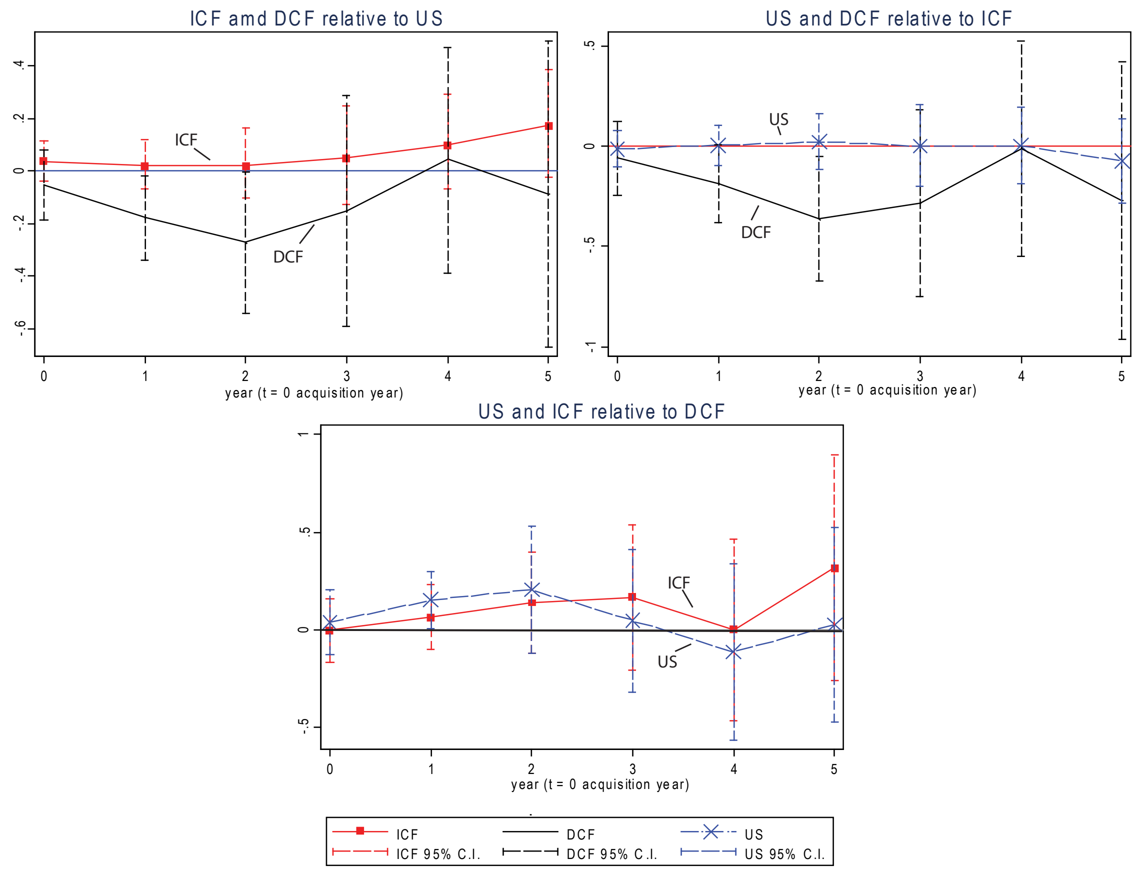
Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: Operating income before depreciation is the most basic level of profit measure in Compustat. The average effects on profits are for target firms in year t following acquisition relative to the year before acquisition and relative to US, ICF, and DCF as base case, respectively. The 95% confidence band around the point estimates are based on bootstrapped standard errors.

Figure 2.3: Dynamics of Average Effects on Log Sales



Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: The average effects on log sales are for target firms in year t following acquisition relative to the year before acquisition and relative to US, ICF, and DCF as base case, respectively. The 95% confidence band around the point estimates are based on bootstrapped standard errors.

Figure 2.4: Dynamics of Average Effects on Log Employment



Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: The average effects on log employment are for target firms in year t following acquisition relative to the year before acquisition and relative to US, ICF, and DCF as base case, respectively. The 95% confidence band around the point estimates are based on bootstrapped standard errors.

Table 2.1: Number of Observations for each Type of Acquisition

	US to US	ICF to US	DCF to US
Number of completed M&As with public US target	22,971	1,768	306
Number of delisted firms in year of acquisition	1,357 (5.9%)	61 (3.5%)	7 (2.3%)
Number of target firms that are acquired more than once	4,874 (21.2%)	388 (21.9%)	73 (23.9%)
Number of transactions with multiple bidders	1,268 (5.5%)	86 (4.9%)	16 (5.2%)

Source: Author's calculation based on SDC Thompson 1979–2006.
Notes: Percentages in parentheses are of total number within the given category.

Table 2.2: Summary Statistics of Acquisitions

	US to US N = 22,971	ICF to US N = 1,768	DCF to US N = 306
Top 5 Acquiring Nations		UK 452 Canada 396 Japan 193 France 139 Germany 120	Hong Kong 92 Singapore 42 Mexico 31 South Korea 23 Taiwan 18
Majority Control > 50%	9,206 (40.0%)	786 (44.4%)	76 (24.8%)
Number of Withdrawn Deals	3,976	256	25

Source: Author's calculation based on SDC Thompson 1979–2006.

Table 2.3: Industry Characteristics of Target Firms

			Acquirer Origin			Median		
Target NAICS	Industry	Freq.	US	IND	DEV	Profit/Assets	Sales ($mil)	Empl (mil worker)
11	Agriculture	81	30	3	0	0.129	101.48	0.809
21	Natural Resources	942	375	50	13	0.112	31.34	0.104
22-23	Utilities, Construction	781	293	24	2	0.110	334.03	1.205
31-33	Manufacturing	9181	3,380	442	67	0.126	94.10	0.873
42-45	Wholesale and Retail Trade	2142	733	60	12	0.123	303.24	2.000
48-49	Transportation and Warehousing	536	212	18	0	0.126	298.37	1.980
51	Information	2009	682	68	9	0.101	61.00	0.408
52	Finance and Insurance	4771	1,934	88	15	0.025	96.00	0.900
53-56	Real Estate and Adm Services	1846	918	91	14	0.112	46.87	0.449
62-81	Recreation, Food, and Entertainment	1354	609	33	8	0.128	88.11	1.900

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: Industries are grouped by 2-digit NAICS codes.

Table 2.4: Evidence of Selection

	(ICF = 1, US=0)	(DCF = 1, US=0)	(ICF = 1, DCF=0)
Profits/Assets	-0.000	**-0.026***	**-0.036****
	(0.01)	(0.01)	(0.02)
Log Sales	**-0.050***	**-0.213*****	**0.184*****
	(0.03)	(0.08)	(0.06)
Log Employment	**-0.114*****	**0.242*****	**0.148****
	(0.03)	(0.06)	(0.08)

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: For each pair of comparison groups, the dependent variable (Profit, Sales, Employment) is regressed on the respective dummy variable (listed in column heading) for all periods before the acquisition year. All regressions include year-, state-, and industry-fixed effects.
*, **, **** significance at 10%, 5% and 1% level, respectively

Table 2.5: Multinomial Logit

	Mean Derivatives (Unconditional Probability)		
Treatment	DCF	ICF	US
Age	0.000	0.000	0.000
OIBD/Asset	-0.003	-0.026	0.029
Log Cash	0.000	0.001	-0.001
Log Sales	0.002	-0.003	0.002
Net Income/Asset	-0.003	0.000	0.002
Log Assets	-0.001	0.002	-0.001
Log Employment	-0.001	0.003	-0.002
Log Debt	-0.003	0.004	-0.001
Log Net PPE	0.003	0.003	-0.005
Year-fixed effects		yes	
Industry-fixed effects		yes	
State-fixed effects		yes	
		P-values of joint test	
Year-fixed effects= 0		**0.000**	
Industry-fixed effects = 0		**0.000**	
State-fixed effects = 0		**0.001**	
Observations		6056	
Pseudo R^2		0.100	

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: Mean derivatives based on covariates from one year before acquisition period.

Table 2.6: Balancing Test between ICF-Acquired (=1) and U.S.-Acquired (=0) Targets

		Means				t-test	
Variable	Sample	Treated	Control	SDiff	%reduct in SDiff	t-stat	p>|t|
Age	Unmatched	22.640	22.374	2.3		0.53	0.597
	Matched	22.640	22.527	1.0	57.5	0.16	0.871
Profits/Assets	Unmatched	0.024	0.060	-13.6		-2.99	**0.003**
	Matched	0.024	0.049	-9.5	30.4	-1.44	0.151
Log Cash	Unmatched	1.869	1.840	1.3		0.29	0.772
	Matched	1.869	1.835	1.6	-17.1	0.26	0.798
Log Sales	Unmatched	4.816	4.763	2.6		0.60	0.549
	Matched	4.816	4.798	0.9	66.4	0.14	0.889
Log Assets	Unmatched	5.095	5.139	-2.2		-0.49	0.625
	Matched	5.095	5.102	-0.3	84.5	-0.06	0.956
Log Empl	Unmatched	0.131	0.052	4.3		0.96	0.338
	Matched	0.131	0.088	2.4	45.3	0.38	0.700
Log Debt	Unmatched	2.879	2.824	2.0		0.45	0.655
	Matched	2.879	2.834	1.7	17.4	0.27	0.788
Net Income/Asset	Unmatched	0.082	-0.044	-11.8		-2.42	**0.016**
	Matched	0.082	-0.057	-7.7	34.5	-1.20	0.229
Log Net PPE	Unmatched	3.494	3.322	7.9		1.75	**0.080**
	Matched	3.494	3.405	4.1	48.1	0.66	0.509

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: SDiff is calculated based on the formula in Section 2.5.4.

Table 2.7: Balancing Test between DCF-Acquired (=1) and U.S.-Acquired (=0) Targets

		Means				t-test	
Variable	Sample	Treated	Control	SDiff	%reduct in SDiff	t-stat	Variable
Age	Unmatched	19.893	23.109	-28.2		-2.53	**0.011**
	Matched	19.893	22.682	-24.4	13.3	-1.57	0.117
Profits/Assets	Unmatched	0.028	0.078	-25.5		-2.10	**0.035**
	Matched	0.028	0.075	-23.6	7.4	-1.49	0.139
Log Cash	Unmatched	1.732	1.876	-6.6		-0.58	0.565
	Matched	1.732	1.874	-6.5	1.2	-0.42	0.674
Log Sales	Unmatched	4.736	4.868	-6.8		-0.58	0.565
	Matched	4.736	4.857	-6.2	8.6	-0.40	0.688
Log Assets	Unmatched	4.921	5.227	-15.7		-1.33	0.183
	Matched	4.921	5.201	-14.3	8.6	-0.93	0.355
Log Empl	Unmatched	-0.094	0.133	-11.4		-1.05	0.292
	Matched	-0.094	0.110	-10.3	10.0	-0.66	0.507
Log Debt	Unmatched	2.495	2.994	-17.9		-1.64	0.101
	Matched	2.495	2.960	-16.7	6.7	-1.07	0.286
Net Income/Asset	Unmatched	-0.109	-0.020	-21.3		-2.43	**0.015**
	Matched	-0.109	-0.026	-19.9	6.8	-1.24	0.216
Log Net PPE	Unmatched	3.386	3.496	-4.8		-0.44	0.661
	Matched	3.386	3.513	-5.6	-15.5	-0.36	0.720

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: SDiff is calculated based on the formula in Section 2.5.4.

Table 2.8: Balancing Tests Between DCF-Acquired (=1) and ICF-Acquired (=0) Targets

		Means				t-test	
Variable	Sample	Treated	Control	SDiff	%reduct in SDiff	t-stat	p>|t|
Age	Unmatched	26.630	25.256	11.7		1.04	0.298
	Matched	26.745	25.885	7.4	37.4	0.50	0.616
Profits/Assets	Unmatched	0.040	0.031	4.6		0.35	0.724
	Matched	0.038	0.017	11.3	-146.4	0.68	0.495
Log Cash	Unmatched	2.508	1.941	24.9		2.13	0.034
	Matched	2.550	2.121	18.8	24.4	1.28	0.202
Log Sales	Unmatched	5.613	4.896	32.6		2.71	**0.007**
	Matched	5.622	5.206	18.9	41.9	1.37	0.173
Log Assets	Unmatched	5.604	5.250	16.8		1.42	0.157
	Matched	5.618	5.400	10.3	38.6	0.71	0.478
Log Empl	Unmatched	0.615	0.179	21.7		1.85	**0.065**
	Matched	0.610	0.259	17.5	19.4	1.22	0.225
Log Debt	Unmatched	3.433	3.243	6.8		0.60	0.548
	Matched	3.427	3.586	-5.7	16.6	-0.39	0.693
Net Income/Asset	Unmatched	0.041	-0.055	6.6		0.51	0.612
	Matched	0.042	-0.082	19.0	-186.4	1.10	0.272
Log Net PPE	Unmatched	3.928	3.759	7.2		0.61	0.545
	Matched	3.921	3.957	-1.5	78.6	-0.10	0.916

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: SDiff is calculated based on the formula in Section 2.5.4.

Table 2.9: Additional Balancing Test between ICF-Acquired (=1) and U.S.-Acquired (=0) Targets

		Means				t-test	
Variable	Sample	Treated	Control	SDiff	%reduct in SDiff	t-stat	p>|t|
Multiple acquisition dummy	Unmatched	0.00987	0.00199	10.3		2.58	**0.010**
	Matched	0.00987	0.00194	10.3	-0.7	1.27	0.203

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006,
Compustat North America 1979–2006.

Notes: Dummy variable equals one if the firm was a target of acquisition by both U.S. firms and ICFs.

Table 2.10a: Differences in Profits between ICF- and U.S.-Acquired Targets in Year *t* after Acquisition

Difference in Differences Combined with Kernel Matching Estimates								
	Profits/Asset				Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	ICF (=1)	US (=0)	ICF (=1)
0	0.010	0.025	0.42	0.677	3,527	306	0	0
1	-0.009	0.037	-0.25	0.801	2,727	243	0	0
2	**0.055**	0.025	2.17	0.030	2,430	221	0	0
3	**0.082**	0.027	3.02	0.003	2,173	203	0	0
4	**0.057**	0.032	1.76	0.079	1,968	175	0	0
5	**0.095**	0.030	3.18	0.001	1,774	157	0	0

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.10b: Differences in Log Sales between ICF- and U.S.-Acquired Targets in Year *t* after Acquisition

Difference in Differences Combined with Kernel Matching Estimates									
	Log Sales				Common Support		Off Support		
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	ICF (=1)	US (=0)	ICF (=1)	ICF (=1)
0	**0.110**	0.037	2.97	0.003	3,564	307	0	0	0
1	**0.183**	0.066	2.78	0.005	2,745	240	0	0	0
2	**0.220**	0.081	2.73	0.006	2,440	219	0	0	0
3	**0.248**	0.099	2.50	0.012	2,176	203	0	0	0
4	**0.255**	0.087	2.95	0.003	1,979	176	0	0	0
5	**0.286**	0.102	2.80	0.005	1,778	158	0	0	0

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.10c: Differences in Log Employment between ICF- and U.S.-Acquired Targets in Year *t* after Acquisition

Difference in Differences Combined with Kernel Matching Estimates								
	Log Employment				Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	ICF (=1)	US (=0)	ICF (=1)
0	0.036	0.039	0.90	0.367	2,714	241	0	0
1	0.021	0.047	0.44	0.661	2,126	186	0	2
2	0.021	0.064	0.32	0.746	1,847	162	0	2
3	0.050	0.096	0.52	0.604	1,596	144	0	3
4	0.099	0.098	1.01	0.313	1,351	119	0	3
5	**0.171**	0.103	1.67	0.095	1,152	103	0	3

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.11a: Differences in Profits between DCF- and U.S.-Acquired Targets in Year *t* after Acquisition

Difference in Differences Combined with Kernel Matching Estimates								
	Profits/Asset				Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	DCF (=1)	US (=0)	DCF (=1)
0	-0.054	0.046	-1.17	0.243	3,527	84	0	0
1	-0.014	0.037	-0.37	0.713	2,727	74	0	0
2	0.055	0.049	1.12	0.262	2,430	64	0	0
3	0.003	0.035	0.10	0.920	2,173	54	0	0
4	**0.050**	0.030	1.65	0.099	1,968	47	0	0
5	**0.061**	0.034	1.78	0.075	1,774	43	0	0

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.11b: Differences in Log Sales between DCF- and U.S.-Acquired Targets in Year *t* after Acquisition

Difference in Differences Combined with Kernel Matching Estimates								
Log Sales					Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	DCF (=1)	US (=0)	DCF (=1)
0	-0.053	0.048	-1.09	0.275	3,564	84	0	0
1	**-0.202**	0.079	-2.57	0.001	2,745	74	0	0
2	**-0.279**	0.073	-3.83	0.000	2,440	64	0	0
3	**-0.233**	0.089	-2.62	0.009	2,176	55	0	0
4	**-0.289**	0.175	-1.65	0.098	1,979	47	0	0
5	-0.244	0.157	-1.55	0.121	1,778	43	0	0

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.11c: Differences in Log Employment between DCF- and U.S.-Acquired Targets in Year *t* after Acquisition

Difference in Differences Combined with Kernel Matching Estimates								
Log Employment					Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	DCF (=1)	US (=0)	DCF (=1)
0	-0.052	0.076	-0.68	0.497	2,714	61	0	0
1	**-0.178**	0.071	-2.49	0.013	2,126	51	0	0
2	-0.272	0.173	-1.57	0.117	1,847	44	0	0
3	-0.152	0.215	-0.71	0.480	1,596	38	0	0
4	0.043	0.235	0.18	0.856	1,351	30	0	0
5	-0.088	0.265	-0.33	0.739	1,152	26	0	0

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.12a: Differences in Profits between DCF- and ICF-Acquired Targets in Year *t* after Acquisition

Difference in Differences Combined with Kernel Matching Estimates								
Profits/Asset					Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	ICF (=0)	DCF (=1)	ICF (=0)	DCF (=1)
0	0.027	0.106	0.25	0.799	306	79	0	8
1	0.136	0.160	0.85	0.396	243	67	0	7
2	0.060	0.066	0.90	0.368	221	57	0	7
3	-0.061	0.051	-1.20	0.232	203	49	0	5
4	0.094	0.120	0.79	0.432	175	42	0	5
5	0.003	0.049	0.06	0.954	157	40	0	3

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.12b: Differences in Log Sales between DCF- and ICF-Acquired Targets in Year *t* after Acquisition

Difference in Differences Combined with Kernel Matching Estimates								
Log Sales					Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	ICF (=0)	DCF (=1)	ICF (=0)	DCF (=1)
0	**-0.145**	0.084	-1.73	0.083	307	76	0	8
1	-0.297	0.184	-1.61	0.107	240	67	0	7
2	**-0.531**	0.144	-3.69	0.000	219	57	0	7
3	**-0.408**	0.199	-2.05	0.040	203	50	0	5
4	**-0.497**	0.267	-1.86	0.063	176	42	0	5
5	**-0.470**	0.255	-1.85	0.065	158	40	0	3

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.12c: Differences in Log Employment between DCF- and ICF-Acquired Targets in Year t after Acquisition

Difference in Differences Combined with Kernel Matching Estimates								
Log Employment					Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	ICF (=0)	DCF (=1)	ICF (=0)	DCF (=1)
0	0.047	0.168	0.28	0.780	241	56	0	5
1	-0.169	0.168	-1.01	0.314	188	47	0	4
2	**-0.415**	0.209	-1.98	0.047	164	40	0	4
3	-0.313	0.359	-0.87	0.383	147	35	0	3
4	0.044	0.278	0.16	0.874	122	28	0	2
5	-0.332	0.371	-0.89	0.372	106	23	0	3

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.13: Matching Estimates between Foreign- and Domestically Acquired Targets in Year t after Acquisition

Difference in Differences Combined with Kernel Matching for Foreign (=1) and U.S. (=0)						
(Bootstrapped standard errors based on reps=100 in parentheses)						
t	Profits/Assets		Log Sales		Log Employment	
0	-0.013	(0.027)	**0.088**	(0.040)	0.004	(0.041)
1	-0.024	(0.043)	0.037	(0.077)	-0.052	(0.070)
2	0.029	(0.031)	-0.009	(0.095)	-0.121	(0.086)
3	**0.093**	(0.032)	0.019	(0.109)	-0.129	(0.136)
4	0.070	(0.055)	0.057	(0.102)	-0.079	(0.111)
5	**0.078**	(0.033)	0.111	(0.122)	0.030	(0.133)

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.14: Matching Estimates between Failed U.S. Deals and Failed ICF Deals

Difference in Differences Combined with Kernel Matching for Failed ICF (=1) and Failed U.S. (=0)						
(Bootstrapped standard errors based on reps=100 in parentheses)						
t	Profits/Assets		Log Sales		Log Employment	
0	-0.011	(0.012)	0.026	(0.025)	0.048	(0.024)
1	0.023	(0.018)	0.018	(0.039)	0.058	(0.039)
2	0.008	(0.012)	0.029	(0.053)	0.081	(0.059)
3	0.005	(0.013)	0.068	(0.063)	0.063	(0.060)
4	-0.006	(0.011)	0.069	(0.071)	0.034	(0.074)
5	-0.016	(0.012)	0.011	(0.078)	-0.023	(0.076)

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: The standard errors are bootstrapped using 100 repetitions.

Table 2.15: Simple Difference-in-Differences Estimates without Matching

ICF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	**-0.081**	(0.043)	**-0.258**	(0.135)	**-0.290**	(0.135)
1	**-0.073**	(0.033)	**-0.371**	(0.145)	**-0.299**	(0.145)
2	-0.034	(0.034)	**-0.431**	(0.149)	**-0.396**	(0.149)
3	-0.014	(0.034)	**-0.429**	(0.153)	**-0.371**	(0.153)
4	-0.060	(0.037)	**-0.302**	(0.162)	**-0.351**	(0.162)
5	-0.020	(0.037)	-0.248	(0.171)	-0.249	(0.171)
DCF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.007	(0.090)	-0.212	(0.280)	-0.116	(0.307)
1	0.103	(0.068)	-0.265	(0.290)	-0.160	(0.323)
2	**0.126**	(0.072)	**-0.513**	(0.300)	**-0.567**	(0.337)
3	0.090	(0.073)	**-0.641**	(0.313)	**-0.819**	(0.355)
4	**0.137**	(0.077)	**-0.841**	(0.328)	**-0.741**	(0.370)
5	**0.154**	(0.078)	**-0.855**	(0.343)	**-0.669**	(0.393)

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: Values in bold have at least a 5% level of significance.

Table 2.16: Matching Estimates for Horizontal Deals

Difference in Differences Combined with Kernel Matching						
ICF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	**0.050**	(0.025)	**0.241**	(0.085)	**0.087**	(0.053)
1	**0.070**	(0.037)	**0.403**	(0.138)	**0.167**	(0.093)
2	0.429	(0.470)	**0.470**	(0.198)	0.051	(0.172)
3	0.050	(0.049)	**0.578**	(0.226)	0.036	(0.214)
4	**0.099**	(0.037)	0.173	(0.189)	0.050	(0.189)
5	0.068	(0.066)	0.148	(0.228)	0.187	(0.191)
DCF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	-0.077	(0.079)	**-0.131**	(0.078)	0.056	(0.107)
1	0.010	(0.031)	**-0.188**	(0.084)	-0.154	(0.101)
2	0.427	(0.445)	**-0.348**	(0.103)	**-0.348**	(0.183)
3	0.039	(0.042)	**-0.430**	(0.148)	**-0.353**	(0.191)
4	0.049	(0.065)	**-0.436**	(0.239)	-0.464	(0.327)
5	**0.098**	(0.058)	-0.395	(0.335)	**-0.673**	(0.311)
DCF (=1) and ICF (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	-0.124	(0.093)	**-0.342**	(0.119)	-0.086	(0.121)
1	-0.070	(0.048)	**-0.540**	(0.176)	**-0.386**	(0.169)
2	0.146	(0.119)	**-0.605**	(0.249)	-0.276	(0.440)
3	0.043	(0.064)	**-0.660**	(0.280)	-0.132	(0.604)
4	-0.108	(0.097)	-0.042	(0.449)	-0.050	(0.613)
5	0.058	(0.138)	-0.131	(0.539)	**-0.988**	(0.482)

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: Values in bold have at least a 5% level of significance.

Table 2.17: Matching Estimates for Sample without Attrition

Difference in Differences Combined with Kernel Matching						
ICF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	**0.035**	(0.020)	**0.154**	(0.050)	**0.088**	(0.034)
1	0.033	(0.025)	**0.194**	(0.072)	**0.120**	(0.051)
2	**0.066**	(0.024)	**0.213**	(0.098)	0.102	(0.072)
3	**0.086**	(0.032)	**0.245**	(0.084)	**0.160**	(0.084)
4	**0.092**	(0.031)	**0.301**	(0.101)	**0.173**	(0.093)
5	**0.119**	(0.036)	**0.311**	(0.118)	0.155	(0.097)
DCF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	-0.033	(0.029)	-0.048	(0.069)	-0.029	(0.113)
1	-0.047	(0.044)	**-0.118**	(0.068)	-0.089	(0.142)
2	0.002	(0.031)	**-0.248**	(0.119)	-0.215	(0.161)
3	0.008	(0.036)	**-0.264**	(0.113)	-0.052	(0.198)
4	0.042	(0.035)	**-0.356**	(0.189)	-0.042	(0.272)
5	**0.073**	(0.037)	**-0.250**	(0.141)	-0.130	(0.309)
DCF (=1) and ICF (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	**-0.074**	(0.037)	**-0.132**	(0.082)	-0.103	(0.132)
1	**-0.084**	(0.046)	**-0.265**	(0.095)	-0.215	(0.149)
2	-0.009	(0.056)	**-0.455**	(0.149)	**-0.372**	(0.214)
3	-0.040	(0.046)	**-0.442**	(0.151)	-0.244	(0.286)
4	-0.035	(0.053)	**-0.622**	(0.270)	-0.293	(0.276)
5	-0.004	(0.051)	**-0.552**	(0.238)	-0.378	(0.444)

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: Values in bold have at least a 5% level of significance.

A APPENDIX

A.1 List of countries included in the sample:

(1) United States

(2) Industrial countries: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, United Kingdom

(3) Developing countries: Algeria, Argentina, Brazil, China, Costa Rica, Ecuador, Hong Kong, Indian, Indonesia, Kuwait, Malaysia, Mexico, Nigeria, Papua New Guinea, Russia, Saudi Arabia, Singapore, South Africa, South Korea, Taiwan, Thailand, Uganda, Uzbekistan, Venezuela

A.2 HMY Setup

Preferences across varieties of a differentiated product have the standard CES form, with an elasticity of substitution $\varepsilon = 1/(1-\alpha) > 1$. These preferences generate a demand function $A^i p^{-\varepsilon}$ in country i, where A^i is exogenous to the supplier. The supply side is characterized by monopolistic competition. Each variety is produced by a single firm and there is free entry into the industry. Firms produce varieties under a technology that features a constant marginal cost $(1/\tau)$ and a fixed overhead cost in terms of the unique composite factor of production (labor), which is a numeraire. The monopolistic competitive setup leads to the sales price of $p = \tau/\alpha$, which is essentially a constant markup over marginal cost. Then the demand function implies output $A^i(\tau/\alpha)^{-\varepsilon}$ and the resulting costs are $\alpha A^i(\tau/\alpha)^{1-\varepsilon}$. Finally, revenues and operating profits are the following:

$$r(\tau) = A^i(\tau/\alpha)^{1-\varepsilon}$$

$$\pi(\tau) = (1-\alpha)r(\tau) - f,$$

where f denotes fixed cost. Therefore, both sales and profits are monotonic functions of productivity τ.

A.3 Optimal Bandwidth Selection

Table A.3: Optimal Bandwidth using the Gaussian Kernel

	Outcome Variables	Optimal Bandwidth	Minimized RMSE	Min Bandwidth	Max Bandwidth	Grid Size
DCF = 1 US = 0	Profits	0.0188	0.0792	0.0002	0.2898	62
	Log Sales	0.0325	0.2360	0.0002	0.2898	62
	Log Empl	0.0562	0.2135	0.0002	0.2898	62
ICF = 1 US = 0	Profits	0.0261	0.5536	0.0002	0.3352	52
	Log Sales	0.0376	0.2354	0.0002	0.3352	52
	Log Empl	0.0936	0.2133	0.0002	0.3352	52
DCF = 1 ICF = 0	Profits	0.0138	0.1431	0.0026	0.3973	53
	Log Sales	0.0576	0.3388	0.0026	0.3973	53
	Log Empl	0.3202	0.2169	0.0026	0.3973	53

Source: Author's calculations based upon the following data sets: SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: The endpoints of the grid for bandwidth search are (Xmax-Xmin)/N and (Xmax-Xmin)/2. Each step increments the previous bandwidth by a factor of 1.1.

A.4 Matching Protocol

The idea of matching on balancing scores is to estimate $E(Y|, S = m)$ by forming a comparison group of selected participants in l that has the same distribution for the balancing score (here $P^{l|ml}(x)$) as the group of participants in m. By virtue of the property of being a balancing score, the distribution of X will also be balanced in the two samples. The estimator of $E(Y^l|, S = m)$ is the mean outcome in that selected comparison group (using the weight provided by the Gaussian kernel as specified in equation (6)). Propensity score matching estimates are robust to the functional form of the conditional expectations. The exact matching protocol is adapted from Lechner (2002) and tailored to the purpose of this paper, which employs a kernel matching procedure:

(1) Specify and estimate a multinomial logit model to obtain $[\hat{P}^{US}(x), \hat{P}^{OECD}(x), \hat{P}^{DEV}(x)]$.[28]

(2) Restrict sample to common support: for each pairwise comparison, delete all observations with probabilities larger than the smallest maximum and smaller than the largest minimum.

(3) Estimate the respective (counterfactual) expectations of the outcome variables. For a given value of m and l the following steps are performed:

(4) Choose one observation in the subsample defined by acquisition status m and delete it from that pool.

(5) Construct the conditional probabilities $\hat{P}^{l|ml}(x)$ using the predicted marginal probabilities from step (1) and place them in the weighting function to calculate Gaussian weights based on equation (6).

(6) Compute the respective conditional expectation by constructing sample means using the Gaussian weights constructed in step (5).

(7) Repeat steps 3-6 for all combinations of m and l, and compute the treatment effects.

A.5 Further Robustness Checks

A.5.1 U.S. Acquiring Firms and Foreign Affiliates

It is conceivable that U.S. firms that have foreign affiliates prior to acquiring a domestic firm are on average more productive than those without foreign affiliation. Therefore, I redo the analysis using a sample that includes U.S. acquirers that have foreign affiliation and another sample with US acquirers without foreign affiliation. The information on whether or not a U.S. firm has foreign affiliation is gathered from the Corporate Affiliations database provided by LexisNexis Business Data Group. This resource provides insight into nearly

[28] Alternatively, a multinomial probit can be used to obtain marginal probabilities. I discuss this further in the robustness check section.

200,000 parent companies, affiliates, subsidiaries, and divisions that are based in the United States and throughout the world. Given the U.S. acquiring firms in my sample, I was able to identify the affiliation information for about half of them. About half of the identified U.S. firms in my sample have foreign affiliations. Tables A.5.1a and A.5.1b display the estimates for U.S. acquirers with and without foreign affiliations, respectively. The results are similar to the estimates using the entire sample.

Table A.5.1a: Matching Estimates for Sample of U.S. Acquirers with Foreign Affiliation

Difference in Differences Combined with Kernel Matching						
ICF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.004	(0.032)	0.122	(0.036)	0.023	(0.042)
1	-0.006	(0.042)	**0.164**	(0.061)	0.026	(0.046)
2	0.028	(0.031)	**0.178**	(0.088)	0.022	(0.065)
3	**0.067**	(0.028)	**0.236**	(0.107)	0.040	(0.104)
4	0.050	(0.033)	**0.230**	(0.095)	0.059	(0.092)
5	**0.068**	(0.029)	**0.220**	(0.101)	0.103	(0.111)
DCF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	-0.063	(0.049)	-0.040	(0.051)	-0.050	(0.075)
1	-0.025	(0.044)	**-0.208**	(0.089)	**-0.166**	(0.069)
2	0.024	(0.054)	**-0.312**	(0.098)	-0.268	(0.170)
3	-0.009	(0.029)	**-0.236**	(0.094)	-0.148	(0.234)
4	0.037	(0.033)	**-0.304**	(0.189)	0.005	(0.198)
5	0.047	(0.035)	**-0.290**	(0.173)	-0.165	(0.308)

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: Values in bold have at least a 5% level of significance.

Table A.5.1b: Matching Estimates for Sample of U.S. Acquirers w/o Foreign Affiliation

Difference in Differences Combined with Kernel Matching						
ICF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.030	(0.028)	**0.142**	(0.047)	0.051	(0.041)
1	-0.015	(0.046)	**0.224**	(0.068)	0.032	(0.054)
2	0.056	(0.051)	**0.264**	(0.094)	0.010	(0.071)
3	**0.068**	(0.031)	**0.263**	(0.102)	0.064	(0.085)
4	**0.060**	(0.030)	**0.286**	(0.102)	0.106	(0.103)
5	**0.079**	(0.029)	**0.333**	(0.118)	0.166	(0.103)
DCF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	-0.047	(0.049)	-0.024	(0.058)	-0.026	(0.080)
1	-0.026	(0.039)	**-0.154**	(0.086)	**-0.155**	(0.084)
2	0.058	(0.060)	**-0.229**	(0.094)	**-0.282**	(0.148)
3	-0.007	(0.036)	**-0.220**	(0.107)	-0.137	(0.237)
4	0.042	(0.029)	-0.260	(0.185)	0.047	(0.231)
5	0.051	(0.035)	-0.198	(0.174)	-0.107	(0.315)

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: Values in bold have at least a 5% level of significance.

A.5.2 Majority and Minority Acquisitions

Among the M&A deals, some acquiring firms buy more than 50 percent of the target firm's shares and hold majority control of the target firm after the M&A deal. For both U.S. and ICF acquirers, about 40 percent of the deals result in majority control, whereas DCF acquirers obtain majority of control only 20 percent of the time. Tables A.5.2a and A.5.2b show estimates when M&A deals involve majority control and minority shares, respectively. Due to the limited number of ICF and DCF majority acquisitions, I conduct the analysis only on two combinations of comparisons (ICF vs. US and DCF vs. US). The results are not as significant as their counterparts when using the whole sample. Nonetheless, the magnitudes are similar. For the minority transactions, the results are the same as in the whole sample.

Table A.5.2a: Matching Estimates for Sample of Majority Deals

Difference in Differences Combined with Kernel Matching						
ICF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	1.294	(1.278)	**0.051**	(0.030)	0.015	(0.046)
1	3.253	(3.322)	**0.141**	(0.076)	-0.117	(0.086)
2	7.728	(5.725)	0.036	(0.142)	-0.172	(0.123)
3	0.061	(0.056)	-0.138	(0.149)	-0.312	(0.194)
4	0.254	(0.177)	-0.251	(0.228)	-0.345	(0.260)
5	0.299	(0.203)	-0.123	(0.191)	-0.142	(0.293)
DCF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.830	(1.012)	-0.257	(0.266)	-0.670	(0.562)
1	3.501	(3.172)	-0.572	(0.360)	-0.512	(0.369)
2	6.359	(5.177)	**-1.027**	(0.574)	**-0.877**	(0.193)
3	-0.121	(0.208)	**-0.665**	(0.275)	**-0.750**	(0.247)
4	0.207	(0.251)	-0.906	(0.593)	**-0.855**	(0.454)
5	0.261	(0.249)	-1.180	(0.790)	**-1.247**	(0.632)

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.
Notes: Values in bold have at least a 5% level of significance.

Table A.5.2b: Matching Estimates for Sample of Minority Deals

Difference in Differences Combined with Kernel Matching						
ICF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.051	(0.062)	**0.088**	(0.043)	0.029	(0.061)
1	-0.027	(0.048)	**0.149**	(0.074)	0.042	(0.057)
2	0.031	(0.033)	**0.226**	(0.093)	0.056	(0.092)
3	**0.079**	(0.026)	**0.290**	(0.122)	0.134	(0.121)
4	0.033	(0.029)	**0.318**	(0.099)	**0.192**	(0.107)
5	**0.071**	(0.041)	**0.339**	(0.130)	**0.264**	(0.125)
DCF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.077	(0.073)	-0.003	(0.056)	0.012	(0.067)
1	-0.028	(0.035)	**-0.151**	(0.082)	**-0.150**	(0.075)
2	0.015	(0.027)	**-0.203**	(0.084)	-0.241	(0.171)
3	0.019	(0.034)	**-0.177**	(0.107)	-0.092	(0.246)
4	0.044	(0.033)	-0.231	(0.190)	0.144	(0.222)
5	**0.059**	(0.036)	-0.131	(0.170)	0.067	(0.333)
DCF (=1) and ICF (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.152	(0.162)	-0.035	(0.074)	0.216	(0.255)
1	0.184	(0.186)	-0.083	(0.192)	-0.023	(0.255)
2	0.018	(0.040)	**-0.409**	(0.162)	-0.338	(0.284)
3	-0.045	(0.073)	-0.271	(0.262)	-0.413	(0.437)
4	0.128	(0.116)	**-0.520**	(0.279)	0.019	(0.365)
5	0.055	(0.061)	-0.363	(0.263)	-0.101	(0.488)

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: Values in bold have at least a 5% level of significance.

A.5.3 Multiple Acquisitions

Over the sample period 1979–2006, several target firms experience multiple acquisitions. In the main analysis, I record the first acquisitions in calculating the matching estimates. Table A.5.3a provides outcome results including all transactions involving each target firm. The magnitude of the estimates remains unchanged compared with those obtained from the whole sample. The estimates on profits, however, are not significant for the comparison between U.S.- and ICF-acquired firms and between U.S.- and DCF-acquired firms. In contrast, the sales estimates are robust to the alternative sample specification. Table A.5.3b contains the results with a sample that excludes target firms that receive multiple acquisitions, and they are similar to those in the whole sample.

Table A.5.3a: Matching Estimates for Sample including Multiple Acquisitions

Difference in Differences Combined with Kernel Matching						
ICF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.127	(0.106)	**0.039**	(0.015)	0.016	(0.016)
1	0.136	(0.132)	**0.049**	(0.025)	-0.007	(0.026)
2	0.238	(0.231)	**0.106**	(0.032)	0.025	(0.019)
3	0.005	(0.021)	**0.123**	(0.036)	0.040	(0.027)
4	0.085	(0.074)	**0.130**	(0.037)	0.031	(0.034)
5	0.177	(0.117)	**0.134**	(0.043)	0.045	(0.032)
DCF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.065	(0.092)	-0.028	(0.023)	-0.034	(0.031)
1	0.084	(0.125)	**-0.079**	(0.035)	-0.036	(0.032)
2	0.131	(0.156)	**-0.120**	(0.047)	-0.068	(0.051)
3	**-0.044**	(0.024)	**-0.140**	(0.050)	-0.086	(0.065)
4	0.037	(0.065)	**-0.143**	(0.041)	**-0.133**	(0.078)
5	0.113	(0.101)	**-0.136**	(0.052)	-0.128	(0.108)
DCF (=1) and ICF (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.012	(0.062)	-0.030	(0.031)	0.023	(0.080)
1	0.067	(0.085)	-0.073	(0.049)	0.105	(0.123)
2	0.070	(0.113)	**-0.169**	(0.048)	**-0.122**	(0.058)
3	0.041	(0.118)	**-0.166**	(0.075)	**-0.178**	(0.080)
4	-0.016	(0.050)	**-0.214**	(0.058)	-0.157	(0.106)
5	-0.048	(0.038)	**-0.203**	(0.064)	-0.159	(0.118)

Source: Author's calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: Values in bold have at least a 5% level of significance.

Table A.5.3b: Matching Estimates for Sample excluding Multiple Acquisitions

Difference in Differences Combined with Kernel Matching						
ICF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.535	(0.504)	**0.094**	(0.054)	**0.097**	(0.044)
1	0.864	(0.719)	0.123	(0.112)	-0.103	(0.166)
2	1.353	(1.252)	0.227	(0.190)	-0.021	(0.133)
3	**0.160**	(0.054)	**0.255**	(0.213)	0.142	(0.218)
4	0.066	(0.095)	**0.347**	(0.166)	0.182	(0.208)
5	**0.196**	(0.075)	**0.449**	(0.192)	**0.553**	(0.269)
DCF (=1) and U.S. (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	0.424	(0.485)	-0.138	(0.087)	-0.148	(0.146)
1	0.763	(0.703)	**-0.282**	(0.151)	**-0.331**	(0.153)
2	1.207	(1.120)	**-0.431**	(0.199)	-0.365	(0.268)
3	-0.026	(0.052)	**-0.435**	(0.167)	**-0.447**	(0.224)
4	**0.105**	(0.054)	**-0.393**	(0.202)	-0.407	(0.367)
5	0.084	(0.062)	-0.319	(0.211)	-0.440	(0.442)
DCF (=1) and ICF (=0)						
t	Profits/Assets		Log Sales		Log Employment	
0	-0.070	(0.060)	-0.191	(0.154)	-0.143	(0.137)
1	-0.024	(0.163)	-0.252	(0.351)	0.208	(0.496)
2	**-0.247**	(0.104)	-0.564	(0.443)	-0.581	(0.424)
3	**-0.332**	(0.139)	-0.018	(0.804)	-0.767	(0.700)
4	0.280	(0.306)	-0.432	(0.782)	0.432	(0.823)
5	**-0.261**	(0.148)	**-1.509**	(0.749)	0.127	(0.866)

Source: Author’s calculations based upon the following data sets:
SDC Thompson 1979–2006, Compustat North America 1979–2006.

Notes: Values in bold have at least a 5% level of significance.

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CHAPTER III

Foreign Ownership and Firm Performance: Emerging-Market Acquisitions in the United States[1]

3.1 Introduction

This paper examines the recent upsurge in foreign acquisitions of U.S. firms, specifically focusing on acquisitions made by firms located in emerging markets. Neoclassical theory predicts that, on net, capital should flow from countries that are capital-abundant to countries that are capital-scarce.[2] Yet increasingly emerging-market firms are acquiring assets in the developed world. In particular, the recent spate of cross-border acquisitions by Indian and Chinese companies is the subject of heated debate in policy circles. For example, the acquisition bid by CNOOC, the Chinese state-owned oil company, to takeover Unocal met with considerable resistance in Washington and was ultimately thwarted. This paper provides a systematic analysis of what happens to U.S. firms when emerging-market acquisitions are successfully completed. Using transaction-specific acquisition data and firm-level accounting data, the goal of this study is to determine how U.S. firms that are acquired by firms from emerging markets fare relative to their non-acquired counterparts.

[1]This chapter represents joint work with Anusha Chari and Kathryn Dominguez.

[2]According to estimates by the International Monetary Fund (IMF), the developing economies as a group had a current account surplus of $640 billion in 2007 (IMF, 2007). Because the financial counterpart to this surplus is a deficit on the financial accounts, it represents the net capital outflow to the industrial economies. Just two years earlier, in 2005, net capital flowed in the other direction (the developing economies as a group reported a gross capital inflow of $720 billion).

Evidence from developed-market foreign direct investment (FDI) flows to emerging markets suggests that foreign ownership is associated with improvements in plant productivity (Aitken and Harrision, 1999, Perez-Gonzales, 2005, Arnold and Javorcik, 2005, Petkova, 2007).[3] The sources of productivity gains are generally attributed to the ability of foreign multinationals to transfer superior technology, bring organizational capital and provide access to international capital markets (Caves, 1996). In the case of recent emerging-market acquisitions, while the role of sovereign wealth funds and the build-up of U.S. dollar reserves in emerging-markets are seen as motivations for acquisitions in developed-markets, the productivity-improving role of technology transfers from emerging- to developed-markets are not obvious.

Traditional theories of FDI also rely on comparative input costs or market access as the motivating rationale for investment flows from developed to emerging markets. Whereas industrial country acquirers often seek lower labor costs in emerging-markets, emerging-market acquirers may relocate (or insource) manufacturing activity while keeping existing distribution networks in the host country of the acquired business. These differences in motivation for FDI may, in turn, suggest that the post-acquisition performance of target firms will be influenced by the country of origin of the acquiring firm.

The most common motivations for overseas expansions by emerging-market firms include: 1) entering new markets, 2) obtaining natural resources, and 3) acquiring advanced technology and related brand equity.[4] An example which highlights these factors is Lenovo's 2004 purchase of IBM's personal computer business. This acquisition involved entry into the U.S. market, acquisition of technology, and of an established brand.[5] Even unsuccessful acquisitions, such as CNOOC's bid for Unocal, point to emerging market demand for natural resources.

[3] FDI includes "Greenfield" investment in new assets in a foreign country, and acquisition of pre-existing foreign assets (also termed "Brownfield" investment).

[4] See reports by Citigroup (2005) and Boston Consulting Group (2005).

[5] Lenovo had the right to use the IBM brand for five years, but actually dropped it after three years, apparently because its own brand name was already so well established.

The transaction-specific data on cross-border Mergers and Acquisitions (M&As) used in this paper come from the Thompson Financial SDC Platinum database that records all M&As involving U.S. firms that were announced between January 1, 1980 and July 1, 2007. We focus on publicly traded U.S. targets both because open financial markets in the U.S. have led to a substantial number of cross-border M&As, and because public U.S. firms are required to disclose detailed accounting data. It is also worth noting that Forbes (2008) finds evidence that foreigners hold greater shares of their investment portfolios in the United States if they have less developed financial markets, suggesting that our focus on FDI by emerging market firms may provide insights into the implications of broader investment trends into the U.S.

The work that follows complements the existing literature on post-acquisition firm performance. The focus on acquisitions made by emerging country firms allows us to test the general applicability of theories of FDI flows for firms in apparently capital scarce markets.

To evaluate the impact of emerging-country acquisitions on U.S. firm performance we examine both stock market and accounting measures. The stock market measure, abnormal announcement returns, provides a forward-looking estimate of expected shareholder value creation. After the acquisition has taken place accounting measures of profitability, investment, sales and employment allow us to evaluate the ex post performance of U.S. targets.

The first empirical challenge we face in estimating post-acquisition performance is one of causality versus selection. Are emerging-market firms simply picking certain types of acquisition targets or do foreign acquisitions change target-firm performance? There is some evidence in the literature of how acquirers select targets. In particular, the Froot and Stein (1991) model shows that asymmetric information could lead foreign firms to buy U.S. firms in times when the value of the U.S. dollar is low relative to the foreign currency. They provide empirical evidence of a negative relationship between the value of the dollar and FDI flows into the U.S. using aggregate FDI data, and this relationship is also explored in Chen (2008b) using more detailed firm-level data. Harris and Ravenscraft (1990) find evidence that foreign firms prefer technology-intensive industries and Slaughter (2007) describes how U.S. states differ in their incentive packages and taxes with regards to foreign acquirers.[6] We also find evidence of selection in that emerging country firms tend to acquire public U.S. targets with relatively high levels of sales, employment and total assets.

Crucial to any comparison between pre-and post-acquisition performance of target firms is therefore the issue of selecting an appropriate expected performance benchmark in the absence of the acquisition (Andrade et. al., 2001). The fact is that some firms get acquired while others do not. Ideally, one would like to compare the performance of a firm that receives foreign investment to the performance of the firm's identical twin with no foreign investment.[7]

In this paper we ask the counterfactual question: what would have happened to those firms that did, in fact, receive foreign ownership, if they had not received it? While this exact counterfactual is not typically observable, propensity score matching, which involves selecting a "control" group of non-acquired firms closely matched to the "treatment" group of acquired firms, is one way to artificially create sets of such twins. Propensity score matching can then be combined with difference-in-differences estimates to further eliminate time-invariant and unobservable differences between the acquired and non-acquired firms.

In order to measure the performance of U.S. target firms after they are acquired, we focus on the accounting measure of operating income before depreciation, amortization and taxes (OIBD). In order to control for the relative size of the target firm, we scale OIBD

[6]At the Federal level there were few legal restrictions on FDI into the United States during the time period studied here, although more stringent laws were recently put into place in order to restrict FDI that threatens U.S. "national security"; these restrictions came into effect in 2007. See: http://www.ustreas.gov/offices/international-affairs/cfius/.

[7]An alternative question, which is explored in Chen (2008a), is whether, given that a firm is acquired, the country of origin of the acquirer matters (so that the control group is other acquired firms rather than non-acquired firms).

by total assets, thus focusing on return on assets (ROA). We also track changes in other aspects of target firm operations, such as investment, employment, and sales following the acquisition.

We find that the stock price response of target firms is positive and significant around the time of acquisition announcement. Average cumulative returns on the target stock price within a three-day window around the announcement date of the acquisition increase by 8%. This return remains significant and positive when we extend the window to ten and twenty-one business days.

Correspondingly, we find that after acquisition the performance of acquired targets tends to improve. The target firm's return on assets increases by 16% in the five years following acquisition. Further, there is strong evidence that acquiring firms undertake significant restructuring of target firms. Measures of employment, sales and plant, property and equipment in the target firms decrease in the years after acquisition.

The pattern of increasing profitability (income/assets) and declining sales is consistent with improvements in firm-efficiency following acquisition. For instance if firms shut down or get rid of unprofitable divisions, sales would go down but profits as a percent of assets would increase. Also, declining employment and net PP&E suggest downsizing of divisions to improve overall profitability as a percent of assets. Declining sales in the target firms along with the downsizing of employment are also consistent with the comparative input cost hypothesis where acquirers from emerging-markets may be in the position to exploit the low wages in their home countries by downsizing labor-intensive activities in the foreign country following the acquisition.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature. Section 3 introduces the various datasets employed in the empirical analysis. The details of the difference-in-differences propensity score matching estimator are explained in Section 4. Section 5 presents the empirical results and section 6 concludes.

3.2 Related Literature

A large empirical literature compares the productivity of foreign-owned versus domestic-owned firms. Doms and Jensen (1995) find that foreign-owned companies in the U.S. are more productive than domestic-owned ones, but are on average less productive than U.S.-owned multinational companies. A number of studies have investigated the causal link between foreign ownership and plant performance, where the target firm is usually situated in an emerging market while the acquirer firm is from a developed market.

Aitkin and Harrison (1999) conclude from a sample of Venezuelan firms that foreign ownership is correlated with productivity improvements. Using detailed plant-level information from Mexico, Perez-Gonzales (2005) finds that multinational control leads to large improvements in total factor productivity, particularly in industries that rely on technological innovations from their parent companies. Arnold and Javorcik (2005) use plant-level data from Indonesia and find that foreign ownership leads to significant improvements in productivity in the year of acquisition as well as in subsequent years. Petkova (2008) conducts a similar study using Indian plant level data and concludes that foreign owned plants only experience improvements in productivity at a three-year horizon.

In the developed-market context, a series of papers concentrating on acquisition targets in the United Kingdom, Girma et al. (Girma, 2005; Girma et al., 2006, 2007) document improvements in growth rates of firm performance following foreign acquisitions. These studies, however, do not specifically differentiate between emerging and developed country acquirers. Antkiewicz and Whalley (2006) highlight several case studies of recent completed and failed attempts by Chinese companies to acquire firms in the OECD. They suggest that the recent wave of Chinese outbound M&A is driven by the necessity to acquire access to resources, new technology and distribution networks in the target country.

Our study is also related to studies analyzing the effects of foreign and domestic M&As on firm stock market performance. Harris and Ravenscraft (1991) examine the effects of inbound U.S. FDI on shareholder wealth over the period 1970-1987 and find that target firm wealth gains are significantly higher in cross-border takeovers than in domestic acquisitions. While they do not focus on the country of origin of the acquiring firms, over their sample period, there were very few emerging-market acquisitions of U.S. firms. [8]

Healy, Palepu and Ruback (1992) analyze the operating performance for the combined firm in domestic acquisitions relative to the industry median and show that the operating cash flows of merged firms actually drop from their pre-merger level on average, but that the non-merging firms in the same industry drop considerably more. Thus, the post-merger combined operating performance improves relative to the industry benchmark. Andrade et. al (2001) use an annual cross sections methodology similar in spirit to Fama and Macbeth (1973) and find that post-merger operating margins (cash flow to sales) improve, on average, relative to industry benchmarks. Using propensity score matching, we find that the return on assets for acquired firms increases significantly relative to the matched control group of non-acquired firms.

3.3 Data Description

Our data sample contains all M&As involving U.S. firms initiated by firms in emerging markets that are announced between January 1, 1980 and July 1, 2007, and are reported by SDC Platinum, a database from Thompson Financial. The data include all public and private M&A transactions involving at least 5% ownership[9] of a target firm in the U.S.[10] SDC collates information from over 200 English and foreign language news sources, SEC filings and the filings from its international counterparts, trade publications, news wire reports, and proprietary surveys of investment banks, law firms, and other advisory firms.

[8]Edwards and Krugman (1995) provide a comprehensive empirical analysis of the growth of inward U.S. FDI from other industrial countries, focusing on economic and national security implications.

[9]The IMF and the OECD define FDI using a 10% threshold, though a broader definition of FDI is ownership of an amount of shares or voting power that allows participation in the management or control of the target firm.

[10]See Appendix B for a full list of the markets included in the database.

For each transaction, the SDC database provides the date on which the transaction was first announced as well as the date on which the transaction became effective. The database provides characteristics of the target and acquiring firms including: name, nation, industry sector, and primary North American Industry Classification System (NAICS). The database also includes transaction-specific information on percent of shares acquired, the percent of shares owned before and after the transaction is completed, the percent of shares sought by the acquiring firm, and the method of payment.

Over the sample period, SDC covered 7,996 completed M&A transactions between a foreign acquirer and a U.S. target. Out of that total number, 2,368 M&A transactions (30%) were conducted between foreign firms and publicly traded U.S. targets. The focus of the analysis in the paper is on the subsample of 480 outbound M&A transactions by emerging country firms and U.S. target firms that remain publicly traded after acquisition. Furthermore, we eliminate countries that are tax havens, e.g. Bahamas, Bermudas[11], etc. which leaves us with a sample of 259 M&A transactions. Among the remaining deals, 81 transactions involve multiple acquisitions of the same target. We only include the first of multiple acquisitions in our dataset as we are interested in what happens to a U.S. target when it is first acquired by an emerging-market firm. This trims our sample to 214 transactions. Where information is available, these observations cover M&A transactions that result in a change in majority control in the target firm as well as acquisitions of minority shares. Most of our observations include information on the method of payment, the value of the transaction, and the NAICS codes of the respective acquirer and target firms.

Data on the U.S. target firms come from Compustat and the Center for Research in Securities Prices (CRSP). Compustat reports financial statement data and CRSP contains stock return information. Information provided in SDC on our target firms allows matching across these databases. During this process, we lose observations because some of the target firms are renamed after acquisition or are delisted. The availability of data in Com-

[11] See Appendix B for a list of tax-haven markets as defined by the OECD (2008).

pustat varies significantly by year and by variable. For example, the employment variable is only reported on a voluntary basis in Compustat. Out of the original 214 transactions between emerging country acquirers and public U.S. targets in the SDC dataset, roughly 120 firms (56%) have performance variables reported in Compustat over the five years post acquisition and 175 firms (81%) have usable stock returns data in CRSP.

Table 3.1 presents information by country of origin on the number and value of acquisitions of U.S. firms. The top five emerging market countries whose firms acquired U.S. targets over the period 1980-2007 are: Hong Kong, Singapore, Mexico, South Korea, and Taiwan. Figure 3.1 displays the number of publicly traded U.S. firms that were acquired by emerging country firms by year; acquisitions occurred in each of the years in our sample. In about half of all M&As reported in SDC information is available on the value of the deal. Figure 3.2 presents this information together with the number of deals and the industry in which the target firm is located. In the figure the surface area of each bubble shows the total value of deals within each one-digit industry sector, while the location of the bubble is determined by the average value and the total number of deals within an industrial sector. The figure indicates that in about half of all transactions the target firm is in the manufacturing sector and the average value of acquisitions in the manufacturing sector is much larger than the value of acquisitions in other industries.

Tables 3.2and 3.2 display the top 10 deals by acquisition value between emerging country firms and public U.S. targets. About half of the top twenty M&A transactions are horizontal, meaning that the acquirer and the target are in the same industry. In our full sample about one sixth of the deals involve horizontal M&As and about one third of the deals involve an acquisition of 50 percent or more of the target. Finally, Table 3.3 provides average accounting information (OIBD, sales and employment) for the target firms sorted by NAICS industry.

3.4 Empirical Strategy

3.4.1 Difference-in-Differences Matching Estimation

It seems unlikely that emerging country firms acquire U.S. firms at random. As discussed in the introduction, ideally, in order to evaluate the impact of foreign ownership we would like to have information on the set of prospective firms from which the target was selected. In other words, we would like to compare the performance of a firm that receives foreign investment to the performance of the firm's identical twin (or multiple) with no foreign investment. While this sort of counterfactual is not generally observable, we use propensity score matching techniques to construct a control group of non-acquired U.S. firms that closely match the U.S. targets. A firm is "selected" into the control group if it is sufficiently similar to acquired U.S. firms on the basis of the key determinants of the acquisition decision. In other words, our goal is to find a set of control firms that are a priori equally likely to be acquired by an emerging-market firm as those firms which ultimately are acquired.

Let $A_{i,t} \in \{0,1\}$ be a dummy variable indicating whether a U.S. firm is acquired by an emerging-market firm at time t and let $y^1_{i,t+u}$ denote target firm performance u periods after the acquisition takes place, where $u \geq 0$. The performance of a matched non-acquired U.S. firm is given by $y^0_{i,t+u}$. For a given U.S. firm, we will only observe performance in one of the two states; foreign acquisition ($y^1_{i,t+u}$), or not ($y^0_{i,t+u}$). The average effect of an emerging-market firm acquisition of a U.S. target is the following:

$$E[y^1_{i,t+u} - y^0_{i,t+u}|A=1]$$
$$= E[y^1_{i,t+u}|A=1] - E[y^0_{i,t+u}|A=0] - \{E[y^0_{i,t+u}|A=1] - E[y^0_{i,t+u}|A=0]\}$$

The term in the first line is the average treatment effect on the treated (ATET), and the term in the second line in braces is a "selection" term, which is zero if the assignment to the treatment and control groups is random. Our assumption is that firms have observable characteristics, **X**, that make them attractive targets. Our approach is to match acquired and non-acquired firms on the basis of these **X**s and then calculate the treatment differential (the effect of being acquired) on each of the outcome variables of interest. The average of the differential over all acquired firms and all **X**s measures the average effect of foreign acquisition. Formally, Angrist and Krueger (2000) show that effect of the treatment on the treated is given by

$E[y^1_{i,t+u} - y^0_{i,t+u}|A=1] = E\{E[y^1_{i,t+u}|X,A=1] - E[y^0_{i,t+u}|X,A=0]|A=1\} = E[\Delta_x|A=1]$, where $\Delta_x = E[y^1_{i,t+u}|X,A=1] - E[y^0_{i,t+u}|X,A=0]$. The underlying assumption is that all the firms (whether acquired or not) have the same expected performance under domestic ownership. This is referred to as the conditional independence assumption (CIA):

$E[y^0_{i,t+u}|X,A=1] = E[y^0_{i,t+u}|X,A=0] = E[y^0_{i,t+u}|X]$.

For the CIA to be satisfied, the vector **X** should contain all variables that affect both acquisition and performance outcomes. The choice of variables included in **X** is described in more detail below. Another assumption required for matching is that it is not possible to predict the probability of a foreign acquisition perfectly, i.e. $0 < Pr(A=1|X) < 1$.

Matching on a vector of variables is difficult since it requires weighting differences in one dimension against another. Rosenbaum and Rubin (1983) provide a solution to this dimensionality problem by matching firms on propensity scores, which in our context is the conditional probability of being acquired by an emerging county firm given **X**:

$P_i = Pr(A_{i,t} = A(X_{i,t-1}))$.

This matching technique allows us to take into account differences in observable characteristics across the firms in our database. We then combine matching with difference-in-differences analysis to eliminate the differences between the acquired and control firms that are unobservable and time invariant.

Rather than treating each of our firms linearly and with the same weight, our difference-in-differences estimator paired with propensity score matching allows us to include only acquired firms within the common support and picks control firms according to the metric function specific to the matching method. We limit the common support to only contain those treated firms that do not lie above the maximum or below the minimum propensity score for the matched control group. Similarly, matched control group firms that lie above the maximum or below the minimum propensity score for the treated firms are also dropped from the analysis.

In our analysis, we use the Mahanalobis distance metric, which allows us to confine the matching between the acquired and control firms to the same 2-digit industry. Mahanalobis metric matching by itself uses the observable covariates directly, by minimizing a distance defined for covariate values $X_{1(treated)}$ and $X_{2(treated)}$ as

$$\{(X_1 - X_2)^T S_c^{-1} (X_1 - X_2)\}^{\frac{1}{2}},$$

where S_c is the control sample covariance matrix. For the combined method, all non-acquired U.S. firms within intervals surrounding each acquired firm's propensity score are identified as potential matches, and then Mahalanobis metric matching is applied to the subset of covariates, in our case 2-digit industry characteristics, to make final selections from these potential matches. Finally, the standard errors from the matching estimation are bootstrapped as suggested by Becker and Ichino (2002).

3.4.2 Evidence of Selection

In order to examine whether our assumption that firms are not randomly selected for acquisition is justified we check whether firm characteristics prior to acquisition are correlated with subsequent foreign ownership. Our test involves a regression of our various performance measures on two dummy variables. The first dummy variable indicates those U.S. firms with foreign ownership in year t. The second dummy variable is switched on three years prior to the ownership change, for those U.S. firms that were eventually foreign acquisition targets. We also control for industry, region and year fixed effects in the regression. The estimation results, presented in Table 3.4, illustrate that future foreign acquisition targets are larger in size, measured by log sales and log total assets, than non-acquired domestic firms up to three years before acquisition. Furthermore, the regression estimates indicate that acquired firms have more employees and higher debt than non-acquired firms. These systematic differences indicate that foreign investors do not choose target firms at random. Our analysis of the post acquisition performance of U.S. firms takes this selection into account.

3.4.3 Timing Issues

Unlike longitudinal matching studies, where treatment occurs uniformly at one point in time, the firms in our data set are targets of acquisition at varying times. This variation in treatment timing poses the challenge of how to assign counterfactual treatment dates to the firms that are not acquired by emerging-market firms. We follow Petkova's (2008) approach of proportional-random acquisition time assignment. We determine the fraction of the total number of acquisitions that occur in each calendar year during our sample period, and then assign the hypothetical treatment year to the firms in the control group in the same proportion as their occurrences in the acquisition group. For example, if one tenth of all acquisitions occurred in 1995 in our sample of targets, then one tenth of all firms in the control group receive the hypothetical treatment year 1995. Before assigning the date, we make sure that the control firm's year of incorporation precedes the treatment year and that the firm remains non-acquired throughout the entire span of our data.

3.4.4 Propensity Score Matching Estimation

After assigning the hypothetical foreign acquisition dates to the control firms that are not acquired (do not receive treatment) over our sample period, we need to realign the time series data for each firm. More specifically, in the year of acquisition (actual or hypothetical), we set $t = 0$, in the year following the acquisition $t = 1$, and in the year prior to the acquisition, $t = -1$, etc. The propensity score is the estimated probability of being acquired in period $t = 0$ based on firm characteristics in period $t = -1$. We estimate this probability using a probit model, where the dummy variable $A_{i,t}$ equals 1 in the year a firm is the actual target of acquisition and zero otherwise.[12]

3.4.5 Choice of Covariates

We select our control group of non-acquired firms based on a set of observable characteristics that comprise the vector $\mathbf{X}$. The control variables include factors that drive both the acquisition and performance of the firm, such as: age, size (measured by log of total assets, log of sales and log of employment), operating income, debt, cash, net income, and net property, plant, and equipment. In the estimation, the values of each of these variables are from the year prior to the actual or hypothetical acquisition year.[13] The "age" of a firm indicates the level of development of a potential target. Variables such as total assets and sales convey information about the market power of the target firm as well as its productive capacity. Operating income before depreciation (OIBD) and net income describe the profitability of the target firm. Debt and cash variables are indicators of the internal structure of the firm. Measures of property, plant and equipment gauge the physical capital stock of a firm. Lastly, we include year, region and industry dummies in the vector of control variables, where industry dummies are based on 2-digit NAIC codes and regional dummies are based on the U.S. state where the target firm is located.

[12] Alternatively, we could also assign zero to a target firm where there has been an acquisition announcement that eventually fell through. Due to the limited amount of data, however, this analysis was not feasible.

[13] In choosing the year preceding the acquisition, there arises a concern of an "Ashenfelter Dip." This term is based on the finding in Ashenfelter (1978) that in job program evaluations, participants tend to experience a temporary decline in earnings prior to enrolling in a program. In this data set of target firms, however, there is no visible decline in target firm performance in the year prior to acquisition. As a robustness check we also use variables in different years prior to acquisition, the results remain unchanged.

3.5 Results

3.5.1 Preliminary Evidence: Stock Market Reaction to Acquisition Announcements

If capital markets are semi-strong form efficient with respect to public information, stock prices will quickly adjust following an acquisition announcement, incorporating any expected value changes (Andrade et al, 2001). The two commonly used event windows are the three days immediately surrounding the acquisition announcement, and a longer window beginning several days prior to the announcement and ending at the close of the acquisition. We examine the abnormal stock return for the acquired targets around various different windows of time surrounding the announcement of the acquisition.

We calculate the mean cumulative return of the target stock price within a one, three, and twenty day window of the announcement date. We assume that stock prices follow a single factor market model. Our estimation period is 280 days before and up until 30 days preceding the event date. Using a standardized value of the cumulative abnormal return, we test the null hypothesis that the return is equal to zero.[14]

Table 3.5 displays announcement period abnormal returns for U.S. targets that are acquired by emerging country firms. The announcement period cumulative abnormal return over the three-day window is 8.9% for 175 completed acquisitions. When the event window is expanded to three days prior to the acquisition announcement and ending three days after the announcement, the mean abnormal return is essentially identical. Over an even longer window of twenty days, the mean abnormal return increases to 9.7%. In comparison to domestic U.S. M&As, where target firms' average three-day abnormal return is around 16% for the three-day window and rises to 24% over the longer event window of 20 days (Andrade et al. (2001)), acquisitions of U.S. targets by emerging-country firms tend to have lower abnormal returns.

[14] In future work we plan to also compare target firm returns to both their matched control firm returns and their industry average return on the announcement date.

3.5.2 Propensity Score Matching Estimates

Our approach to constructing an appropriate comparison group of non-acquired firms involves a two-step matching process. The first step, a probit regression, estimates the probability of foreign acquisition based on past values of various measures of firm performance (age, OIBD, cash, sales, assets, employment, debt, income) as well as state, year and industry fixed effects. The results of the probit indicate that firms with more cash, and those firms located in certain states and from specific industries are more likely to be acquired. We impose a common support by dropping treatment observations (firms that are acquired) whose propensity score is higher than the maximum or less than the minimum propensity score of the firms that are not acquired. The second step involves using the Mahalanobis distance metric to select firms for the control group that are within the same 2-digit industry as the acquired firms.

Figure 3.3 provides an illustration of the effects of our two-step Mahalanobis matching approach. The three densities plotted in the figure depict the predicted probability, i.e. propensity score, of acquisition for the acquired firms (red), the non-matched and non-acquired firms (blue), and the Mahalanobis metric matched non-acquired firms (green). The Mahanalobis matching estimator performs extremely well as evidenced by the proximity between the density of the acquired firms and that of the Mahanalobis matched non-acquired firms.[15] In terms of our two step process, if we did not "select" our control group, this group would include all U.S. firms that are not acquired (the blue line). Our two-step matching involves constructing an appropriate counterfactual for each acquired firm given the set of observable covariates available for the firms. The propensity score provides a summary index of all the covariates combined, so that matching essentially brings the group of control firms closer to the acquired firms on all available dimensions.

[15] We also try alternative matching estimators, such as kernel matching and propensity score reweighting. The difficulty with kernel matching is the selection of an appropriate bandwidth parameter. Although the point estimates based on propensity score reweighting are similar to our Mahalanobis results, the properties of the standard errors from propensity score reweighting are less clear.

The density plot in Figure 3.3 reveals that among the non-acquired firms a large proportion have almost zero probability of being acquired. A simple difference-in-difference estimator would treat these firms the same as those non-acquired firms that are more likely to be acquired. The Mahanalobis matching estimator, in contrast, only selects firms that are similar to the acquired firms both in terms of propensity score as well as in industry. In other words, propensity score matching in this context ensures that our comparisons involve firms that are very similar prior to acquisition. One could argue that this approach biases against finding differences in post acquisition performance (given that the firms are so similar prior to acquisition), but it also ensures that our tests will not simply be picking up differences in acquired and non-acquired firm performance that are unrelated to acquisition.

3.5.3 Balancing Test

One way to assess the performance of our propensity score matching is to calculate the standardized differences for the covariates in our probit regression. Specifically, for each covariate, we take the average difference between the acquired firms and the matched control firms and normalize it by the pooled standard deviation of the covariate in the acquired and control group samples. Based on Rosenbaum and Rubin (1985), we calculate the following measure:

$$SDiff(X_k) = 100\frac{\frac{1}{n_1}\sum_{i\in\{A_i=1\}}[X_{ki}-\sum_{j\in\{A_j=0\}}W(P_i,P_j)X_{kj}]}{\sqrt{\frac{var_{i\in\{A_i=1\}}(X_{ki})+var_{j\in\{A_j=0\}}(X_{kj})}{2}}},$$

where n_1 is the number of acquired firms and n_0 is the number of non-acquired firms in the control group.

Table 3.6 shows that our propensity score method does a good job of matching a set of control group firms that were not acquired to the set of firms that were acquired by emerging-market firms along the dimensions of the observable covariates. The balancing test results indicate that the differences in our matched parameters are all well below 20[16] indicating that our approach is capable of grouping together relatively similar firms. In particular, the covariates log cash, log sales, log employment, and log of net property, plant and equipment before matching show significant differences in means between acquired and non-acquired firms. After matching, however, the means of the covariates between the two groups are not significantly different.

For instance, consider the firm-size characteristic as measured by log sales. The first row of coefficients for log sales compares the acquired (treated) firms with the non-acquired (control, unmatched) firms. In other words, the "unmatched control" refers to the set of firms that would have otherwise comprised the control group had we not undertaken propensity score matching. The coefficients for log sales in the first row suggest that the acquired firms are significantly larger, on average, than the unmatched set of control firms. The difference in size is statistically significant as evidenced by the t-statistic and p-values in the final two columns. The second row presents mean log sales numbers for the acquired firms along with the "matched control" firms that were not acquired. In stark contrast, the differences in log size are not significantly different across the treated and control groups when matching takes place. In fact the reduction in bias as a result of propensity score matching along the dimension of log sales is about 83%. The reduction in bias for other observable covariates ranges from 20% for the firm-age variable to 96% for the firm-cash variable.

3.5.4 Post-Acquisition Performance

Tables 3.7a-d present our difference-in-differences Mahalanobis matching results for various measures of post-acquisition firm-performance. The post-acquisition year is denoted by $t = \{0, 5\}$. The second column presents the matched coefficient estimate. Esti-

[16] A value for the standardized difference between treated and matched control mean values suggested by Rosenbaum and Rubin (1983).

mates in bold indicate statistical differences in measured post-acquisition performance for acquired and matched non-acquired firms. Common support refers to the set of firms for whom the propensity score range overlaps across control (non-acquired) and treated (acquired) firms. Off support refers to the number of treated (acquired) firms whose propensity score lay above the maximum value or below the minimum value for the control (non-acquired) firms. Note that changes in post-acquisition performance are calculated relative to year $t = -1$, prior to the acquisition.

Table 3.7a presents results for OIBD scaled by total assets, also referred to as return on assets (ROA). These estimates indicate that the ROA for acquired firms declines significantly compared to the firms in the "propensity score matched" control sample in the year of acquisition. It appears that profits continue to decline in years 1-3 following the acquisition but the decline is not statistically significant. In years four and five after the acquisitions the ROA increases significantly for acquired firms (relative to the non-acquired firms in our control group). In particular, the ROA increases by 8.3% in year four and 7.8% in year five for the acquired firms relative to the control sample and also relative to the year prior to the acquisition. The time-series pattern in the ROA numbers is consistent with restructuring in the early years following the acquisition leading to improved profitability in later years. We also conducted an F-test of joint significance that shows that the post-acquisition increase in profitability is jointly significant across the five years following the acquisition.

The advantage of our methodology is that we are able to identify the timing of the profitability improvements. Propensity score matching also requires large samples with substantial overlap between groups of the treated (acquired) and control (matched non-acquired) firms. From Table 3.7a, we see that the sample size of control firms under "common support" are an order of magnitude higher than the treated group suggesting that our estimates are measured with high precision. Moreover, the numbers under "off-support" suggest that there is substantial over lap in the treated and control samples since only two firm years of treated observations are excluded from the estimation. A caveat that remains is that while propensity score matching attempts to identify matched twins in the control group and difference-in-differences estimation accounts for time-invariant, unobservable differences across treated and matched firms, hidden bias may remain because matching only controls for observed variables to the extent that they are perfectly measured (Shadish, Cook and Campbell, 2002). Also, to the extent that there are unobservable time-varying differences in firm characteristics across the treated and control samples, we are unable to account for them. However, it is not clear what unobservable and yet time-varying firm characteristics could vary across the two samples of firms.

The results in Table 3.7b-d indicate that employment, net property, plant, and equipment (PP&E), and sales all decrease significantly for acquired firms (again, relative to matched control non-acquired firms) in the year of and the five years after the acquisition. While the decline in employment and net PP&E is significant only in the early years, the decline in sales appears to persist across the five years following the acquisition.

The pattern of increasing profitability (income/assets) and declining sales is consistent with improvements in firm-efficiency following acquisition. For instance if firms shut down or get rid of unprofitable divisions, sales would go down but profits as a percent of assets would increase. Also, declining employment and net PP&E suggest downsizing of divisions to improve overall profitability as a percent of assets.

The results of increasing profitability are also consistent with the hypothesis that foreign ownership is associated with improvements in plant productivity (Aitken and Harrision, 1999, Perez-Gonzales, 2005, Arnold and Javorcik, 2005, Petkova, 2007). Declining sales in the target firms along with the downsizing of employment are also consistent with the comparative input cost hypothesis. Acquirers from emerging-markets come from environments where labor costs are low and they may be in the position to "insource" jobs by exploiting the low wages in their home countries by downsizing labor-intensive activities in the foreign country following the acquisition. However, the U.S. target also experiences improvements in profitability with more streamlined but efficient operations following restructuring by the emerging-market acquirer.

3.5.5 Simple Difference-in-Differences Estimation

To highlight the importance of constructing an appropriate benchmark for comparison to evaluate post-acquisition performance we conduct a simple difference-in-differences estimation without propensity score matching. Here the underlying assumption is that US targets are chosen at random by emerging-market acquirers. Tables 3.8a-d present the results. From the coefficient estimates we may erroneously conclude that there is no significant difference in the post-acquisition performance between the treated (acquired) and control (non-matched non-acquired) firms. The estimates suggest that OIBD/assets, employment, net PP&E and sales are not significantly different across the two groups of firms following the acquisition. The simple difference-in-differences are essentially comparing the post-acquisition performance of targets to the performance of all non-acquired U.S. firms. If the acquired firms are bigger on average (as indicated in Table 3.4) in terms of assets, sales and employment before the acquisition, and continue to be statistically different along these dimensions after the acquisition in comparison to the sample of all non-acquired firms, simple difference-in-differences estimates would lead to the inference that emerging-market acquisitions do not significantly alter the performance or operations of the target firms.[17] However, a comparison of the target firms with a set of hypothetical twin firms in the matched control set suggest that emerging-market acquirers undertake significant restructuring of the target firms following the acquisition. The post-performance indicators from Section 3.5.4 show that the acquirers downsize unprofitable divisions, as evidenced by falling sales and employment concomitant with a significant increase in overall firm-profitability. This simple example serves to illustrate the importance of constructing a

[17] In unreported results we find that the observable characteristics (such as size and employment) that distinguish the acquired and full (unmatched) set of non-acquired firms do not change significantly three years post-acquisition.

careful benchmark from which to evaluate post-acquisition performance and the advantage of propensity score matching in this context.

3.6 Robustness Checks

SDC Platinum also provides information about acquisitions that are announced but not completed or withdrawn. Using this sample of failed transactions we can examine whether the firms that were potential acquisition targets differ from their non-acquired counterparts. If it is foreign ownership that drives the post-acquisition performance of the acquired firms, then we expect that following propensity score matching, the firms that were "potential" targets should perform similarly to the firms that are in the matched control sample but not the subject of foreign interest since the foreign acquisition was never successfully completed. Although it is not possible to test this hypothesis given the limited number of failed acquisitions, Table 3.9 provides suggestive evidence; the eighteen potential targets in our sample experience declines in employment and increases in sales in the year the M&A transaction is announced and are similar to a group of matched non-acquired firms in the years after the failed acquisitions, suggesting that post-acquisition performance of acquired firms is driven by the transfer of ownership to foreign hands. However, given the small number of failed acquisitions in our sample, more formal statistical analysis is not possible.

We also perform a number of additional robustness checks that involve dividing our sample of acquired firms into various subgroups consisting of: 1) majority and minority control acquisitions, 2) acquisitions financed solely by cash, 3) only manufacturing firms, 4) acquiring firms located in Hong Kong, Singapore, Taiwan and South Korea, and lastly, 5) firms not in the same industry as the acquiring firm. The estimates are shown in Table 3.10 (Panels A-H). The statistical significance of the results varies due to sample sizes. For example, for the group of horizontal acquisitions, in which both acquiring and target firms share the same industry, the sample size is much smaller than that for diversifying acquisitions. Thus, although the magnitudes of the estimates are similar to those of the whole sample, the statistical significance is not. Overall, the robustness checks confirm the results in the main analysis when using the full sample.

3.7 Conclusion

This paper undertakes the first systematic analysis of the performance of U.S. firms that are acquired by firms located in emerging markets. To do so, we examine both stock market and accounting based measures of firm performance following the announcement of an acquisition of a U.S. firm by an emerging-market firm. In particular, we use transaction-level M&A information along with firm-level financial statement data to examine the post-acquisition performance of publicly listed U.S. targets.

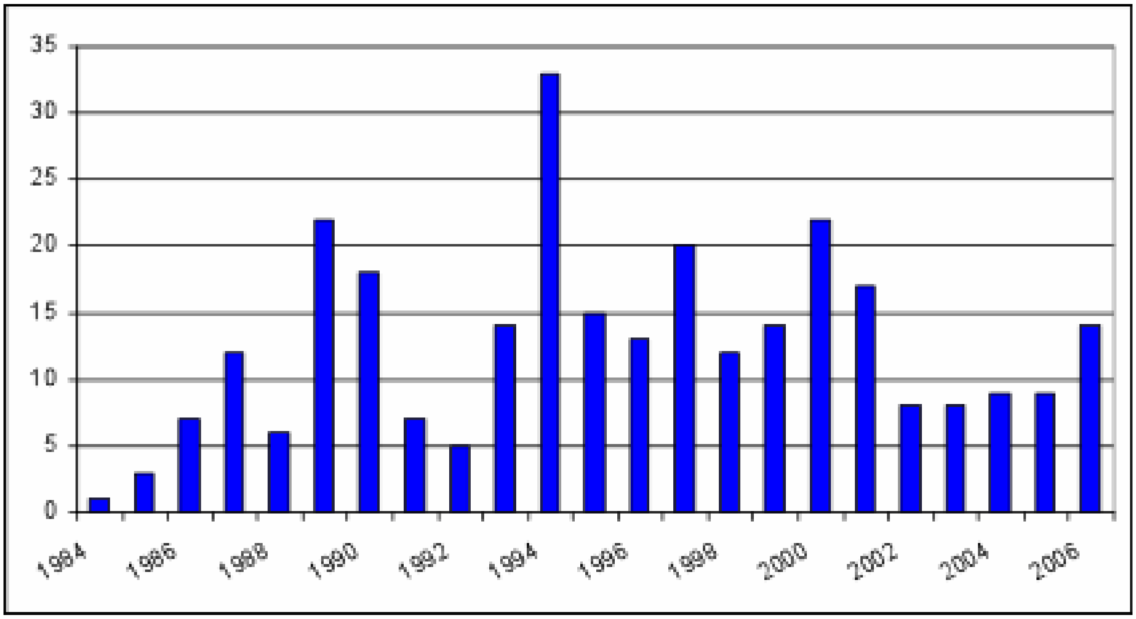
Our results suggest that emerging country firms tend to acquire public U.S. targets with relatively high levels of sales, employment and total assets. The selection of acquisition target is therefore non-random. To address the issue of selection, we employ propensity score matching to carefully construct a matched sample of control firms that were not acquired. The matching methodology is combined with difference-in-differences estimation to eliminate time-invariant unobservable firm characteristics. The stock price response of these U.S. targets is positive and significant around the time of the acquisition announcement. Following the acquisition, the performance of target firms tends to improve. In particular, the return on assets in target firms increases by 16%, on average, in the five years following the acquisition. The evidence also suggests that U.S. target firms undergo significant restructuring after acquisition by an emerging-market firm. In particular, employment and capital decrease, suggesting that divisions may be sold off or closed down. This conjecture is also supported by the fact that sales also decline after acquisition.

Our results indicate that (i) acquisitions by firms from emerging markets influence post-acquisition performance of target firms (sales and employment decline, profits rise); and

(ii) there is selection along observable characteristics based upon which emerging market firms choose acquisition targets in the U.S. (higher sales, assets, employment). In the paper we attempt to control for (ii) using propensity-score-matching and difference-in-difference estimation. There remains the possibility that selection based on time-variant unobservable characteristics (that are orthogonal to the observable characteristics used in our propensity score matching) may be driving our results. However, the evidence presented in the paper strongly indicates that emerging market firm acquisitions impact the performance of U.S. target firms. More generally, the results in the paper serve to illustrate the importance of constructing careful benchmarks from which to evaluate post-acquisition performance and the advantage of propensity score matching in this context.

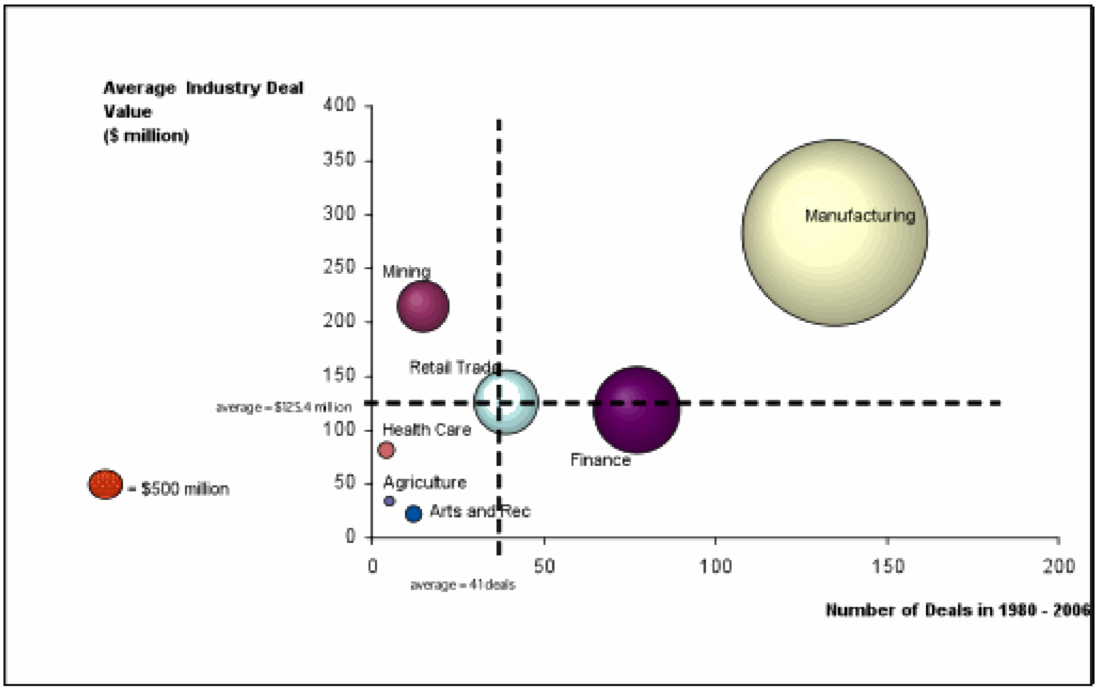
Figures and Tables

Figure 3.1: Emerging-Market Firm Acquisitions of U.S. Targets by Year



Source: SDC Thomson M&A database. This figure shows the number of acquisitions of U.S. firms by emerging-market firms in each year of our sample 1980-2007.

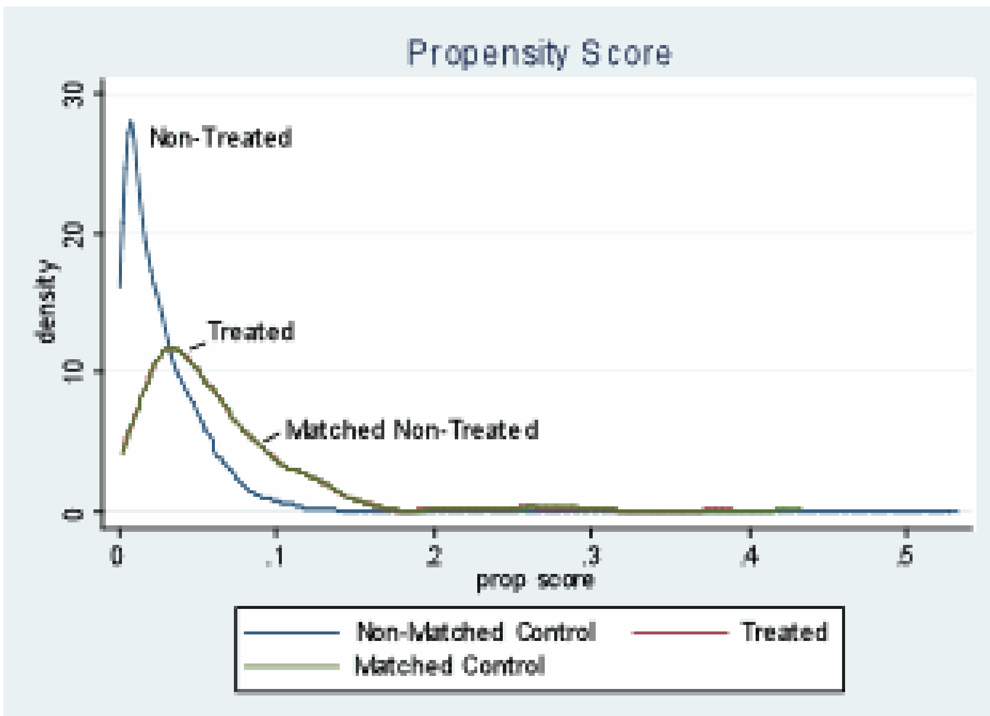
Figure 3.2: Number and Value of M&A Deals by Target Sector



Source: SDC Thompson M&A Database.

Notes: The figure presents information on the industries in which the target firms belong along with the number (horizontal axis) and average value of the transaction (vertical axis). The surface area of each bubble shows the total value of deals within each one-digit industry sector, while the location of the bubble is determined by the average value and the total number of deals within an industrial sector.

Figure 3.3: Propensity Scores for Acquired (treated), Control (matched non-treated) and non-treated and non-weighted Firms



Source: Authors' calculations based on SDC Thompson M&A Database and Compustat North America 1980 – 2006.

Notes: This figure provides an illustration of the effects of our two-step Mahalanobis matching approach. The three densities plotted in the figure depict the predicted probability, i.e. propensity score, of acquisition for the acquired firms (red), the non-weighted and non-acquired firms (blue), and the Mahalanobis metric matched non-acquired firms (green).

Table 3.1: Number and Value of Acquisitions of U.S. targets by firms in Emerging Markets, 1980-2007

Acquiring Country	Number of Transactions	% of Total Transactions	Nominal Transaction Value ($ mil)
Hong Kong	57	26.64	3309.572
Singapore	36	16.82	6412.92
Mexico	26	12.15	9346.126
Taiwan	13	6.07	731.567
Saudi Arabia	11	5.14	1463.797
South Korea	11	5.14	319.409
India	10	4.67	154.346
Russian Fed	7	3.27	932.947
Argentina	5	2.34	5035.794
China	5	2.34	44.83
Bahrain	4	1.87	1478.356
Kuwait	4	1.87	5.745
Malaysia	4	1.87	38.11
Brazil	3	1.4	4.313
Egypt	2	0.93	8.905
South Africa	2	0.93	1900.151
Thailand	2	0.93	27.12
Other	10	4.67	
Total	**214**	**100%**	

Source: SDC Thomson M&A Database.

Notes: This table provides a break down of transactions by acquiring country. The first column lists the name of the acquiring country. The second column presents the number of transactions. The third column presents the fraction of total transactions accounted for by the acquiring country. The final column presents the total nominal transaction value in millions of US$ by acquiring country.

Table 3.2: Transaction Characteristics of the Top Ten Emerging Country Firm Acquisitions of U.S. Targets, 1980-2007

Date Announced	**Target Name**	**Target Industry**	**Acquirer Name**	**Acquirer Industry**	**Percent Acquired**	**Transaction Value ($mil)**	**Acquirer Nation**	**Payment Method**
6/12/2006	Maverick Tube Corp	Mfg. steel tubular prod	Tenaris SA	Mfg. seamless steel pipe prod	100	3095.57	Argentina	Cash
9/29/2000	Southdown Inc	Mfg. cement; limestone mining	CEMEX SA DE CV	Mfg.,whl cement, ready-mix prod	100	2846.18	Mexico	Cash Liabilities
11/22/1999	DII Group	Mfg. electronic components	Flextronics International Ltd	Mfg. electn components	100	2591.41	Singapore	Common Stock
2/12/2007	Hydril Co LP	Mfg. oil,gas drilling equip	Tenaris SA	Mfg. seamless steel pipe prod	100	2212.17	Argentina	Cash
11/20/2006	Oregon Steel Mills Inc	Mfg. steel prod	Evraz Group SA	Mfg. whl steel	90.87	2087.97	Russian Fed	Cash

Notes: The table displays the top 10 deals by acquisition value between emerging country firms and public U.S. targets based on the 214 completed transactions in our sample.

Table 3.2: Transaction Characteristics of the Top Ten Emerging Country Firm Acquisitions of U.S. Targets, 1980-2007 cont.

Date Announced	Target Name	Target Industry	Acquirer Name	Acquirer Industry	Percent Acquired	Transaction Value ($mil)	Acquirer Nation	Payment Method
2/28/1995	Maxus Energy Corp	Oil and gas exploration, prodn	YPF SA	Oil and gas explo- ration,prodn	100	1843.82	Argentina	Cash Liabilities
2/10/2004	ChipPAC Inc	Mfg. semi- conductors	ST Assembly Test Services Ltd	Mfg. semi- conductor testing	100	1458.68	Singapore	Amer. Dep. Receipt
6/19/2000	United Asset Mgmt. Corp	Investment management services	Old Mutual South Africa	Insurance company	100	1456.67	South Africa	Cash
9/24/1999	ASARCO Inc	Mine, smelt, refine metals	Nueva Grupo Mexico SA de CV	Mining invt. holding co.	90.48	1073.27	Mexico	Cash
6/23/1999	VoiceStream Wireless Corp	Provide cellular services	Hutchison Whampoa Ltd	Pvd telecom svcs	6.03	957	Hong Kong	Cash

Notes, cont.: The transaction characteristics include target and acquirer names, nations and industries, the announcement date, the percent acquired, transaction value and method of payment. Source: SDC Thompson –M&A Database.

Table 3.3: Number of Acquisitions of U.S. Targets by Emerging-Market Firms & Industry Characteristics, 1980-2007

NAICS	Industry	Obs.	Firms	Acq. Firms	OIBD (mean, $mil)	Total Assets (mean, $mil)	Sales (mean, $mil)	Empl (mean, mil)
11	Agriculture	2,015	81	5	78.64	1,025.18	1,540.33	22.12
21	Natural Resources	13,486	1,287	12	61.62	483.75	296.16	1.68
22	Utilities	10,085	495	2	24.12	247.60	184.01	0.40
23	Construct.	3,733	315	1	34.46	384.54	198.72	1.90
31-33	Manufact.	92,935	7,604	118	94.72	824.18	1,000.49	6.74
42	Wholesale Trade	9,217	805	8	101.75	1,243.46	1,509.49	7.02
44-45	Retail Trade	10,802	978	16	77.87	743.30	1,475.87	7.76
48-49	Transport	6,417	576	10	251.86	2,886.27	2,441.86	14.35
51	Information	22,753	2,627	30	201.39	1,754.11	737.93	3.21
52	Finance & Insurance	30,786	4,828	20	2,244.27	65,056.48	8,545.27	18.72
53	Real Estate	6,042	531	8	5.35	147.09	41.96	0.18
54	Professional Services	10,097	1,050	6	31.94	200.14	168.12	1.07
56	Admini.Services	4,743	492	1	-1.67	20.90	17.80	0.09
62	Health Care	4,049	441	2	16.42	121.52	131.32	2.03
71	Entertainment	1,848	193	2	0.83	14.33	11.88	0.18
72	Food Services	5,245	469	10	17.36	159.18	167.09	2.59

Notes: This table presents summary statistics for U.S. target by industry from Compustat North America. The first column presents the industry code. Column 2 presents the industry description followed by the number of firm-year observations, the total number of firms in the industry and the number of firms acquired by emerging-market firms. OIBD/Assets presents the average operating income before depreciation, amortization and taxes ($ million). The last two columns present average sales ($ million) and employment (million) by industry.

Table 3.4: Evidence of Selection in the Three Years Preceding Acquisition

	Sales	Asset	OIBD	Cash	Debt	Employment
D_foreign$_t$	**0.906*** **	**0.952*** **	0.281	**0.815*** **	**0.896*** **	**0.737*** **
	(0.19)	(0.19)	(0.21)	(0.20)	(0.24)	(0.20)
D_futureacq$_t$	**0.898*** **	**0.897*** **	**0.553*** **	**0.925*** **	**0.753*** **	**0.790*** **
	(0.10)	(0.10)	(0.11)	(0.11)	(0.13)	(0.10)
Observations	236223	244249	182936	217800	197547	161948
R-squared	0.172	0.231	0.193	0.197	0.203	0.186

Notes: These regressions test whether U.S. firm performance prior to acquisition is correlated with subsequent foreign ownership. The dependent variables are sales, assets, OIBD, cash, debt and employment and the independent variables include: D_ foreign$_t$ (a dummy variable which indicates those U.S. firms with foreign ownership at time t), D_futureacq$_t$ (a dummy variable which indicates those U.S. firms that become acquisition targets of emerging-market firms three years prior to the ownership change), and industry, region and year fixed effects. The dependent variables are expressed in log terms. All significant coefficients are in bold and indicate that foreign investors do not choose target firms at random. * indicates significance at 10%; ** significant at 5%; *** significant at 1%. Standard errors are in parentheses.

Table 3.5: Cumulative Abnormal Stock Returns for Acquisition Targets

Days	Number of Obs	Mean CAR	Patell Z
(-3,+3)	175	8.87%	13.669***
(-1,+1)	175	8.53%	20.068***
(-10,+10)	175	9.71%	8.537***
(-20,+20)	175	11.13%	6.466***
(-30,+30)	175	11.44%	4.871***

Notes: The sample covers acquisitions of U.S. targets by emerging-market firms between January 1, 1980 and July 1, 2007. The day of first mention of the acquisition in SDC Thompson is taken as day '0'. Abnormal gain to the U.S. target is computed as the cumulative abnormal return based on a single factor market model. The estimation period is 280 days before and up until 30 days before the event day. The CAR is the cumulative average abnormal return and is described in detail in Section 3.5.1 of the paper. The Patell Z statistic is based on the Patell (1976) test that assumes cross-sectional independence. It is constructed by standardizing CAR by the respective standard errors. It follows a standard normal distribution under the null hypothesis.

Table 3.6: Balancing Tests

		Means				t-test	
Variable	Sample	Treated	Control	SDiff	%reduct in SDiff	t-stat	p>|t|
Age	Unmatched	24.02	23.92	0.90		0.10	0.92
	Matched	24.02	24.11	-0.70	20.10	-0.05	0.96
OIBD	Unmatched	198.92	306.99	-8.70		-0.82	0.41
	Matched	198.92	233.18	-2.80	68.30	-0.34	0.73
Log Cash	Unmatched	2.42	1.90	20.90		2.20	0.03
	Matched	2.42	2.40	0.70	96.70	0.06	0.96
Log Sales	Unmatched	5.38	4.87	22.60		2.29	0.02
	Matched	5.38	5.46	-3.70	83.50	-0.31	0.76
Log Assets	Unmatched	5.56	5.27	12.50		1.28	0.20
	Matched	5.56	5.63	-3.20	74.50	-0.26	0.79
Log Empl	Unmatched	0.52	0.15	17.50		1.89	0.06
	Matched	0.52	0.60	-3.60	79.50	-0.29	0.77
Log Debt	Unmatched	3.31	3.06	8.20		0.88	0.38
	Matched	3.31	3.72	-13.40	-63.50	-1.11	0.27
Net Income	Unmatched	0.33	73.73	-12.60		-1.07	0.29
	Matched	0.33	23.17	-3.90	68.90	-0.42	0.68
Log Net PPE	Unmatched	3.99	3.58	16.10		1.69	0.09
	Matched	3.99	4.11	-5.00	69.20	-0.40	0.69

Notes: These tests check whether our matching approach is capable of grouping together relatively similar firms. The table presents the average difference in each of the covariates between the: (1) acquired firms and the unmatched non-acquired firms, and (2) the acquired firms and the matched (reweighted) non-acquired firms. Differences are normalized by the pooled standard deviation of the covariate in the two samples.

Table 3.7: Post-Acquisition Performance Characteristics (Propensity Score Matching and Difference-in-Differences)

Notes: This table documents difference-in-difference estimates for the post-acquisition performance between acquired and "matched control" firms that were not acquired. Panels A-D report post acquisition OIBD/Assets, log employment, log net PP&E and log sales, respectively. The post-acquisition year is denoted by $t = \{0, 5\}$. The second column presents the matched coefficient estimate. Estimates in bold indicate statistical differences in measured post-acquisition performance for acquired and matched non-acquired firms. Common support refers to the set of firms for whom the propensity score range overlaps across control (non-acquired) and treated (acquired) firms. Off support refers to the number of treated (acquired) firms whose propensity score lay above the maximum value or below the minimum value for the control (non-acquired) firms.

(a) Post-Acquisition Performance (OIBD/Asset)

Difference-in-Differences combined with Mahalanobis matching estimates								
Profits/Asset					Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	DCF (=1)	US (=0)	DCF (=1)
0	**-0.058**	0.035	-1.66	0.097	4,750	126	0	0
1	-0.016	0.034	-0.47	0.638	4,203	113	0	1
2	0.015	0.059	0.26	0.793	3,788	100	0	0
3	-0.007	0.059	-0.12	0.906	3,434	84	0	1
4	**0.083**	0.040	2.04	0.041	3,060	72	0	0
5	**0.078**	0.037	2.11	0.035	2,743	68	0	0

(b) Post-Acquisition Employment

Difference-in-Differences combined with Mahalanobis matching estimates								
Employment					Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	DCF (=1)	US (=0)	DCF (=1)
0	**-0.089**	0.051	-1.74	0.081	3,063	94	0	0
1	**-0.164**	0.071	-2.30	0.021	2,683	82	0	0
2	-0.202	0.168	-1.20	0.228	2,345	74	0	0
3	-0.268	0.220	-1.22	0.223	1,897	60	0	0
4	-0.234	0.199	-1.17	0.240	1,621	50	0	0
5	-0.389	0.269	-1.44	0.148	1,397	45	0	0

Table 3.7: Post-Acquisition Performance Characteristics (Propensity Score Matching and Difference-in-Differences), cont.

(c) Post Acquisition Net PP&E

Difference-in-Differences combined with Mahalanobis matching estimates								
Net PP&E					Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	DCF (=1)	US (=0)	DCF (=1)
0	**-0.191**	0.094	-2.04	0.041	4,760	127	0	0
1	**-0.213**	0.129	-1.65	0.098	4,203	113	0	1
2	**-0.292**	0.145	-2.02	0.044	3,780	101	0	0
3	-0.158	0.176	-0.90	0.369	3,422	85	0	1
4	-0.266	0.214	-1.24	0.215	3,043	73	0	0
5	-0.415	0.259	-1.60	0.109	2,726	67	0	0

(d) Post-Acquisition Sales

Difference-in-Differences combined with Mahalanobis matching estimates								
Sales					Common Support		Off Support	
t	Matching Estimate	Bootstrapped Std. Err.	Z-Stat	P>|z|	US (=0)	DCF (=1)	US (=0)	DCF (=1)
0	**-0.104**	0.063	-1.66	0.098	4,761	126	0	0
1	**-0.215**	0.084	-2.56	0.011	4,196	113	0	1
2	**-0.283**	0.104	-2.73	0.006	3,770	101	0	0
3	**-0.239**	0.117	-2.05	0.040	3,425	85	0	1
4	-0.280	0.172	-1.63	0.104	3,048	73	0	0
5	**-0.323**	0.159	-2.03	0.042	2,737	68	0	0

Table 3.8: Post-Acquisition Performance Characteristics (Simple Difference-in-Differences)

Notes: This table documents simple difference-in-difference estimates for the post-acquisition performance between acquired and control (non-acquired) firms. Panels A-D report post acquisition OIBD/Assets, log employment, log net PP&E and log sales, respectively. The post-acquisition year is denoted by $t = \{0, 5\}$. The second column presents the simple difference-in-differences coefficient estimate. Estimates in bold indicate statistical differences in measured post-acquisition performance for acquired and non-acquired firms.

(a) Post-Acquisition Performance (OIBD/Asset)

Simple Difference-in-Differences						
t	Coefficient Estimate	Std. Err.	Z-Stat	P>|z|	Untreated	Treated
0	-0.061	0.061	-0.99	0.322	4,750	126
1	0.167	0.985	0.17	0.865	4,203	114
2	0.358	1.287	0.28	0.781	3,788	100
3	0.089	0.285	0.31	0.755	3,434	85
4	0.209	0.56	0.37	0.708	3,060	72
5	0.103	0.23	0.45	0.656	2,743	68

(b) Post-Acquisition Employment

Simple Difference-in-Differences						
t	Coefficient Estimate	Std. Err.	Z-Stat	P>|z|	Untreated	Treated
0	-0.092	0.307	-0.30	0.765	3,063	94
1	-0.070	0.321	-0.22	0.827	2,683	82
2	-0.356	0.333	-1.07	0.285	2,345	74
3	-0.587	0.361	-1.63	0.104	1,897	60
4	-0.524	0.380	-1.38	0.167	1,621	50
5	-0.335	0.392	-0.85	0.394	1,397	45

Table 3.8: Post-Acquisition Performance Characteristics (Simple Difference-in-Differences), cont.

(c) Post Acquisition Net PP&E

Simple Difference-in-Differences						
t	Coefficient Estimate	Std. Err.	Z-Stat	P>|z|	Untreated	Treated
0	-0.225	0.326	-0.69	0.489	4,760	127
1	-0.277	0.339	-0.82	0.414	4,203	114
2	-0.350	0.352	-0.99	0.320	3,780	101
3	-0.423	0.375	-1.13	0.260	3,422	86
4	-0.529	0.396	-1.33	0.182	3,043	73
5	-0.701	0.409	-1.71	0.087	2,726	67

(d) Post-Acquisition Sales

Simple Difference-in-Differences						
t	Coefficient Estimate	Std. Err.	Z-Stat	P>|z|	Untreated	Treated
0	-0.063	0.296	-0.21	0.831	4,761	126
1	-0.220	0.306	-0.72	0.473	4,196	114
2	-0.335	0.315	-1.06	0.288	3,770	101
3	-0.379	0.335	-1.13	0.258	3,425	86
4	-0.460	0.357	-1.29	0.197	3,048	73
5	-0.454	0.364	-1.25	0.213	2,737	68

Table 3.9: Failed Transactions

Target Name	Acquirer Name	Acquirer Nation	Date Announced	Date Withdrawn	Target Change in Employment	Target Change in Sales
Wits Basin Precious Minerals	Easyknit Enterprises Hldgs Ltd	Hong Kong	11/29/2006	11/1/2007	NA	NA
KDI Corp	Impala Pacific Corp (Ariadne)	Hong Kong	4/28/1986	8/21/1986	-0.538	-0.033
SSMC Inc	Berjaya Corp(Malaysia)Bhd	Malaysia	2/6/1989	3/22/1989	NA	NA
Aeronca Inc	Korean Airlines Co Ltd	South Korea	6/10/1986	10/7/1986	NA	NA
AT&T Latin America Corp	Southern Cross Latin America	Argentina	1/7/2003	9/3/2003	NA	NA
American Maize-Products Co	Usaha Tegas Sdn Bhd	Malaysia	2/27/1995	7/14/1995	NA	NA
Bear Stearns Cos Inc	Jardine Strategic Holdings Ltd	Hong Kong	9/30/1987	10/23/1987	-0.046	0.009
Cole National Corp	Moulin Intl Hldgs Ltd	Hong Kong	4/15/2004	7/25/2004	NA	0.173
CalMat Co	Investor Group	Hong Kong	10/19/1987	10/30/1987	0.220	0.402
FNB Rochester Corp,NY	Cukurova Holding AS	Turkey	5/9/1990	9/4/1990	NA	NA
Friedman Industries Inc	Investor	Venezuela	11/7/1986	5/5/1987	NA	NA
Emerson Radio Corp	Semi-Tech(Global) Co Ltd	Hong Kong	3/15/1991	4/1/1992	NA	NA
Metromedia International Group	Investor Group	UAE	10/2/2006	12/31/2006	-0.370	NA
Phoenix Medical Technology Inc	MBf International(MBF Hldg)	Hong Kong	8/8/1990	10/4/1990	NA	NA
Builders Transport Inc	TriSun Medical America Inc	China	3/19/1990	10/4/1990	NA	0.053
Tesoro Petroleum Corp	Oakville NV(Kuo Invt Ltd)	Hong Kong	5/31/1990	12/20/1990	-0.057	0.268
Unocal Corp	CNOOC	China	6/22/2005	8/2/2005	NA	0.224
Union Texas Petroleum Holdings	Chinese Petroleum Corp (CPC)	Taiwan	9/28/1990	12/19/1990	NA	NA

Notes: This table enumerates M&A transactions that were announced but failed to be completed. Columns 1-3 present the target name, acquirer name and acquirer nation. Columns 4 and 5 present the dates the transactions were announced and withdrawn. Columns 6 and 7 present the change in the announced target's change in employment and sales in the year the transaction was announced.

Table 3.10: Robustness Checks (Propensity Score Matching and Difference-in-Differences)

Notes: This table documents difference-in-differences estimates for the post-acquisition performance between acquired and matched non-acquired control firms. Each panel reports post-acquisition OIBD/Assets, log sales and log employment. t={0,5} denotes the post-acquisition year. Each column presents the Mahalanobis propensity score matched difference-in-differences coefficient estimate and bootstrapped standard errors based on reps=100 in parentheses.. Estimates in bold indicate statistical differences in measured post-acquisition performance for acquired and matched non-acquired firms.

(a) Majority Acquisitions

t	OIBD/Asset		Log Sales		Log Employment	
0	-0.309	(0.250)	-0.354	(0.184)	-0.423	(0.283)
1	0.090	(0.175)	-0.280	(0.308)	-0.167	(0.457)
2	0.325	(0.423)	-0.694	(0.483)	0.006	(0.626)
3	-0.220	(0.183)	-0.136	(0.472)	0.045	(0.691)
4	-0.166	(0.168)	-0.455	(0.787)	-0.016	(1.087)
5	-0.160	(0.171)	-0.808	(1.093)	-0.179	(1.452)

(b) Minority Acquisitions

t	OIBD/Asset		Log Sales		Log Employment	
0	-0.001	(0.024)	-0.086	(0.066)	-0.037	(0.050)
1	-0.008	(0.031)	-0.193	(0.083)	-0.116	(0.082)
2	0.012	(0.027)	-0.215	(0.114)	-0.183	(0.162)
3	0.009	(0.069)	-0.208	(0.135)	-0.232	(0.262)
4	0.099	(0.053)	-0.231	(0.183)	-0.164	(0.208)
5	0.096	(0.040)	-0.269	(0.166)	-0.304	(0.279)

(c) Cash Acquisitions

t	OIBD/Asset		Log Sales		Log Employment	
0	-0.052	(0.039)	-0.099	(0.079)	-0.101	(0.054)
1	0.009	(0.034)	-0.182	(0.092)	-0.144	(0.086)
2	0.031	(0.097)	-0.255	(0.114)	-0.161	(0.178)
3	0.008	(0.074)	-0.216	(0.144)	-0.242	(0.269)
4	0.105	(0.051)	-0.271	(0.171)	-0.249	(0.247)
5	0.090	(0.043)	-0.293	(0.183)	-0.449	(0.300)

Table 3.10: Robustness Checks (Propensity Score Matching and Difference-in-Differences), cont.

(d) Manufacturing Acquisitions

t	OIBD/Asset		Log Sales		Log Employment	
0	-0.044	(0.038)	-0.104	(0.091)	-0.045	(0.048)
1	0.005	(0.039)	-0.191	(0.126)	-0.144	(0.092)
2	0.044	(0.039)	-0.150	(0.128)	-0.296	(0.174)
3	0.084	(0.126)	-0.089	(0.153)	-0.490	(0.205)
4	0.091	(0.071)	-0.296	(0.253)	-0.464	(0.316)
5	0.069	(0.061)	-0.302	(0.278)	-0.510	(0.330)

(e) East Asian Acquirers from Hong Kong, Singapore, Taiwan and South Korea (excluding India and China)

t	OIBD/Asset		Log Sales		Log Employment	
0	-0.101	(0.065)	**-0.127**	(0.075)	**-0.148**	(0.051)
1	-0.039	(0.040)	**-0.256**	(0.087)	**-0.270**	(0.097)
2	0.016	(0.066)	**-0.311**	(0.155)	-0.292	(0.232)
3	-0.038	(0.069)	**-0.278**	(0.159)	-0.430	(0.293)
4	0.076	(0.049)	**-0.368**	(0.205)	-0.441	(0.305)
5	0.044	(0.045)	-0.390	(0.263)	**-0.580**	(0.273)

(f) East Asian Acquirers including India and China

t	OIBD/Asset		Log Sales		Log Employment	
0	-0.004	(0.028)	-0.075	(0.100)	-0.003	(0.099)
1	0.013	(0.050)	-0.163	(0.140)	-0.006	(0.118)
2	0.015	(0.047)	-0.235	(0.125)	-0.071	(0.190)
3	0.034	(0.111)	-0.189	(0.185)	0.013	(0.310)
4	0.092	(0.065)	-0.146	(0.247)	0.168	(0.417)
5	0.131	(0.079)	-0.222	(0.221)	0.082	(0.623)

Table 3.10: Robustness Checks (Propensity Score Matching and Difference-in-Differences), cont.

(g) Horizontal Acquisitions

t	OIBD/Asset		Log Sales		Log Employment	
0	-0.033	(0.063)	-0.064	(0.107)	0.008	(0.103)
1	0.029	(0.040)	-0.063	(0.193)	-0.159	(0.180)
2	0.084	(0.066)	-0.142	(0.283)	-0.501	(0.531)
3	0.082	(0.053)	-0.220	(0.289)	-0.669	(0.509)
4	0.008	(0.083)	-0.350	(0.390)	-0.569	(0.629)
5	0.029	(0.096)	-0.120	(0.519)	-0.327	(0.735)

(h) Diversifying Acquisitions

t	OIBD/Asset		Log Sales		Log Employment	
0	-0.063	(0.043)	-0.111	(0.077)	-0.105	(0.059)
1	-0.025	(0.036)	-0.244	(0.084)	-0.164	(0.081)
2	0.003	(0.067)	-0.304	(0.116)	-0.155	(0.174)
3	-0.026	(0.076)	-0.244	(0.132)	-0.187	(0.242)
4	0.096	(0.056)	-0.268	(0.170)	-0.160	(0.248)
5	0.087	(0.045)	-0.358	(0.202)	-0.400	(0.329)

(i) Diversifying and Minority Acquisitions

t	OIBD/Asset		Log Sales		Log Employment	
0	-0.027	(0.023)	-0.039	(0.060)	-0.028	(0.079)
1	-0.062	(0.032)	-0.264	(0.093)	-0.178	(0.093)
2	0.022	(0.055)	-0.206	(0.126)	-0.269	(0.150)
3	0.299	(0.273)	-0.164	(0.167)	-0.210	(0.265)
4	0.013	(0.058)	-0.275	(0.174)	-0.173	(0.231)
5	0.007	(0.079)	-0.181	(0.228)	-0.375	(0.287)

APPENDIX B

Acquiring Countries in the sample: Algeria, Argentina, Bahrain, Brazil, China, Costa Rica, Croatia, Ecuador, Egypt, Hong Kong, India, Indonesia, Kuwait, Malaysia, Mexico, Nigeria, Papua N Guinea, Russian Fed, Saudi Arabia, Singapore, South Africa, South Korea, Taiwan, Thailand, Trinidad & Tobago, Uganda, Uzbekistan, Venezuela

Tax Haven Countries (as defined by the OECD, 2008) excluded from the sample: Bahamas, Bermuda, British Virgin Islands, Cayman Islands, Cyprus, Netherlands Antilles, Panama

APPENDIX C

Steps followed in our propensity score matching methodology:

1. Run Probit regression where:

   (a) Dependent variable: Y=1, if a firm is acquired by an emerging-market firm; Y = 0, otherwise.

   (b) Choose appropriate conditioning variables, covariates which are observable firm characteristics such as age, size, profitability, financing-mix, etc.

   (c) Obtain propensity score: predicted probability (p) or log[p/(1-p)].

2. Match each acquired firm to one or more non-acquired firms based on propensity score. We use Mahalanobis metric matching in conjunction with propensity score matching to choose one non-acquired firm from multiple matches

restricted to be within the same two-digit industry as the acquired firm. Procedure:

(a) Calculate the distance between the acquired firm and all non-acquired firms in the same industry. The distance, d(i,j) can be defined by the Mahalanobis distance: d(i,j) = where X1 and X2 are propensity scores for acquired firm i and non-acquired firm j, and Sc is the sample covariance matrix of the matching variables from the full set of control group firms.

(b) The non-acquired firm, j, with the minimum distance d(i,j) is chosen as the match for acquired firm i, and both are removed from the pool.

(c) Repeat the above process until matches are found for all acquired firms.

(d) The standard errors from the matching estimation are bootstrapped following Becker and Ichino (2002).

3. Run multivariate difference-in-difference regression to eliminate time-invariant, unobservable differences between acquired (treated) and non-acquired (matched control) firms to examine post acquisition firm performance.

Appendix D

Table D.1: Details of Sample Construction

	N	Percent
Number of Transactions with a Foreign Acquirer and US Target	7,996	
Number of transactions with a Foreign Acquirer and a Public US Target	2,368	29.60%
Number of Completed Transactions with Emerging-Market Acquirer and public US Target	480	20%
Number of Transactions with Tax Haven Country* as domicile of Acquirer	221	46%
Number of Firms with Multiple Acquisitions	45	17%

Source: SDC Thompson M&A database.

*Notes: Countries are listed in Appendix B.

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CHAPTER IV

Exchange Rates and Foreign Direct Investment: The Case of Foreign Direct Investment into the United States

4.1 Introduction

Foreign direct investment (FDI) flows into the United States have been marked by substantial swings in the last two decades. Although the exchange rate has been attributed as one of the potential factors responsible for these fluctuations, theory and empirical studies have generated mixed support for a link between exchange rates and FDI. There are several channels through which the exchange rate may affect FDI. Earlier work by Froot and Stein (1991) present theoretical arguments of how currency movements alter relative wealth across countries, and they come to the conclusion that a U.S. dollar depreciation might have encouraged the inflow of foreign capital into the U.S. during the 1980s. Alternatively, Cushman (1985) offers an explanation for the link between the exchange rate and FDI that is based on the manner in which currency movements affect relative production costs.[1] With the integration of global markets, FDI flows are not only originating from industrialized countries, but increasingly also from developing countries. As evidenced in the previous two chapters, the intention and consequences of FDI from developing countries are inherently different than those originating from industrialized countries. The relative wealth levels and production costs in developing countries are different from those in industrialized countries, and if they indeed play a role in determining the relationship between FDI and the exchange rate, it is only plausible that the channels through which exchange rates and FDI are linked might also differ by the country of origin of the acquiring firm. All the previous empirical studies, except for Blonigen (1997), who focuses solely on Japanese acquisitions of U.S. assets, have relied on balance of payments data, which aggregates several types of FDI (mergers and acquisitions, greenfield investments, and new plant expansions) and do not differentiate by investor country. The models, however, make specific assumptions about the type of FDI for which a certain relationship with the exchange rate should hold. For instance, Froot and Stein explicitly state that their model is "literally applicable to small, privately owned companies" as well as "only foreign acquisitions of existing assets, and not about new capital formation initiated by foreigners" (Froot and Stein 1991). Dewenter (1995) is the first empirical study to use transaction-specific mergers and acquisitions (M&A) data in analyzing the relationship between exchange rates and FDI. Her paper tests exchange rate sensitivity from 1975–1989 across acquirer countries (only industrialized countries), buyer liquidity, and target industries. In addition to updating Dewenter (1995), this paper uses information on the type of acquirer firms, the country of origin of the acquirer, including the developing countries, as well as the payment method of the M&A deals to test the implications of the theoretical model.

The basic framework of this paper is built on the model provided in Froot and Stein (1991). Their model suggests that only credit-constrained foreign investors are affected by

[1] Another explanation of why the exchange rate and FDI are correlated involves the role of risk. Risk averse investors might seek FDI as a way to hedge against possible exchange rate volatility. In this case, however, it is the second moment or the variance of the exchange rate that is of interest, and although an interesting topic in its own right, the focus of this paper is only on the first moment of the exchange rate.

exchange rate swings. More specifically, for a set of investors that are credit-constrained, informational imperfections make external financing more costly by limiting the loans available to investors, thereby, forcing investors to use part of their own wealth to finance a project. Then assuming that all things are equal between foreign and domestic investors, a depreciation in the dollar exchange rate leads to an increase in the wealth position of foreign acquirers relative to domestic acquirers. This in turn allows the foreign entrepreneurs to bid a higher price on U.S. assets relative to domestic entrepreneurs and hence leads to higher aggregate inflow of FDI. In extending their model, I propose that the information asymmetry will differ by acquirer country of origin. In particular, the degree of financial development influences the credit-constraint across investor country which is a key factor in predicting the effects of exchange rate changes on FDI. For the empirical analysis, I use a detailed, transaction-specific data set of foreign acquisitions of U.S. target firms from 1979–2008 to update and examine prior tests of the relationship between the dollar exchange rate and FDI. These data provide investment flows for cross-border (as well as domestic) acquisitions, which make up the largest share of FDI. In addition to examining the exchange rate sensitivity across acquirer characteristics (country of origin, liquidity, and target characteristics (industry)), I also use information on the public status of acquirers, method of payment, and the level of financial development of the acquirer firm country. Furthermore, as a robustness check, this paper also looks at the relationship between the exchange rate and domestic M&A for which the models have implicit predictions.

When using the same measure of aggregate FDI as Froot and Stein for the extended period of 1979–2008, the value of the dollar is not significantly correlated with FDI. Once applying the regression to acquisition investment inflows and a bilateral exchange rate measure, however, a depreciating dollar is significantly correlated with an increase in acquisition FDI consistent with the model's prediction. Furthermore, it is also important to take into account the payment method of the deal, as it reflects whether or not a firm is credit-constrained. Lastly, when including financial development as an additional explanatory variable, the exchange rate variable still has statistical significance in explaining FDI inflows.

The paper proceeds as follows. Section 2 covers the theoretical background based on Froot and Stein. Section 3 describes the data set and provides basic summary statistics. The regression analysis and discussion of the results are in Section 4. Section 5 performs robustness checks using a different measure of FDI and alternative controls. Finally, Section 6 reviews the new findings uncovered in the empirical tests and provides insights into discrepancies between the model's predictions and the data.

4.2 The Effect of Exchange Rate Changes on Acquisition FDI

In a model with imperfect capital markets as proposed by Froot and Stein (1991), U.S. target firms are sold by auction to the highest bidder. Future target earnings are random and depend on the entrepreneurial ability of the acquirer. Investors bid the net present value (NPV) of expected target earnings, if they have sufficient cash or "wealth." If investors do not have sufficient wealth, they must borrow all or part of the purchase price. The imperfection in the capital market stems from informational asymmetries about an asset's payoffs in the sense that lenders are unable to fully observe the target firm's output. Because they must incur a monitoring cost, they will not lend the full value of the asset. Therefore, credit-constrained investors will not be able to purchase the U.S. asset solely with externally obtained funds, but have to finance it partially with their own wealth. Anything that expands investor borrowing capacity, or increases their wealth, allows them to raise their bids closer to expected NPV. To the extent that foreigners hold more of their wealth in non-dollar denominated form, a depreciation of the dollar increases the relative wealth position of foreigners and hence allows them to bring their credit-constrained bids closer to expected NPV.

Thus, the model would predict, that only for firms that are credit-constrained and subject to information asymmetry, a depreciation in the domestic exchange rate leads to an increase in acquisition FDI. Table 4.1 depicts the set of possible reservation bid prices under different scenarios of asymmetric information and credit-constraints given by the model. Only under the presence of both asymmetric information and credit-constraint is the reservation bid price dependent on both the borrowing capacity and the wealth of the firm. According to the model then, that is the only case, in which the exchange rate can influence the wealth of the foreign investor relative to that of the domestic investor. Moreover, costly state verification is more literally applicable to privately owned companies. As Froot and Stein state in their paper, public companies often issue public equity, which is inconsistent with the model.

One of the key assumptions in the model is that capital markets are fully integrated and that both domestic and foreign investors have access to the same loan opportunities that finance risky investments. Since data samples in previous studies focused solely on industrialized countries, this assumption of well-integrated financial markets might apply. Global markets, however, are generally not fully integrated, especially, in developing countries, firms have more restricted access to lenders than do firms in industrialized countries. I will make the more realistic assumption that a firm's level of credit-constraint depends on its own country's financial development. It is often harder for creditors to identify and seize assets in developing countries than in industrial countries. A potential underlying reason for this is the level of financial market development. A large literature has focused on the measurement of financial market development and its direct relation to collateral constraints.[2] It is likely that acquirers from less financially developed markets will be more credit-constrained. Then given this assumption, an acquirer from this less financially developed market has to rely more on its wealth in order to finance the investment, and the model would therefore, predict that exchange rate swings would have larger effects on their acquisition FDI decisions.

[2]See, for example, Wurgler (2000), Morck et al. (2000) and Islam and Mozumdar (2007).

Lastly, as Froot and Stein emphasize in their paper, this is only a partial equilibrium model that focuses on just one of numerous factors driving FDI. By no means are the results suggestive that the exchange rate is the only important determining variable of FDI inflows. In making the simplifying assumptions, the model provides a narrow view of the role of the exchange rate in driving foreign investments, but it does not exclude other explanations for why exchange rates would matter in determining FDI.

4.3 Data Description

The firm level data on Mergers and Acquisitions (M&A) come from a database produced by Thompson Financial Securities Data (SDC). SDC collates information from over 200 English and foreign language news sources, SEC filings and the filings from its international counterparts, trade publications, news wire reports, and proprietary surveys of investment banks, law firms, and other advisory firms. For each transaction, the SDC database provides information about the date on which the transaction was announced and the date on which the transaction became effective. The database also provides some characteristics of the target and acquiring firms such as name, nation, industry sector, and primary Standard Industry Classification (SIC) codes. Many of the transactions contain transaction-specific information such as the percent of shares acquired, the percent of shares owned before and after the transaction is completed, the percent of shares sought by the acquiring firm, and the method of payment. In particular, the following daily information is available for all deals in the world between January 1, 1979 and December 31, 2008: (i) announcement date, (ii) date the deal is effective, (iii) target and acquiring firms' names, (iv) target and acquiring firms' country of origin, (v) target and acquiring firms' industrial sector, (vi) value of deal in US dollar, (vii) form of payment(s) used in deal, e.g., cash, stocks, (viii) public status of target and acquiring firm, and (ix) percent of shares acquired.

The sample period is 1979–2008, and the data includes 30,168 daily announced transactions where a foreign firm acquired a stake in a US firm. Furthermore, out of the total announced deals, 16,514 were actually completed during the same sample period, of which 15,753 involved at least a 10% ownership change in a firm. Among those completed transactions, 8,254 cross-border deals report the transaction value. According to diGiovanni (2005), the number of deals with no values appears to be random. The main analysis is conducted using only the completed deals. As for domestic M&A activity, there are a total of 134,788 completed deals, of which 66,962 report their transaction value. By aggregating the dollar value of the acquisitions, I construct the quarterly dollar value of acquisition FDI into the United States and separately a parallel measure of domestic M&A activity. As an alternative measure of acquisition FDI, I also use the quarterly aggregate number of M&A deals.[3]

The data on FDI inflows, Gross National Product (GNP) and Consumer Price Index (CPI) come from the International Financial Statistics (IFS) from the Balance of Payment (BOP) statistics provided by the International Monetary Fund (IMF). The exchange rate measure is either the IMF real exchange rate index or the average local currency/U.S. dollar exchange rate multiplied by the ratio of the U.S. CPI to the local CPI for the bilateral real exchange rate. All exchange rate indices are set equal to 100 in 2000. An increase in the real exchange rate indicates a dollar appreciation for any of these exchange rate numbers. Figure 4.1 compares the cumulative dollar value of acquisition FDI into the United States from SDC with the IMF FDI inflows. As seen in the graph, acquisitions comprise a large share of total foreign investment into the United States; in fact, the correlation of the two time series is 0.899.[4] Table 4.2 provides the country breakdown of acquirer nations of U.S.

[3]There are both advantages and disadvantages to using the number or the value of acquisition FDI as the dependent variable. By using the number of acquisitions, each transaction is treated the same although some acquisitions might dominate in value over others. On the other hand, by using the value of the acquisition FDI, the larger transactions might overshadow the overall effects of exchange rates on FDI. In the following analysis, I will use both measures of FDI.

[4]In some quarters, the cumulative SDC value of FDI exceeds the IMF's BOP measure of FDI because SDC lists FDI values according to announcement date, while the BOP data report deals as they are completed. Hence, some of the deals in the later period might have been announced but not yet completed and thus appear in the SDC value but not the BOP.

assets. The United Kingdom and Canada have the largest shares of acquisitions in the U.S. over the entire period, with the UK's total value of acquisition exceeding Canada's value. Interestingly, emerging countries like Mexico, India and Hong Kong have increased their acquisition activities in recent years. Figure 4.2 provides a breakdown of acquirer public status. About 18 percent (2,610) of all deals are executed by private acquiring firms. To appropriately assess the validity of the Froot and Stein model, I conduct separate tests using the subset of only private acquiring firms.

It is also interesting to break down the deals by payment method. As the model implies, only firms that face a financial constraint as well as asymmetric information will be affected by the exchange rate in their bidding power. The way an acquiring firm finances the M&A is thus revealing of the wealth position of a firm. For example, if a firm holds a large amount of cash denominated in the foreign currency, then a depreciation of the dollar gives this firm's wealth position an extra boost; whereas it would not have been possible for the firm to bid up to the NPV of the target's profits before the exchange rate depreciation, it is possible to do so afterwards. Among all private acquirer firms, 34 percent (1,023) of all cross-border transactions use cash as the sole financing method. About 45 percent of the private deals involve payment methods such as issuing debt and liabilities. Table 4.3 provides a summary of cash and debt financed deals over various time periods and by foreign and domestic M&A deals. The share of each respective financing method tends to be fairly stable across time for all types of acquirers, except for the unusually high share of debt financing of domestic M&A deals during the period of 1978–1988. For the subsample of only private acquirers, however, foreign firms have increased the share of debt financed deals whereas US firms have substantially decreased debt financing over the years.

Unfortunately, the Thompson database only includes data starting in 1979, thus making it impossible to directly compare the results to those of Froot and Stein (1991) which covers the period 1973–1988. To motivate their model, Froot and Stein graphed detrended inflows of FDI into the U. S. along with a measure of the real value of the U.S. dollar for the period 1973–1988. In Figure 4.3, I plot a measure of the demeaned IMF real exchange rate index and detrended net FDI inflows measured as percent of U.S. GNP over the period 1975–2008. Note that my measure of the IMF real exchange rate index starts in 1975, which differs from that of Froot and Stein, since their measure was discontinued in February of 1992.[5] The relationship is still visually striking, despite adding another twenty years worth of data. An OLS regression of FDI against the exchange rate reveals, however, that the relationship is not statistically significant when extending the time horizon.

Lastly, measures of financial development are constructed by using the sum of banking system's claims on private sectors to GDP ratio and stock capitalization to GDP ratio. The bank claims on private sectors are from the International Financial Statistics, IMF. The stock market capitalization data are from the S&P Emerging Market Database for developing countries and the World Federation of Exchange for Advanced countries. I also consider alternative measures such as corruption and institutional indices which are strongly correlated with financial development; the measures are based on Wei (2006).

4.4 Empirical Results

Froot and Stein regress the BOP measure of FDI flows relative to the U.S. GNP against a real exchange rate index for the U.S. dollar and a time trend and find their FDI ratio to be statistically and significantly negatively correlated with the value of the dollar over the period 1973–1988. Stevens (1998) replicates Froot and Stein's empirical approach and concludes that the result is not robust for subperiods of 1973–1988 and when the period is further extended through 1991. Dewenter (1995) finds no statistical evidence for a relationship between the level of the exchange rate and foreign investment relative to domestic investment after controlling for relative corporate wealth and the overall level of investment. Her study is the first to use extensive transaction-specific FDI data over the period 1975–1989. Her dataset, however, does not allow her to differentiate between the pub-

[5] See Stevens (1998).

lic status of the acquirer firms. Dewenter also tries to control for the wealth position of a firm using a relative stock market index as a wealth proxy. More specifically, she uses a weighted average of five country stock indices relative to the United States, where the weights are based on each country's share of investment flows. The problem with this methodology is that only publicly traded acquirer firms are included in Dewenter's exercise, whereas Froot and Stein's model calls specifically for private investors. My empirical tests will extend the approaches by the previous authors by adding more years to the data and more importantly, I use the more appropriate data of only private acquisitions to test the implications of the model. Instead of using a wealth proxy, I look at the payment method to control for the wealth positions of acquiring firms. This method has the advantage that my control for wealth is firm specific.

As a first step, I examine the Spearman rank correlations, a nonparametric test that allows for a nonlinear relationship between acquisition FDI flows and the real U.S. dollar. Table 4.4 provides the Spearman correlations for quarterly aggregate, country, and industry FDI flows, both in dollar value as well as in number of deals. Interestingly, for the top ten acquiring nations of U.S. assets, the relationship between the real bilateral exchange rate and acquisition FDI varies across country. In particular, Canadian, Irish and Swedish acquisition FDI tends to be positively correlated with the value of the dollar, meaning that a stronger dollar is associated with higher levels of FDI from Canada and Sweden. The relationship across target industries seems more uniform, apart from retail trade and public administration, a stronger dollar is generally accompanied with lower inflows of FDI.

In order to investigate the cross-country relationship further, Table 4.5 provides the Spearman rank correlations between the real bilateral exchange rate and acquisition FDI for all countries in the sample. The last two columns depict the correlations for private acquisition deals. Canada and Germany are the only two countries, where the exchange rate is significantly correlated with acquisition FDI by private firms. More specifically, as the real value of the dollar appreciates, Canadian firms increase the number of acquisition FDI deals into the US, whereas German firms decrease the number of acquisition FDI deals into the US. The model's prediction is consistent with the negative relationship between the exchange rate and FDI inflow found for the German firms in the data. A closer look at the financing method of German acquisition firms reveal that out of a total 831 completed deals, 31 percent are financed with all cash, 60 percent of all deals do not reveal the method of payment, which leaves about 9 percent of the deals financed with external funds. The exchange rate and FDI relationship for Canada is not consistent with the model's prediction. A more detailed look at the Canadian deals reveals that about 30 percent of the deals involved outside finances. It is interesting to note how most developed countries, i.e. with better financial development, tend to have statistically significant relationships between the exchange rate and acquisitions FDI into the U.S., whereas most emerging markets with less developed financial markets tend to have no significant relationship between the exchange rate and FDI. A more detailed interpretation of the different exchange rate relationships across acquirer countries, types and industries will be discussed in a later section.

The next step for examining the relationship between the exchange rate and FDI is to run regressions that estimate the conditional mean of the FDI level given the exchange rate, financing method and the general level in overall investment activity. Froot and Stein regress various components of foreign capital inflows deflated by U.S. GNP on the log of the real value of the dollar and a time trend using quarterly data from 1973 to 1988. The only component that is significantly linked with the exchange rate in their study is aggregate FDI. More specifically, a depreciation in the dollar leads to a higher inflow of aggregate FDI. Instead of using the aggregate level of FDI, I first regress the absolute value of aggregate acquisition FDI on the real exchange rate index and a time trend:

$$\text{Value of Agg Acquisition FDI}_t = \beta_0 + \beta_1 FX_t + \beta_2 TREND_t, \quad (1)$$

where t is in quarterly interval, FX is the real trade-weighted U.S. dollar exchange rate index, and the *TREND* is a linear time trend.[6] Next, I conduct regressions of cross-country

[6] Alternative results with non-linear time trends were similar.

acquisition FDI on the real bilateral exchange rate and time trend:

$$\text{Value of Agg Acquisition FDI}_{it} = \beta_0 + \beta_1 BX_{it} + \beta_2 TREND_t, \text{(2)}$$

where *i* signifies the acquirer country, *t* is in quarterly interval, *BX* is the real average local currency to U.S. dollar bilateral exchange rate, and the *TREND* is a linear time trend.

As the assumptions of the model imply, however, it should specifically predict a negative relationship between the exchange rate and FDI by private and credit-constrained acquirers. Moreover, the credit-constraint can be aggravated by the financial development of the acquirer country. To address the last important points, I regress (2) with only the subsample of acquisition FDI that are initiated by private firms and where outside funds are used to finance the acquisition deal.

To control for financial institutions, I use various measures of financial development as control variables that are interacted with the exchange rate measure:

$$\text{Value of Agg Acquisition FDI}_{it} = \beta_0 + \beta_1 BX_{it} + \beta_2 FinDev_{it} + \beta_3 BX_{it} * FinDev_{it} + \beta_4 TREND_t, \text{(3)}$$

where *i* signifies the acquirer country, *t* is in quarterly interval, *BX* is the real average local currency to U.S. dollar bilateral exchange rate, *FinDev* is the financial development index of the acquiring firm country, and the *TREND* is a linear time trend.

Lastly, I use daily transaction values of the cross-border M&A deals into the U.S. and regress them on the daily bilateral exchange rate, while controlling for financing method and the private status of the target firms:

$$\text{Daily Acquisition Value}_{it} = \beta_0 + \beta_1 FX_{it} + \beta_2 PrivStat_{it} + \beta_3 FX_{it} * PrivStat_{it} + \beta_4 FinMethod_{it} + \beta_3 FX_{it} * FinMethod_{it} + \beta_4 TREND_t, \text{(4)}$$

where *i* signifies the acquirer country, *t* is in daily interval, *FX* is the real trade-weighted U.S. dollar exchange rate index, *PrivStat* is equal to one if the target firm is private, zero otherwise, *FinMethod* is equal to one if the acquiring firm financed with cash, zero otherwise, and the *TREND* is a linear time trend.

The results of regressions (1) and (2) are reported in Tables 4.6 and 4.7, respectively. Table 4.6 is essentially a replication of Froot and Stein using aggregate acquisition FDI data across country with quarterly frequency. Since SDC only started compiling the data in 1979, the closest period to Froot and Stein's analysis is the time between 1979 and 1988. The aggregated acquisition FDI is negatively correlated with the real exchange rate index at a 10 percent significance level and consequently confirms Froot and Stein's finding. The estimated coefficient can be converted into an estimated exchange rate elasticity. In particular, for the period of 1979–1988, the estimated exchange rate elasticity is -1.6.[7] This coefficient implies that a 10% increase in the exchange rate index, i.e. a 10% appreciation in the value of the U.S. dollar, corresponds to a decline in $451 million in quarterly FDI inflow for the period between 1979 and 1988. The rest of Table 4.6a's columns, however, do not support Froot and Stein's finding. The overall relationship between the exchange rate and the value of the acquisition FDI during the entire period of 1979–2008 is not significant. Using quarterly aggregated number of deals, the relationship between the exchange rate and FDI varies across time period and is not significant for the overall period of 1979–2008. This result confirms Steven's (1998) findings. Table 4.6b reports the respective regressions when only aggregating over private firm FDI deals. Again, the value of private acquisition FDI is significantly negatively correlated with the exchange rate during the period 1979–1988, the period closest to that used by Froot and Stein. Over the period 1989 to 1999, the relationship is reversed, i.e. a stronger dollar is accompanied by more inflow of acquisition FDI. The subsequent periods, however, reveal no statistically significant relationship between the exchange rate and FDI for both value and number of private acquisition FDI.

Table 4.7a shows the results using the bilateral real exchange rate and cross-country

[7] The average value of FDI for that time period = 2,821.6 and FX = 98.4, estimated exchange rate elasticity = [(0.01 x 98.4) x (-47.2)]/2,821.6 = -0.0164.

acquisition FDI, and Table 4.7b uses only private acquisition FDI. The panel regressions using real bilateral exchange rate show a significantly negative relationship, i.e. as the dollar depreciates, FDI inflow increases. The relationship between the bilateral exchange rate and acquisition FDI is statistically significant at 5% level of significance for the entire period of 1979–2008. The estimated coefficient corresponds to an estimated exchange rate elasticity of -9.6[8], which implies that a 1% appreciation in the exchange rate is accompanied by an increase in FDI inflows of $83.5 million. For private acquisitions, however, it is only statistically significant when using the number of acquisition deals, although the coefficient is substantively small.

In order to account for the level of financial development, Table 4.8 shows regression results using cross country private acquisitions on the bilateral exchange rate, a time trend and a measure of the country's level of financial development. The coefficient on the interaction term (BX*FinDev) between the exchange rate and the level of financial development is the value of interest. The coefficient on the interaction term is indeed statistically significant at 1% level of significance for the entire period of 1979–2008 for both value and number of acquisition FDI. Thus, after controlling for the financial development of the acquiring firm country, the estimated exchange rate elasticity is -8.3,[9] similar to the coefficient without controlling for financial development. The positive coefficient on the financial development index is by itself also statistically significant at the 1% level for each time period and for both measures of FDI. Not surprisingly, it indicates that better financial development in the acquirer firm country is correlated with increased inflow of FDI into the United States. Moreover, for the full period of 1979–2008, the exchange rate coefficient is also statistically significant by itself. The positive sign indicates, however, that an appreciation of the U.S. dollar is associated with an increased inflow of FDI into the U.S. This result is interesting because it reveals that including the level of financial development in

[8]The average value of FDI across all countries = 869.3 and BX = 150.3, estimated exchange rate elasticity = [(150.3) x (-0.553)]/869.3 = -0.096.

[9]The average value of FDI across all countries = 869.3 and BX = 150.3, estimated exchange rate elasticity = [(150.3) x (-0.497)]/869.3 = -0.083.

fact reverses the sign of the exchange rate coefficient. In other words, if all acquirer firm countries had the same level of financial development, an appreciation of the U.S. dollar would be associated with an increase in FDI inflows.

Lastly, Table 4.9 shows regression results based on (4) that control for the method of financing and the private status of the target firm. The regressions are generated by using daily transaction values of acquisition FDI inflows and a daily measure of the U.S. exchange rate index. The coefficients on the interaction terms are of particular interest. Over the sample period of 1979–2008, only the interaction term between the financing method and the exchange rate is statistically significantly. The significant negative correlation indicates that as the dollar depreciates, the value of M&A deals increases when a private target firm is acquired with cash financing. The estimated exchange rate elasticity for the cash-financed acquisition FDI is -0.9.[10] This estimate corresponds to an increase in daily cash-financed FDI inflow into the U.S. by $7.7 million if the exchange rate decreases by 10%. This result is not entirely in line with the predictions of the Froot and Stein model. Since cash-financing means that the acquiring firm did not obtain a loan from an outside lender, the acquirer should not have been credit-constrained in the first place. One explanation for this results might be that the SDC data contains a large portion (over 70%) of deals that are financed by cash.

4.5 Robustness Checks

In order to check the robustness of the empirical results, regressions are performed using alternative measures of acquisition FDI. One interpretation that stems from the model is that if the U.S. exchange rate were to appreciate, U.S. firms are in a position to bid higher prices than their foreign competitors, thus, the model would predict a positive relationship

[10] The average value of FDI that are cash-financed = 86.0 and FX = 92.6, estimated exchange rate elasticity = [(0.01 x 92.6) x (-0.86)]/86.0 = -0.009.

between domestic M&A activity and the value of the dollar. Alternatively, the value of FDI relative to domestic M&A activity should be negatively correlated with the U.S. real exchange rate index. Table 4.10a shows the regression results using quarterly aggregated number of acquisition FDI divided by the number of domestic M&A deals against the U.S. real exchange rate index, for all types of acquirers and for the subset of private acquirers over different time periods. Only during the earliest period (1979–1988, the period that mostly relates to Froot and Stein's study) and using all types of acquirers is the relationship between exchange rate and relative FDI significantly negative. This result does not hold for the entire period or for private acquirers. Furthermore, Table 4.10b shows that among private acquirers the payment method does not influence the relationship between the exchange rate and FDI during the overall period of 1979–2008. This result is somewhat consistent with that of Dewenter, who finds no significant relationship between the level of the exchange rate and foreign investment relative to domestic investment after controlling for relative corporate wealth and the overall level of investment. For private acquirers using cash as the financing method, however, the relationship between the exchange rate and relative FDI is significantly negative during the earliest time period.

Table 4.11 provides cross-industry regressions of acquisition FDI on the US real exchange rate index. Acquisition FDI in the manufacturing, wholesale trade and public administration sectors tend to be negatively correlated with the real exchange rate index, whereas the relationship is positive for the service industry. Lastly, as in Dewenter, I added lagged values of the real exchange rate index into the basic OLS regression with the results remaining the same as before.

4.6 Conclusion

This paper has expanded the study on the link between exchange rates and FDI by taking into account differences in acquirer country of origin. It also attempted to use a more detailed and expanded dataset to test the implications of the model proposed by Froot and Stein (1991). The basic model predicts that for credit constrained private firms, a depreciation of the dollar leads to an increase in cross-border acquisition into the U.S. Furthermore, I propose that this effect should be even more pronounced for acquiring firm countries that have low levels of financial development. The regression results confirm some of the theoretical implications. First, the relationship between the exchange rate and cross-border acquisition FDI is highly time sensitive. Froot and Stein obtained their results using the period 1973–1988, and the BOP measures of FDI seems to support their predicted relationship. As Stevens points out, however, this relationship does not hold when extending that time period. Indeed, for the period of 1979–2008, there is no statistically significant relationship between the exchange rate and acquisition FDI. The problem with the acquisition FDI data is that for almost half of the M&A deals, the value of the acquisition is not reported, thus, the aggregated value of acquisition FDI lacks precision which could underlie in the lack of significance. The aggregated number of acquisitions is a better measure, since every deal that is announced is recorded. As the paper points out, however, a more fitting way to test the data is to concentrate on private acquisition FDI data only, and in fact, the results indicate that the regression of the daily value of private acquisition FDI on the daily bilateral exchange rate yields the predicted negative relationship once controlling for the payment method and private statuses of target firms.

The level of financial development matters in predicting acquisition FDI inflow. Once controlling for that, however, the coefficient on the exchange rate is still statistically significant. This may be due to the fact that developing countries with low levels of financial development have pegged exchange rates that do not vary much over time.[11] In addition, a majority of the existing acquisitions originate from firms in industrialized countries. For many developing country firms that have only recently started to acquire U.S. assets, there is a lack of data regarding the specifics of those deals.

[11] See Reinhart and Rogoff (2004).

The main puzzling finding that is inconsistent with the model's prediction is when controlling for the wealth position of the firm, the relationship between the exchange rate and FDI is negative for cash financed deals and positive for debt financed deals. The model's prediction is that under cash financing, the acquirer firm is not using external funds, since it is not credit-constrained. With debt financing, however, the firm is using external financing and thus, the model would predict a negative relationship between the exchange rate and FDI. The reason for the different signs on the exchange rate coefficient can be manifold. One plausible explanation is that foreign acquiring firms that have a large amount of cash experience a boost in their wealth position when the U.S. dollar depreciates and hence can bid at a higher price than the U.S. domestic acquirer. The depreciation in the exchange rate in that case has made it possible for firms to forgo external financing. Froot and Stein's model implies that the wealth position is exogenous and independent of the exchange rate. The last interpretation, however, implicitly assumes that a change in the exchange rate cannot affect the credit-constraint of a firm. Future research, therefore, could venture into a variation of the model where wealth is a function of the exchange rate.

The positive relationship for the debt financed relationship is harder to interpret using the model. In fact, the model predicts a negative relationship for debt financing firms, since they rely on external funds. For debt financing firms to increase their acquisition FDI in times of a high dollar, it must be that there are unaccounted factors at play here, since the model's predictions do not yield this result. The positive relationship indicates that an appreciation of the dollar makes debt financed FDI more desirable. One way to attain this result is to modify the profit streams of the M&A in the model. So far, the profits are denoted in the domestic currency and exogenous of the exchange rate. It is plausible to think of a scenario, where foreign investors receive profits that are dependent on the exchange rate. For example, if the dollar were to appreciate, then the future stream of profits from the U.S. asset for foreign investors would increase in value as well. In light of the higher future expected profits, the lenders would be more willing to provide external funding to those foreign investors during periods of dollar appreciation. This idea is related to one of the models provided by Cushman (1985), where the relationship between the exchange rate and FDI depends on the input and revenue stream of the U.S. asset. Future research could incorporate important features of several of these models and exploit the rich firm-level data that has become available in recent years.

Figures and Tables

Figure 4.1: Comparison of Quarterly U.S. FDI Inflows

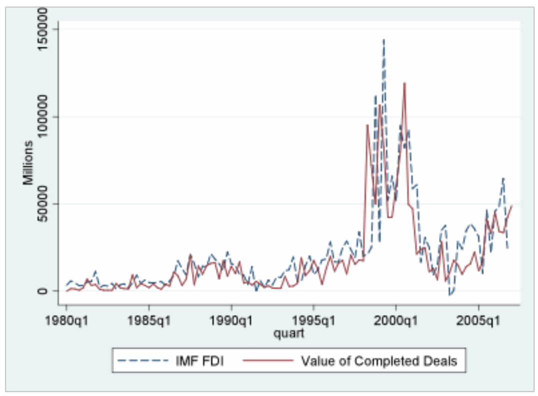

Figure 4.2: Breakdown by Acquirer Private Status

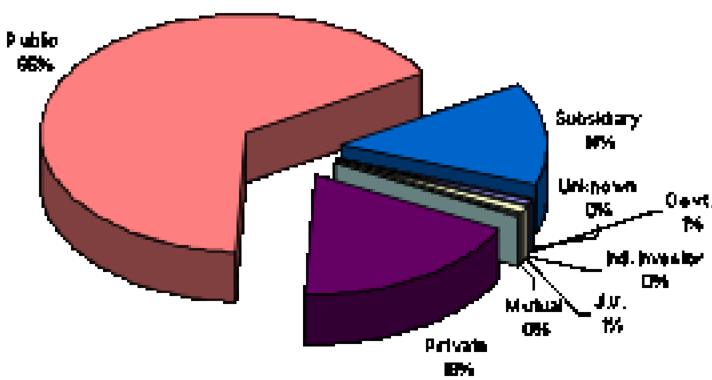

Figure 4.3: U.S. Net Foreign Direct Investment Inflows and the Real Exchange Rate

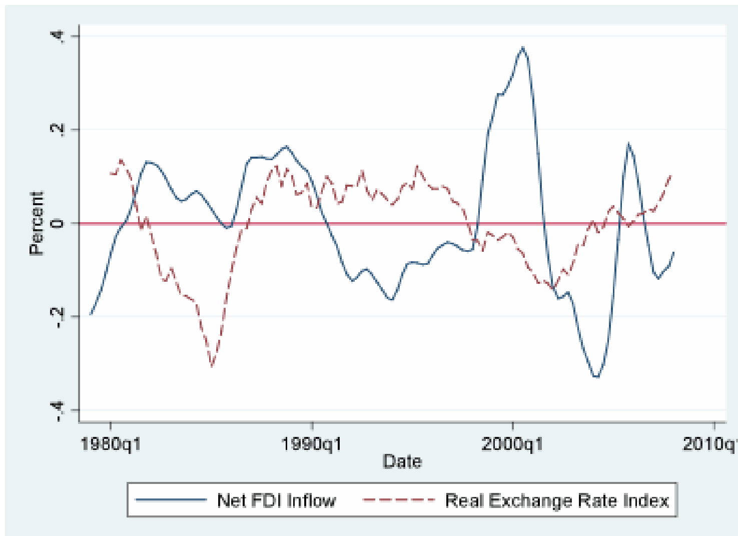

Table 4.1: Reservation Bid Price

	Financial Constraint	No Financial Constraint
Asymmetric Information	Loan + Wealth	NPV of Target Profits
No Asymmetric Information	NPV of Target Profits	NPV of Target Profits

Table 4.2: Breakdown of Acquirer Nations of U.S. Assets

Country	Total Number of Transactions	% of Total Transactions	Nominal Transaction Value ($ mil)	% of Total Transaction Value		
				1979-1988	1989-2000	2001-2008
United Kingdom	3698	24.4	559816.8	32.0	32.7	17.6
Canada	3663	24.1	278126.8	16.8	9.6	20.7
Japan	1262	8.3	100626.6	10.2	1.5	3.2
Germany	846	5.6	202824	2.8	12.2	8.1
France	774	5.1	203448.4	10.2	10	10.3
Australia	542	3.6	88142.1	8.7	2.5	6.6
Netherlands	507	3.3	130216.9	6.4	8.0	3.7
Switzerland	432	2.8	100599.3	4.3	4.3	6.4
Sweden	327	2.2	35456.5	1.1	1.5	2.4
Ireland-Rep	256	1.7	16752.1	0.8	0.7	1.1
Hong Kong	231	1.5	12783.1	1.0	0.4	0.9
Italy	197	1.3	23294.5	1.4	0.7	1.9
Israel	180	1.2	16934.5	0.0	0.3	2.1
India	180	1.2	2453.9	0.0	0.1	0.3
Belgium	173	1.1	14479.9	0.2	1.0	0.4
Singapore	161	1.1	12084.6	0.3	0.5	0.9
Finland	142	0.9	12433.9	0	0.9	0.3
Spain	132	0.9	21178.3	0.1	0.8	1.8
Mexico	113	0.7	15722.5	0.0	0.7	1.1
Other	2698	7.7	88995.9	2.8	6.8	7.3
Total	**16514**	**100**	**2016430.1**	**100**	**100**	**100**

Table 4.3: Breakdown of Financing Method

	Acquisition FDI				Domestic M&A			
	1979-1988	1989-1999	2000-2008	1979-2008	1979-1988	1989-1999	2000-2008	1979-2008
All Acquirers:								
Debt Financed	24.45%	36.05%	37.17%	35.98%	54.87%	26.88%	25.90%	27.70%
Cash Financed	34.93%	45.82%	35.65%	40.68%	23.88%	32.56%	26.24%	29.50%
Private Acquirers:								
Debt Financed	17.11%	42.07%	52.60%	44.46%	40.51%	13.64%	10.00%	14.24%
Cash Financed	26.19%	48.11%	36.46%	33.66%	36.88%	40.33%	25.77%	31.80%

Table 4.4: Spearman Rank Correlations of Quarterly FDI Flows with Real U.S. Dollar

		Value FDI	Number of FDI
A.	Aggregate flows with Exchange Rate Index	**-0.41****	**-0.50****
B.	Country Flows with real Bilateral Exchange Rate		
	United Kingdom	-0.12	**-0.28****
	Canada	**0.54****	**0.54****
	Japan	**-0.31****	**-0.51****
	Australia	0.09	0.15
	France	**-0.36****	**-0.53****
	Germany	**-0.35****	**-0.49****
	Netherlands	-0.14	**-0.30****
	Switzerland	0.07	-0.00
	Sweden	**0.25****	**0.22***
	Ireland-Rep	**0.27****	**0.48****
C.	Industry Flows with real Exchange Rate Index:		
	Manufacturing	**-0.40****	**-0.44****
	Services	**-0.42****	**-0.47****
	Finance	**-0.32****	**-0.33****
	Agriculture	-0.09	**-0.51****
	Transportation	**-0.23****	**-0.41****
	Wholesale	**-0.19****	**-0.44****
	Retail Trade	-0.17	-0.19
	Construction	-0.23*	-0.12
	Public Administration	-0.23	-0.35
D.	By Acquirer Public Status:		
	Private Acquirers with real Exchange Rate Index	**-0.42****	**-0.40****
	Public Acquirers with real Exchange Rate Index	**-0.41****	**-0.49****

Notes: * Significant at the 5% level, ** Significant at the 1% level

Table 4.5: Spearman Correlations between Acquisition FDI and Bilateral Exchange Rates

Country	Corr with Value of FDI	Corr with Number of FDI	Corr with Value of FDI by Private Firms	Corr with Number of FDI by Private Firms
Argentina	-0.16	-0.19	0.03	
Australia	0.09	0.15	0.03	0.19
Austria	-0.08	-0.19	-0.05	0.1
Belgium	-0.13	-0.12	0.24	0.35
Canada	**0.54****	**0.54****	**0.24***	**0.37****
Denmark	0.15	**0.33***	NA	-0.65
Finland	-0.14	**-0.28***	0.09	-0.1
France	**-0.36****	**-0.53****	-0.09	-0.21
Germany	**-0.35****	**-0.49****	-0.1	**-0.28****
Hong Kong	-0.01	-0.01	0.16	-0.25
India	-0.1	-0.04	0.04	0.19
Italy	-0.11	**-0.32****	**-0.10***	0.04
Japan	**-0.31****	**-0.51****	**-0.26****	-0.21
Kuwait	**-0.89****	-0.25	**-0.75***	-0.55
Malaysia	-0.29	-0.23	0.18	-0.26
Mexico	**-0.31***	**-0.24****	0.02	-0.21
Neth Antilles	0.05	-0.23	0.26	NA
Netherlands	-0.14	**-0.30****	0.18	-0.17
New Zealand	0	-0.14	-0.45	-0.71
Norway	0.1	-0.08	-0.05	0.06
Singapore	0.09	-0.18	0.09	0.09
South Africa	0.04	0.32	-0.58	-0.06
South Korea	0.06	0.11	0.02	0.14
Spain	**-0.38****	**-0.31***	0.01	-0.2
Sweden	**0.25***	**0.22***	-0.04	-0.19
Switzerland	0.07	-0.01	0.17	0.19
United Kingdom	-0.12	**-0.28****	-0.14	-0.04

Notes: * Significant at the 5% level, ** Significant at the 1% level

Table 4.6: OLS Regressions using the Real Exchange Rate Index

(a) Aggregate Acquisition FDI Measure against the Real Exchange Rate Index

	Dependent Variable:							
	Value of Acquisition FDI				Number of Acquisition FDI			
	1979-1988	1989-1999	2000-2008	1979-2008	1979-1988	1989-1999	2000-2008	1979-2008
FX	**-47.219+**	85.966	-258.662	8.952	-0.362	1.004	-4.732	-0.622
	(25.81)	(111.82)	(203.50)	(53.90)	(0.35)	(2.03)	(2.82)	(0.92)
trend	**173.642*****	142.687	-116.928	**95.286*****	**2.809*****	**2.500+**	-3.932	**2.048*****
	(27.97)	(88.76)	(160.94)	(19.40)	(0.41)	(1.25)	(2.88)	(0.33)
Obs.	34	44	36	114	34	44	36	114
R-sq.	0.546	0.114	0.203	0.143	0.602	0.157	0.397	0.166

(b) Aggregate Private Acquisition FDI Measure against the Real Exchange Rate Index

	Dependent Variable:							
	Value of Acquisition FDI by Private Firms				Number of Acquisition FDI Private Firms			
	1979-1988	1989-1999	2000-2008	1979-2008	1979-1988	1989-1999	2000-2008	1979-2008
FX	**-17.856*****	**103.456****	-109.24	-0.585	-0.205	0.587	**-4.019****	-0.554
	(4.03)	(39.55)	(64.57)	(14.65)	(0.15)	(0.96)	(1.96)	(0.59)
trend	**20.890*****	19.844	-38.521	**31.983*****	**0.751*****	**1.645****	-2.854	**1.169*****
	(4.85)	(13.70)	(49.22)	(6.13)	(0.20)	(0.73)	(1.90)	(0.24)
Obs.	33	44	36	113	33	44	36	113
R-sq.	0.643	0.384	0.116	0.238	0.406	0.154	0.369	0.137

Standard errors in parentheses are robust to heteroskedasticity and serial correlation

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

Table 4.7: OLS Regressions using Real Bilateral Exchange Rates

(a) Cross-Country Acquisition FDI against the Bilateral Real Exchange Rate

	Dependent Variable:							
	Value of Acquisition FDI by Firms				Number of Acquisition FDI Firms			
	1979-1988	1989-1999	2000-2008	1979-2008	1979-1988	1989-1999	2000-2008	1979-2008
BX	-0.206	-0.489	**-1.574****	**-0.553****	**-0.002*****	**-0.005*****	**-0.009*****	**-0.004*****
	(0.13)	(0.37)	(0.77)	(0.24)	(0.00)	(0.00)	(0.00)	(0.00)
trend	**70.398*****	**129.427*****	**-136.728****	**45.634*****	**0.138*****	0.046	-0.064	**0.040*****
	(22.37)	(35.74)	(57.60)	(10.04)	(0.04)	(0.03)	(0.06)	(0.01)
Obs.	387	960	736	2083	387	960	736	2083
R-sq.	0.031	0.017	0.013	0.014	0.045	0.032	0.016	0.026

(b) Cross-Country Private Acquisition FDI against the Bilateral Real Exchange Rate

	Dependent Variable:							
	Value of Acquisition FDI by Private Firms				Number of Acquisition FDI Private Firms			
	1979-1988	1989-1999	2000-2008	1979-2008	1979-1988	1989-1999	2000-2008	1979-2008
BX	-0.014	-0.04	-0.146	-0.043	-0.001	**-0.001****	**-0.002*****	**-0.001*****
	(0.03)	(0.04)	(0.22)	(0.05)	0.00	0.00	(0.00)	0.00
trend	**3.043****	1.027	**10.233*****	**1.842*****	-0.015	-0.006	-0.004	0.004
	(1.42)	(1.06)	(3.92)	(0.51)	(0.02)	(0.01)	(0.02)	(0.00)
Obs.	199	479	384	1062	199	479	384	1062
R-sq.	0.038	0.005	0.018	0.014	0.012	0.011	0.032	0.016

Standard errors in parentheses are robust to heteroskedasticity and serial correlation

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

Table 4.8: Cross-Country Private Acquisition FDI against Bilateral Real Exchange Rates Controlling for Financial Development

	Dependent Variable:							
	Value of Acquisition FDI by Private Firms				Count of Acquisition FDI Private Firms			
	1979-1988	1989-1999	2000-2008	1979-2008	1979-1988	1989-1999	2000-2008	1979-2008
BX	0.011	**0.617*****	-0.102	**0.417*****	0.000	0.000	-0.002	0.000
	(0.090)	(0.287)	(0.742)	(0.136)	(0.001)	(0.001)	(0.002)	(0.000)
FinDev	**209.361****	**808.591*****	**977.303*****	**766.440*****	**2.1680*****	**4.190*****	**4.573*****	**4.004*****
	(85.910)	(245.875)	(228.967)	(138.173)	(0.730)	(0.626)	(0.740)	(0.412)
BX*FinDev	-0.166	**-0.731*****	-0.966	**-0.497*****	**-0.002****	**-0.002*****	**-0.008****	**-0.002*****
	(0.105)	(0.255)	(1.470)	(0.129)	(0.001)	(0.001)	(0.004)	(0.001)
trend	**29.073*****	**40.187****	-27.746	**15.778*****	**0.187*****	0.036	-0.041	**0.055*****
	(7.972)	(16.409)	(20.132)	(2.580)	(0.059)	(0.044)	(0.087)	(0.012)
Obs.	255	686	541	255	1482	686	541	1482
R-sq.	0.09	0.041	0.059	0.042	0.107	0.076	0.063	0.071

Standard errors in parentheses are robust to heteroskedasticity and serial correlation

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

Table 4.9: Daily Transaction Values of FDI on Daily Exchange Rates (1979–2008)

	Dependent Variable: Value of M&A Transaction (in $mil)			
US Ex Index	-0.166	-0.387	0.323	-0.183
	(0.152)	(0.223)	(0.212)	(0.276)
Priv Targ Dummy		**-72.443*****		**-79.536*****
		(25.691)		(26.634)
PrivTarg*ExIndex		0.105		0.112
		(0.271)		(0.272)
Cash Dummy			**87.806*****	39.062
			(28.835)	(29.083)
Cash*ExIndex			**-0.861*****	-0.519
			(0.305)	(0.300)
PrivTarg*Cash*ExIndex				0.097
				(0.078)
Observations	8519	8519	8519	8519
R-squared	0.000	0.002	0.040	0.040

Standard errors in parentheses are robust to heteroskedasticity and serial correlation

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

Table 4.10a: Relative Number of Acquisition FDI to Domestic M&A against the Real Exchange Rate Index

	Dependent Variable:							
	Relative Number of FDI to Number of Domestic M&A				Relative Number of Private FDI to Number of Private Domestic M&A			
	1979-1988	1989-1999	2000-2008	1979-2008	1979-1988	1989-1999	2000-2008	1979-2008
FX	**-0.001****	**0.004*****	0.000	0.000	-0.001	**0.002****	-0.009	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
trend	**0.005****	**-0.004*****	-0.007	**0.001****	**-0.023*****	**-0.002****	-0.031	-0.001
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Obs.	34	44	31	109	32	44	31	107
R-sq.	0.316	0.442	0.178	0.047	0.506	0.246	0.107	0.047

Standard errors in parentheses are robust to heteroskedasticity and serial correlation

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

Table 4.10b: Relative Number of Acquisition FDI to Domestic M&A with different Financing Methods against the Real Exchange Rate Index

	Dependent Variable:							
	All Cash Financed Relative Number of FDI to Number of Domestic M&A				All Debt Financed Relative Number of Private FDI to Number of Private Domestic M&A			
	1979-1988	1989-1999	2000-2008	1979-2008	1979-1988	1989-1999	2000-2008	1979-2008
FX	**-0.009*****	0.002	**-0.006****	0.000	0.001	-0.001	**-0.046+**	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
trend	**-0.142*****	**-0.005*****	-0.024	-0.004	**-0.015*****	0.002	-0.141	0.007
	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.10)	(0.01)
Obs.	18	44	31	93	26	37	30	93
R-sq.	0.933	0.267	0.137	0.051	0.506	0.046	0.124	0.017

Standard errors in parentheses are robust to heteroskedasticity and serial correlation

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

Table 4.11: Number of Acquisition FDI by Industry against the Real Exchange Rate Index over 1979–2008

	Dependent Variable:Acquisition FDI								
	Agriculture	Construction	Manufacturing	Transportation	Wholesale	Retail Trade	Finance	Services	Public Administration
FX	-0.024	-0.003	**-0.540*****	0.046	**-0.085*****	-0.021	0.035	**0.335****	-0.011
	(0.04)	(0.01)	(0.17)	(0.04)	(0.03)	(0.02)	(0.04)	(0.16)	(0.01)
trend	**0.439*****	**0.048+**	**1.489*****	**0.772*****	0.125	0.057	**0.705*****	**3.671*****	-0.016
	(0.09)	(0.03)	(0.38)	(0.09)	(0.07)	(0.05)	(0.10)	(0.37)	(0.01)
Obs.	106	83	108	102	104	101	109	105	20
R-sq.	0.346	0.074	0.416	0.514	0.229	0.059	0.433	0.572	0.176

Standard errors in parentheses are robust to heteroskedasticity and serial correlation

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

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CHAPTER V

Conclusion

The three chapters in this dissertation have studied the relationship between foreign direct investment (FDI), firm performance, and the exchange rate. Each chapter contributes to our understanding of the underlying factors and the impacts of FDI on firm performance. The dissertation uses novel datasets and methodologies to provide new insights into the impacts on target firm performance depending on the country of origin of the acquiring firms and under what circumstances the exchange rate is a key factor in determining FDI.

In Chapter 2, I evaluate the impact of mergers and acquisitions by differentiating the acquiring firm's country of origin. I construct a new dataset on a comprehensive sample of public U.S. firms acquired during 1979—2006 that includes about 26,000 observations. The acquirer firm countries of origin are divided into three groups: a) U.S. domestic acquirers, b) acquiring firms from industrial countries, and c) acquiring firms from developing countries. In evaluating the target firm performance after the acquisition, I use measures of profits, sales, and employment as outcome variables. The analysis reveals three major findings. First, targets acquired by firms from developing and industrial countries increase profits by 6 and 10 percentage points, respectively, compared with firms acquired by an U.S. domestic firms. Second, U.S. targets acquired by firms from industrial countries exhibit higher profits than those acquired by firms from developing countries. Third, compared with domestic acquisitions, foreign industrial firm acquisitions of U.S. companies tend to increase their targets' employment and sales. However, targets acquired by firms located in developing countries experience a decrease in both revenues and total number of employees. This new evidence demonstrates how, by accounting for the acquirer's country of origin, we can more accurately identify the size and channels of gains from mergers and acquisitions. Finally, the propensity score matching results are substantially different from those obtained when not controlling for selection, suggesting that causal inference based on studies that do not use appropriate comparison groups may yield misleading conclusions.

Chapter 3 undertakes the first systematic analysis of the performance of U.S. firms that are acquired by firms located in emerging markets. To do so, my co-authors and I examine both stock market and accounting based measures of firm performance following the announcement of an acquisition of a U.S. firm by an emerging-market firm. In particular, we use transaction-level M&A information along with firm-level financial statement data to examine the post-acquisition performance of publicly listed U.S. targets. Our results indicate that (i) acquisitions by firms from emerging markets influence post-acquisition performance of target firms (sales and employment decline, profits rise); and (ii) there is selection along observable characteristics based upon which emerging market firms choose acquisition targets in the U.S. (higher sales, assets, employment). In the paper we attempt to control for (ii) using propensity-score-matching and difference-in-difference estimation. There remains the possibility that selection based on time-variant unobservable characteristics (that are orthogonal to the observable characteristics used in our propensity score matching) may be driving our results. However, the evidence presented in the paper strongly indicates that emerging market firm acquisitions impact the performance of U.S. target firms. More generally, the results in the paper serve to illustrate the importance of constructing careful benchmarks from which to evaluate post-acquisition performance and the advantage of propensity score matching in this context.

Turning to the determinants of FDI flows, Chapter 4 focuses on the exchange rate. I use a more detailed and expanded dataset to test the implications of the model proposed by

Froot and Stein (1991). The basic model predicts that for credit constrained private firms, a depreciation of the dollar leads to an increase in cross-border acquisition into the U.S. I test whether this effect is even more pronounced for acquiring firm countries that have low levels of financial development. The regression results confirm some of the theoretical implications. The relationship between the exchange rate and cross-border acquisition FDI is highly time sensitive. For the period 1979—2008, there is no significant relationship between the exchange rate and acquisition FDI. The regression of the daily value of private acquisition FDI on the daily bilateral exchange rate, however, yields a negative relationship once controlling for the payment method and private statuses of target firms, as predicted by the model.

This dissertation focuses mainly on U.S. acquisition FDI using firm level data, since the U.S. has been the number one attractor of FDI starting in the late 1980s. My future research will focus on the impact of cross-border M&A on the performance of the acquiring firm when targets are located in different parts of the world. Firm level data on the acquirers will be needed in order to evaluate the overall impact of M&A deals. The methodologies and insights from the three chapters can be extended to a large set of other industrialized as well as developing countries that are experiencing large inflows and outflows of FDI. Complementing the results in this paper, such future studies will increase our general understanding of the effect of M&As on both acquirers and targets and the potential factors that are driving these in- and outflows of FDI.