# Home biased? A spatial analysis of the domestic merging behavior of US firms

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**Abstract**

Using data of US domestic mergers and acquisitions transactions, this paper shows that acquirers have a preference for geographically proximate target companies. We measure the 'home bias' against benchmark portfolios of hypothetical deals where the potential targets consist of firms of similar size in the same four-digit SIC code that have been targets in other transactions at about the same time or firms that have been listed at a stock exchange at that time. There is a strong and consistent home bias for M&A transactions in the US, which is significantly declining during the observation period, i.e. between 1990 and 2004. At the same time, the average distances between target and acquirer increase articulately. The home bias is stronger for small target companies, relatively opaque companies and when acquirers diversify into new business lines, suggesting that local information is the decisive factor in explaining the results. With an event study we show that investors react relatively better to proximate acquisitions than to distant ones. That reaction is more important and becomes significant in times when the average distance between target and acquirer becomes larger, but never becomes economically significant. We interpret this as evidence for the familiarity hypothesis brought forward by Huberman (2001): Acquirers know about the existence of proximate targets and are more likely to merge with them without necessarily being better informed. However, when comparing the best and the worst deals, we are able to show a dramatic difference in distances and home bias: The most successful deals display on average a much stronger home bias and distinctively smaller distance between acquirer and target than the least successful deals. Proximity in M&A transactions therefore is a necessary but not sufficient condition for success. The paper contributes to the growing literature on the role of distance in financial decisions.

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## Introduction

There is growing evidence that spatial distance to investment objects is influencing financial decisions of various types. This paper shows that in mergers and acquisitions (M&A) transactions acquirers have a preference for geographically proximate target companies even in domestic transactions. We use U.S. domestic M&A data from 1990 to 2004 and construct a portfolio of possible alternative targets for each observed deal. With an average headquarter to headquarter distance to all possible targets of 1764 kilometers, the average distance to the chosen target is only 1209 kilometers. This effect is stronger for small and otherwise opaque targets and for firms that are active in different industries than the buyer. Despite a lack of economic relevance for the whole sample, distance plays a role for the success of M&A transactions: The best decile of M&A-deals in terms of capital market reactions for buyers and targets combined in a three-day window around announcement date displays significantly less distance between acquirer and target: An average abnormal return of 13.6% is associated with a median distance of 588 kilometers. This stands in stark contrast to the worst decile, where the average deal has an abnormal return of -11.6% while the sample displays a median distance of 1412 kilometers. There are at least four theoretical arguments that back this finding. First, firms may buy targets close by to build up local monopoly power and thus become able to raise prices and therefore profits. Second, monitoring costs for the newly acquired firm after the transaction might be lower for acquirers which acquire firms close by. A third reason includes lower transportation and integration costs when merging with firms close by. Fourth, firms might have better information about geographically proximate targets and/or are better able to assess the potential and risk of such a transaction. The latter might point to capital market imperfections that persist even when transactions are executed in a time-span of months. For stock trading (Hau 2001) and analysis (Malloy 2005) the physical distance to the respective headquarters plays a decisive role for the success for the traders and analysts, respectively.

The influence of spatial distance on M&A deals is also relevant for judging the achievable degree of integration of capital markets, especially in the European Union. The benchmark market – the U.S. – is showing a spatially biased development, so a perfectly even spatial distribution of M&A activity should be expected even in the long run in Europe.

The international home bias in equity holdings and investment is a long known stylized fact (see Lewis 1999 for an overview) which holds true also for corporate bonds (Portes et al. 2001). Informational advantages have been identified as main drivers of the international home bias (Gehrig 1993; Dvorák 2005; Ahearne et al. 2004; Strong and Xu 2003; Chan et al. 2005). Geographical proximity also explains listing decisions of firms (Pagano et al. 2002; Sarkissian and Schill 2004) internationally.

Internationally, there is mixed theoretical evidence for a propensity of firms to locate foreign direct investments (FDI) in proximate countries.[c] Horizontal FDI is usually seen as substituting exports. The higher the transport costs, increasing with distance, the less advantageous the export and the more horizontal FDI could be expected. Thus, horizontal FDI should increase with distance. However, vertical FDI, fragmenting the production process geographically, should be discouraged with increasing distance due to the increasing transportation costs of intermediate products (Loungani et al. 2002). Data on FDI is usually a mix of horizontal and vertical FDI, so the impact of distance remains uncertain. In empirical studies, companies that pursue foreign direct investments – i.e., mostly international M&A – generally prefer host countries that are close to their headquarters (see Shatz and Venables 2000 for an overview; Berger et al. 2004 for financial institutions). Much of this home bias in foreign direct investment has been attributed to transportation costs and recently to information asymmetries and the costs of overcoming these. However, in an international context, information costs also occur because of dif-

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[c] On average 72 percent of all FDI take place in the form of ‚brown-field' FDI, i.e. mergers and acquisitions. Between developed countries this figures reaches 84 percent and into developing countries 41 percent (UNCTAD 2003).

ferences in language, regulation, currency, culture and legal systems. The effect of distance itself is hard to extract since, e.g., culture and regulatory differences are almost impossible to quantify (see Berger et al. 2000; Buch and DeLong 2004). But not all home bias is related to the international economy (Coval and Moskowitz 1999). This paper focuses on domestic transactions and examines whether acquirers have a preference for geographically proximate target companies within one country. We concentrate on US acquiring firms and domestic transactions, i.e. on a setting with a single currency, language and relatively little variety in regulation, taxation, political risk and culture. This analysis therefore allows for the separation of the distance effect from other possible influences and gives hints on the role of pure distance in international transactions.

The problem with stating a home bias in M&A-transactions is the fact that most economic activity is far from evenly distributed in space but clustered in a few areas (see Ellison and Glaeser 1997 and Krugman 1991 for the US; Midelfart-Knarvik et al. 2000 for the EU): A Silicon Valley-based software firm that buys another software firm close by may just have few other choices geographically because of the high degree of agglomeration of software firms. A bias in equity holdings usually is measured by comparing an observed portfolio with the market portfolio and computing the respective distances. Looking at M&A-transactions, there is no observed portfolio but only one observed deal and there is no market portfolio – so how to analyze whether there is a tendency for firms to merge with other firms close by? We construct a hypothetical portfolio of potential targets for each observed deal and compare the average distance to this portfolio with the distance (and other characteristics) to the observed deal. The potential targets in the hypothetical portfolio are firms in the same industry with about the same size that have been listed at a stock exchange or have been targets in other deals at the time the observed deal took place. Thus, we are able to analyze whether acquiring firms pick their targets closer to them than the average potential target or otherwise, i.e. if there is a home bias in M&A transactions or not. We show that in domestic transactions there is a strong preference for local mergers and acquisitions. Even when controlling for a variety of other characteristics, we find a significant home bias in the transactions. Combined abnormal returns for buyer and seller in a three-day window around announcement date are significantly higher for transactions that take place in short distance to each other, although it is not economically relevant in the whole sample. A look at the most and least successful deals, however, reveals strong discrepancies in the average distances between acquirer and target. Our findings underline the importance of the emerging research area of geographically asymmetric distribution of information in capital market theory.

The rest of the paper is organized as follows. The next chapter displays data and the methodology used for this study. In chapter two we use a binary regression approach to show what the main target characteristics are that drive the decision to merge with a specific target. Chapter three describes a model for measuring proximity preference, i.e. the home bias. In chapter four we explain the extent of the home bias by regressing the results on variables identified in the literature and associated with asymmetric information. Chapter five hosts an event study of capital market reactions to merger announcements with respect to the home bias of an acquirer. Chapter six concludes.

## I. Methodology

### A. Background and Motivation

Finding a home bias would add substantially to the literature on the influence of distance in financial decisions because there is barely another financial decision which covers a longer time span than the decision to buy another firm, and in which more professionals are involved. M&A transactions usually take at least several months from the inception of the strategy to completing the transaction. It is the decision of the senior management of the acquirer, involving investment banks conducting a thorough search for and selection of the target company. It could be expected that firms would benefit by evaluating the broadest possible set of potential targets. A home bias based on information asymmetries means that firms might forego possible gains when not choosing the optimal target. At least four arguments underline the notion of firms buying other firms nearby. First are transport and transaction costs when integrating and running the combined firm. Integration usually involves senior management to a large extent but also exchange of goods and workers at all levels. Traveling back and forth is not only more costly, the larger the distance between the two firms but also more time-consuming. This transport cost effect is visible even at a very small scale in discriminatory pricing in loans (Degryse and Ongena 2005).

Second, it might be more difficult to monitor affiliations that are far away – local managers might find it easier to pursue their own goals instead of those given by the headquarters. Böckerman and Lehto (2003) find evidence for the monitoring hypothesis as a driver of proximate mergers in Finnish data. This is in line with the observation that venture capital firms invest predominantly in firms close to them (Lerner 1995; Zook 2002, Sorenson and Stuart 2001) and with Denis et al. (2002) who find an internationalization discount for listed firms, attributing this to agency costs that increase with distance and international borders.

The third argument is about local monopolies. When merging with a similar firm in the same industry nearby, local competition will become weaker and therefore the possibility to raise prices and profits increases. The more local the demand, the stronger the effect will occur. When building local monopolies is a strong factor in buying proximate targets one should observe a stronger home bias when acquirer and target are operating in the same industry and less home bias in diversifying acquisitions. However, when the industry of the acquirer is already concentrated locally, acquirers looking for an acquisition might be forced by the (local) antitrust authorities to look elsewhere when acquiring firms in the same industry. The latter argument however, would imply that industries with predominantly regional markets would yield other results than industries with predominantly national markets. When breaking up the following analyses into sub-samples of single industries, no clear pattern like that emerges. Industries with national markets (e.g., software packaging) display qualitatively the same results as others. Additionally, local concentration might be more an issue on the plant or shop-level, which are not regarded here, than on the headquarters level.

The fourth argument evolves around the now well-documented 'soft information' that is available only in spatial proximity to one another. When the insufficiency of information – that increases with distance about potential targets – is a relevant source of home bias in M&A decisions, acquirers forego potential profits in finding the best possible deal. Earlier studies found a domestic home bias in other financial transactions usually involve stronger effects in very short-term actions. In his study on the profitability of stock trading that takes place close to the headquarters of the traded firms, Hau (2001) finds that distance matters most for trading at high frequencies. Long and medium frequency trading yielded no extra profits for being proximate to the respective headquarters when compared with other traders located in the same country. Coval and Moskowitz (1999) study the behavior of mutual fund managers in the U.S. that prefer to hold locally headquartered firms and find a strong bias for investments that are close to the location of the fund manager. Investments in large firms tend to be further away than those in small firms. Fund managers that display a strong home bias achieve higher risk-adjusted when investing in those firms nearby (Coval and Moskowitz 2001). Grinblatt and Keloharju (2001a) show that investors in Finland prefer stocks of firms that are headquartered in spatially close locations to those that are further away. Furthermore, Finnish-speaking investors prefer Finnish companies that publish their results in Finnish, and Swedish-speaking investors prefer companies that publish in Swedish. (Finland is a bilingual country, with Finnish and Swedish as the two official languages.) Their data reveals as well that there is a tendency for households to hold stocks of firms whose CEO is of the same cultural (i.e. Finnish or Swedish, respectively) origin. The influence of distance, language and 'culture' is smaller, the savvier investors are. Huberman (2001) and Zhu (2002) report similar results for individual investors in the US. Much in line with the argument presented in this paper, Malloy (2005) analyses the accuracy of analysts' forecasts with regard to their spatial distance to the respective headquarters of the covered firms. He finds that being close the headquarters significantly increases analysts forecast accuracy. The effect is stronger for small or otherwise opaque firms, such as fast-growing firms or firms in remote locations. Not related to investment decisions but in a somewhat similar research, Berger et al. (2000) compare bank efficiency and do not find any disadvantages for domestic U.S. banks operating in other regions than where there organization is headquartered (in fact, they find a slight advantage for those banks in terms of cost efficiency). They conclude that physical distance itself does not matter a lot.

In close proximity to a firm there are more information available than from a distance. This is because people can talk to managers and employees as well as suppliers and clients of the firm, who give (tacit) information that are not easily transferable over distance, like mood, non quantifiable feelings about the future, etc. (Coval and Moskowitz 1999; Polanyi 1958). Also, investors will get some information locally without having to ask for it, by just bump into people and chatting with them (valuable noise). Since face-to-face contact is still the best 'communication technology' (Storper and Venables 2004), being close to one another delivers more, richer and faster information than otherwise. However, physical distance per se does not solely drive either information asymmetries or transportation and integration costs.

However, much information is remotely available, e.g. on the internet, since the mid-1990s that was not readily available before. Petersen and Rajan (2002) report that banks' average distance to lenders has increased over time. Today, Internet information does not only comprise the official company website but also information from clients in blogs or news fora and occasionally reports from employees – in short, much information that would seem local before. We analyze the development of the home bias in M&A transactions over time to see whether information technology has an impact and additionally split our data into two subsets, up to 1996 and thereafter, to analyze whether the success of deals has been changed over time.

Analyzing the home bias for individual investors, Huberman (2001) and Zhu (2002) show that investors in companies close by do not achieve superior results in comparison to more distant investors. They conclude that it is not better information that drives investments into these companies but familiarity. In contrast, Malloy (2005) finds that analysts do have more impact and better forecasts for companies close to them; Coval and Moskowitz (1999) find fund managers to have extraordinary returns when investing in local companies. That suggests that professionals in the financial industry are able to gain from superior ('tacit') information close to the firms whereas individuals just invest in what they are familiar with without profiting from that. For international equity flows, it is also not clear whether it is familiarity or behavioral explanations that drives investment flows in capital markets (see Portes and Rey 2005). Since many M&A decisions are not yielding profits for the acquirer (see Andrade et al. 2001 for an overview) we are interested in whether a domestic home bias in M&A is driven by familiarity or superior information.

## B. Data

Our sample merges several data sets. The primary data source is the Thomson ONE Banker-Deals database, which lists merger and acquisition transactions worldwide. Our sample consists of mergers and acquisitions with an effective transaction date from the beginning of 1990 until the first quarter of 2004 where both, acquirer and target, are located in the U.S. We exclude Alaska, Hawaii and Puerto, and count the District of Columbia as a state; however, robustness checks including Alaska and Hawaii did not alter the results qualitatively. Only those transactions are included where more than 50% of all shares are acquired as well as the location of both, acquirer and target, is known. A total of 46,522 transactions match these criteria. Data about listed firms – targets as well as potential targets – are taken from S&P's COMPUSTAT. As a proxy for the potential deal volume of possible targets that have been listed on a stock exchange but were not actually acquired we take the yearly average market value in the year before the deal took place from COMPUSTAT`s Research Insight database. M&A activity concentrates to a large extent in few industries, and there might be differences between industries in the home bias. A breakdown of the observations of the most important industries is reported in figure 1. To control for potential changes in time we split the dataset in two sub-samples, from 1990 to 1996 – i.e. roughly before the internet became ubiquitous – and from 1997 to 2004.

**Figure 1**

**Most important industries by observation count**

This table shows a breakdown of the most important industries. The top ranking industries are dominated by IT and Banking

| *SIC* | *count* | *avg. Distance* |
|---|---|---|
| 7372 | 2892 | 1567.06 |
| 7375 | 1332 | 1441.99 |
| 6021 | 1230 | 375.73 |
| 6022 | 1198 | 344.14 |
| 6035 | 1062 | 345.59 |
| 6512 | 1046 | 969.97 |
| 7389 | 809 | 1401.79 |
| 7373 | 678 | 1522.51 |
| 7011 | 641 | 1320.24 |
| 4813 | 622 | 1211.03 |

The amount of information available for each deal varies considerably. Most information is available for the roughly 14,000 listed companies recorded in COMPUSTAT. In private deals, often only the names of the companies are recorded, for a mere 34,513 deals the transaction volume is known. The majority of targets are private companies, 59.1 percent or 27488 out of 46,522. The reverse is true for acquirers, were only 42.7 percent (19887) are private.

We match the location of primary business – i.e. the location of the headquarters - of target and acquirer with longitude and latitude data using the U.S.

Census Bureau's Gazetteer reference data. We do not use the state of incorporation for measuring distances because firms choose their incorporation because of tax, bankruptcy or takeover law without necessarily having any physical presence in that state. Most firms are either located in their home state or in Delaware (Bebchuk and Cohen 2003). For listed firms, we calculate abnormal returns around announcement date using Center for Research on Securities Prices (CRSP) data. Following the literature, we calculate the returns on a [-1; 1] event window around announcement date (see Andrade et al. 2001).

The spatial distribution of acquirers and targets is shown in figure 2 below. Not surprisingly, the pattern follows very closely that of general economic activity, with most deals concentrating at the coasts and the large cities. The map shows graphically that acquirers tend to be more concentrated than the targets. To confirm the impression from the map we construct a simple locational Herfindahl-Index (LHI) that measures the locational concentration of acquirers and targets respectively:

$$LHI = \sum_{i=1}^{n} s_i^2$$

Where n is the number of cities where targets (acquirers) are located and $s_i$ the number of target (acquirers) in one city divided by the total number of targets (acquirers) in the sample. The resulting LHI – which theoretically could run from zero to 10000 – is clearly confirming the impression of a stronger concentration of acquirers in the map (the same pattern holds true for deal value-weighted LHI). Since most targets are distinctly smaller than their acquirers, the combined firms might concentrate their headquarters and thus their economic decision making power at the location of the acquirers' headquarters, which are predominantly located in large cities. This observation is in line with the findings by Green (1990) and Rodríguez-Pose and Zademach (2003) for the US until the 1990 and Germany until 1999, respectively.

**Figure 2**

## Spatial distribution of acquirers and targets

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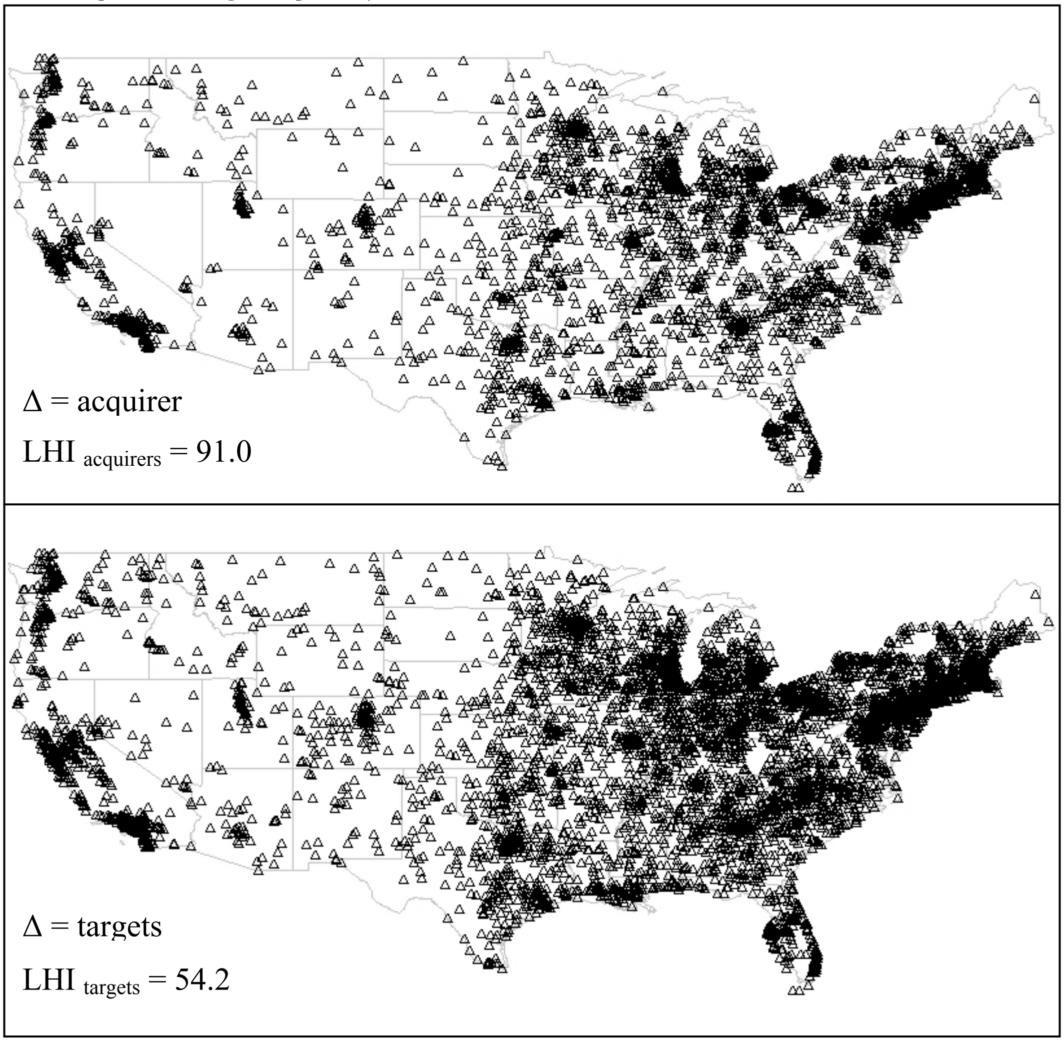


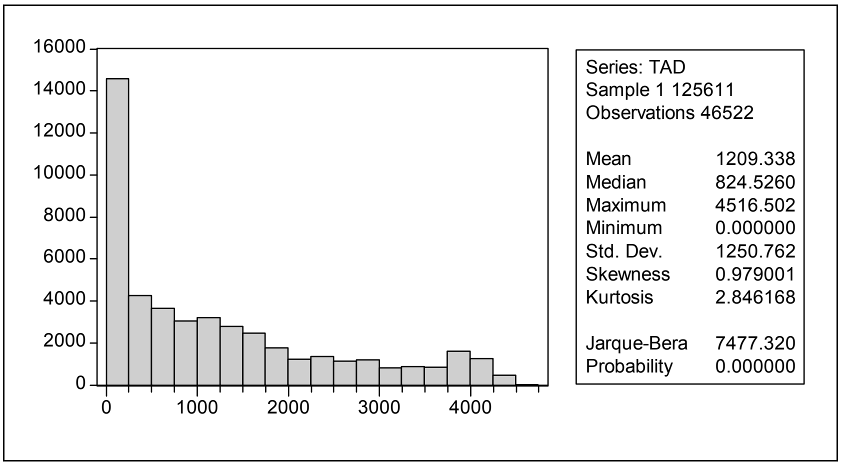

We are, however, more interested in the distance between target and acquirer than in their actual location. Distances between the acquirer's and the target's headquarters are calculated with IBM's DB2 Spatial Extender using the arc length between the two locations in kilometers (see Coval and Moskowitz 1999 for details). We use the distance between headquarters because this is where the decision makers are located, which is of pre-eminent interest for us. Since most targets are comparatively small firms that have only few – if any –

other locations than their respective headquarters, we do not think this poses a problem for the generality of our findings. While it is true that for some firms, e.g. co-location of some plants of acquirer and target might lead to better respective knowledge about each other, interviews with industry specialists and decision makers in large firms indicate that managers at the plant level are usually not involved in the decision of which firm to merge. They are involved in the integration phase that is, however, usually quite separated from the decision and transaction phase. Figure 3 displays the frequency of transactions at varying distances.

**Figure 3**

**Frequency distribution of target acquirer distance TAD**

This histogram shows the frequencies of distances between target and acquirer TAD. The most stunning feature of this frequency distribution is the prevalence of transactions that take place within a 100 kilometers distance between acquirer and target; about one quarter (24.7%) of all acquirers choose targets within that radius. Over 16 percent of the transactions in our sample are carried out within the same city.




The most stunning feature of this frequency distribution is the prevalence of transactions that take place within a 100 kilometers distance between acquirer and target; about one quarter (24.6%) of all acquirers choose targets within that radius. Over 11 percent of the transactions in our sample are carried out within the same city. The more distance between the two firms, the less transactions occur. There is a small but noticeable exemption around 4,000 km, the distance between the two coasts. The average distance between acquirer and target is 1,209 km; the median deal has a distance of 824 km.

## II. Distance and the decision to acquire

### A. binary regression

The findings above impose the idea of a distinctive proximity preference in M&A transactions. But if the acquirer simply did not have the opportunity to buy a more distant firm, a proximity preference does not exist. Hence, we identify a peer company for every chosen target to examine whether distance plays a role in the acquirer's decision making process. To identify whether there is a systematic preference for targets in close distance we conduct a matched pair analysis in a binary regression model. Each deal is assigned a '1' and each possible deal a '0'. For matching reasons we define three criteria a peer has to meet. First, the company has to be in the same four digits Standard Industrial Classification (SIC) industry as the target in the observed transaction. Second, the potential target has to have been available at that time, meaning that a bidder hypothetically could have bought this company. This criterion is met if a company has been a target in a different M&A transaction around that time or was listed at the time of the transaction. We exclude possible targets when the transaction they have been involved in took place more than 18 months before or more than 18 months after the transaction. For the third decisive factor, targets had to have a similar transaction value or, for listed firms, a similar market capitalization plus a premium of 20 percent, the average premium in our sample. We consider possible target firms only when they have a value in the range of +/- 20 percent of the actual transaction volume.

Given these constraints we get a portfolio of eligible target companies for each transaction. To identify the best matching peer company for every actual target we choose the closest firm according to the following algorithm: First, we create a volume ratio to compare the size of the actual target with the size of the potential target. We consider only transactions in which at least 50 percent of the shares are acquired. To match the firm values accordingly in cases when less than 100 percent of the shares are acquired, we have to normalize the value of potential targets. (In the vast majority of cases, more than 90 percent are acquired, so the effect is not large.) We normalize the potential target's transaction volume $tv_j$ by dividing it by the percentage of shares acquired in that deal, $pa_j$ ($0.5 < pa_j \leq 1$); and doing the same for the actual target in the denominator. For listed companies we divide the market value $mv_j$ plus a premium of 20 percent by the normalized actual target's value:

$$volume\ ratio_{i,j} = \left\{ \begin{array}{ll} \dfrac{\mathrm{tv}_j / \mathrm{pa}_j}{\mathrm{tv}_i / \mathrm{pa}_i} & \textit{for potential targets that have been targets in other deals} \\ \dfrac{1.2 * \mathrm{mv}_j}{\mathrm{tv}_i / \mathrm{pa}_i} & \textit{for potential targets that have been listed companies} \end{array} \right\}$$

The *volume ratio* shows the relative deviation from the normalized potential target's value to the normalized actual target's value. According to our definition of what constitutes a potential target, *volume ratio* has a value from [0.8; 1.2]. A *volume ratio* of one reflects identical values of actual and potential target. As a second measure we calculate the time difference in days between the actual transaction date $dt_i$ and the date the potential target has been sold, $dp_j$. We assume that listed companies are available all the time, so for them $dp_j$ equals $dt_i$, i.e. *day difference* is zero.

$$\text{day difference}_{i,j} = dt_i - dp_j$$

To combine these two measures of similarity between each potential target and the actual target, we normalize each of them with respect to their respective maximum deviation, i.e. 20% in value terms or 540 days (18 months) in availability. We create a matching index $MX_{i,j}$ for every hypothetically target j which is defined as follows:

$$MX_{i,j} = \left( \frac{\left|1 - \text{volume ratio}_{\text{i,j}}\right|}{0.2} + \frac{\left|\text{day difference}_{\text{i,j}}\right|}{540} \right)$$

Both arguments have possible values from zero to one. We simply add the values of the arguments to derive the matching index. Among the alternative possible targets for each transaction the one with the smallest $MX_{i,j}$ value is chosen as a peer.

We then construct a binary model to estimate a logit regression on a dummy variable which is one when the target was chosen and zero otherwise. We obtain a model of matched pairs where every actual transaction has one potential transaction assigned. To cope with heteroscedasticity we use quasi-maximum likelihood standard errors in the data to estimate the regression coefficients.

For our analysis we include the potential-target-acquirer-distance *PTAD* as explaining variable as well as further control variables consisting of target characteristics. These characteristics are specified as following. The first four regressors are the same as in Kang and Stulz (1997) as well as Coval and Moskowitz (1999): the target's financial leverage (as ratio of total liabilities to total assets), the firm size (as the log of the target's value *ln(MV)*), the return-on-assets *RoA* and the price-to-book ratio *P/B*. Thus, the model takes the form:

$$\textbf{actual deal Yes/No} = \beta_1 \textbf{PTAD} + \beta_2 \textbf{Leverage} + \beta_3 \textbf{RoA} + \beta_4 \textbf{P/B} + \beta_0 + \varepsilon$$

The target's market value *MV* serves as a proxy for the size of the company. In analogy to Kang and Stulz (1997) as well as Coval and Moskowitz (1999) we use the log of the market value. This has two reasons: First it helps to differentiate small company sizes more distinctively as they are the majority of

M&A transactions in our sample. Second, the relationship between firm size and information availability is not linear: The availability of information about a certain company (e.g. due to accounting regulations, pressure by public interest, etc.) can be assumed to improve with rising company size, but the slope of this information-size-function cannot be infinitely positive. With the next regressor we add the target's leverage. The leverage shows the target's financial distress. This can be one reason of selling the company. For the acquirer a high leverage is a two-way indicator: On the one hand the leverage can show increased risk in operations. On the other hand it acts as an indicator for a higher return on equity. As Coval and Moskowitz (2001) put it: 'The significance of the leverage variable is most likely accounted for by its association with future returns' uncertainty' (Coval and Moskowitz 2001, p 2067). Informed investors might have larger holdings in highly levered firms than less informed investors. These two sides of the medal emphasize our special attention for this variable, especially as Coval and Moskowitz (1999) find a positive impact of leverage on the home bias of US funds managers.

The third variable extends the regression by the return-on-assets ratio. The *RoA* gives an idea of the target's profitability as well as its accounting performance (see Coval and Moskowitz, 1999, 2063). This analysis of the entire US market could be biased by industry specific variations. Since we perform a matched pair analysis only with peers that are in the same four-digit SIC industry, we do not account for industry-specific levels of either *RoA* or *P/B*. The price-to-book ratio *P/B* can be interpreted as indicator for potential growth of the target. However, a small *P/B* can signal either a capital market's underestimation or severe distress of the company (see Coval and Moskowitz 1999, p 2063, and Fama and French 1992).

In our sample information on these variables is available only for 874 transactions and their peers. That group has an equally distributed response variable, i.e. an equal amount of zeros and ones. The distribution of actual transactions (binary variable equals one) has a mean target-acquirer-distance of 1078 km with a median of 473 km. In contrast, the distribution of hypothetical transactions (binary variable equals zero) has a mean potential acquirer-target distance PTAD of 1607 km with a median of 1158 km. In this sample nearly two thirds (65 percent) of all matched pairs have a peer firm that is further away than the actual target. Figure 4 shows the regression results. The full sample is divided into sub-samples for different firm sizes. The smallest category builds the nano caps with a market capitalization of up to 50 million US dollars. The second frame contains the micro caps with at least 50 to 300 million and is followed by the small caps with up to 2 billion dollars. The second largest category includes the mid caps with a market capitalization between 2 and 10 billion dollars. As the last category the large caps embrace enterprises of up to 200 billion dollars. After the firm size distinction we distinguish transactions that take place within one industry ($SIC_{acquirer} = SIC_{target}$) from deals that aim into a new industry ($SIC_{acquirer} \neq SIC_{target}$).

**Figure 4**

**Matched Pair Logit Regression (Firm Characteristics)**

This logit regression's dependent variable takes the value of one for accomplished transactions and the value of zero for hypothetical transactions. The sample consists of matched pairs each having one actual (1) and one potential target (0). A match is defined by the potential target with the smallest *MX* index value which consists of the differences in availability and transaction value. To lower the number of digits *PTAD* is measured in thousand kilometers.

| *Sample* | *PTAD** | *Lev* | *RoA* | *P/B* | *C* | *n* |
|---|---|---|---|---|---|---|
| **All** | **-0.322**<br>-(8.03) | **-0.218**<br>-(1.28) | **0.00050**<br>(0.47) | **0.00514**<br>(1.35) | **0.543**<br>(4.01) | **1748** |
| Nano Cap | -0.477<br>-(3.98) | -0.787<br>-(1.29) | -0.00584<br>-(1.48) | 0.05910<br>(0.56) | 1.986<br>(3.60) | 244 |
| Micro Cap | -0.413<br>-(5.26) | -2.138<br>-(4.81) | 0.00287<br>(0.70) | 0.07334<br>(1.24) | 2.648<br>(6.37) | 572 |
| Small Cap | -0.284<br>-(3.20) | -1.344<br>-(2.68) | 0.01213<br>(1.08) | 0.00427<br>(0.74) | 2.208<br>5.42 | 314 |
| Mid Cap | -0.476<br>-(2.47) | -2.585<br>-(1.72) | 0.07578<br>(2.16) | 0.02288<br>(0.53) | 3.032<br>2.19 | 84 |
| **SIC = SIC** | **-0.249**<br>-(4.84) | **-0.124**<br>-(0.57) | **0.0000249**<br>(0.02) | **0.00429**<br>(1.33) | **0.389**<br>(2.30) | **1004** |
| **SIC ≠ SIC** | **-0.437**<br>-(6.68) | **-0.392**<br>-(1.42) | **0.00187**<br>(0.98) | **0.01398**<br>(1.66) | **0.783**<br>(3.47) | **744** |

* *in thousand kilometers*

The results in figure 4 show that the distance between acquirer and target *PTAD* has a significant negative impact on the propensity of choosing the target. A more quantitative interpretation can be done by taking the antilog of the coefficient. With a $\beta_{PTAD}$ = -0.32 we obtain the odds of $e^{-0.32}$= 0.7261. This suggests that for an increase in distance of one thousand kilometers the probability (odds) of choosing a target decreases by 27.4 percent. Like Grinblatt and Keloharju (2001b) we regressed with OLS for a robustness check; this delivers similar results (not reported). With rising target size the influence of distance remains stable.

As expected, the leverage coefficient has a negative but not consistently significant impact on the decision of an investor to acquire a company. Since leverage is defined between zero and one, the coefficient is hard to interpret. The lack of significance is not surprising as there are two effects in financial leverage that are contrary to each other: Less risk-averse acquirers might seek high equity returns in highly levered firms whereas a risk-averse acquirer would hesitate to invest. The *RoA's* coefficient does not show significance except for Mid Cap sector whereas the *P/B* ratio, the second industry-specific variable has a positive sign. This may reflect that, over all, the market assesses the target in the same way the acquirer does. One possible explanation for short distance M&A could be that the majority of transactions merge for local monopoly. On the contrary, we see a stronger negative impact in inter-industry transactions which we will investigate in the following chapter.

As for a provisional result we conclude that distance seems to play a decisive role in M&A. But further questions arise. After identifying some impact of distance, is there a spatial distortion or rather a proximity preference? How can we quantify this proximity preference, as the mere distance reveals no relative measurement? And last, not least, what drives a potential home bias?

## III. Home bias

### A. Analyzing a home bias without a market portfolio

As mentioned above, the mere fact that most transactions take place with acquirer and target relatively close to each other does not necessarily mean that there is a home bias: It could just be a product of clustering of economic activity and industries in space. A home bias is usually established by comparing the observed portfolio against a market portfolio. That market portfolio might be the global market portfolio as in many home country bias studies (see Lewis 1999 for a survey) or a global free-float portfolio to control for institutional shareholdings in the different countries (Dahlquist et al. 2003). In domestic studies, this is usually a portfolio of all listed companies, often weighted by market capitalization (see, e.g., Coval and Moskowitz 1999). The average distances to the firms in the market portfolio are computed and compared to the average distances to the firms in the observed portfolio of the investors or analysts. A home bias is constituted when the distance to the observed portfolio is smaller than the distance to the market portfolio. Huberman (2001) uses a subset of the market portfolio, i.e. the seven Regional Bell Operating Companies in the US, and shows that individual investors prefer to buy shares of their respective local providers.

When looking at M&A-transactions, there is no observable portfolio but only separate deals. In order to analyze whether there is a home bias, the distance between acquirer and target in each deal will be compared with the average distance to a 'portfolio' of possible targets. There is, however, no obvious market portfolio. To create this benchmark we expand the idea of matched pairs and construct an entire portfolio of hypothetical target firms for every acquirer. Several features of M&A transactions have to be accounted for: First, acquirers do not look around for firms randomly. While some large firms occasionally might buy 'a bargain' in any industry, this is not the standard practice. We assume that acquirers search for firms in specific industries to complement their production portfolio and accordingly create our portfolios industry-specific. To be included in a specific hypothetical portfolio, a firm has to be active in the same industry (at the 4-digit SIC level) as the observed target. Second, most M&A transactions involve private firms – so basing the analysis only on firms that are listed on a stock exchange would ignore a large share of the M&A market. Also, firms listed on a stock exchange are on average larger than private ones, so there would be a bias towards larger transactions. To include also smaller, privately owned firms one could take all existing firms in the US as the universe set. However – third – many of those, e.g. manager-owned firms, may not be for sale at a given time. Including a firm into a portfolio of possible acquisition targets is only justified when there is the possibility of buying them at a market price: Firms have to be either listed on a stock exchange at the time the transaction took place, assuming that all listed firms are actually able for sale. Or it has to have been a target in another M&A-transaction at around the same time the observed deal took place. Thus, we are able to include all the private firms that have been bought in M&A-transactions and so would have been available as possible targets for the acquirer in the observed deal. By doing so, we miss firms that were the owners were willing to sell but could not find a buyer at the asked price. Since this condition might possibly hold true for each and every firm at all times, we treat those firms as if they have not been on the market at all. Lastly, to be included in a specific portfolio, the possible target has to have about the same value, either in terms of the price paid or market capitalization, as the observed target.

We compare the distance between the headquarters of acquirer and target in the observed deal with the average distance between acquirer's headquarters and all possible targets' headquarters in the portfolio. Since by definition all the companies in the portfolio were traded for about the same value, there is no need for controlling for company size. The portfolios also reflect the fact that industries are clustered in few areas: An advertising firm from New York that is buying another advertising firm in New York might not display a large home bias, since most other advertising firms in the portfolio are also New York-based.

Eligible firms have to fulfill several requirements. First, they have to be within the target's industry (4-digit SIC). Although none two firms are the same and acquirers might go for one special firm that possess exactly the resources, we assume that any firm operating in the same industry would be a possible target as well. Given the usual scanning process in M&A transactions, this seems to be a reasonable assumption. Second, only firms that have been a target in another transaction at about the same time or that have been listed in the year the transaction took place are used as potential targets. Although acquirers' decision-making processes are heterogeneous and it is hard to pin down exactly how long an acquirer will search for an eligible target, practitioners state that a typical pro-active acquisition process will last about six to twelve months. Therefore we include a firm that has been a target in another deal in the hypothetical portfolio when it has been a target up to 18 months in advance to the observed deal, as it could have been potentially bought by the acquirer. Also firms that have been targets up to 18 months after the observed deal took place are included, since we assume that these firms were 'on the market' at the time of the deal. Finally, we include only firms of similar value, assuming that acquirers are not looking for firms of very different sizes because of financing constraints, strategic reasons and integration strategy.

We consider firms that have been a target in other transactions with a known transaction volume to be about the same price when they were sold in the range of +/- 20 percent around the price of the observed target. For calculating the range of possible values for listed firms, we include an average acquisition premium of 20 percent in our calculations. We thereby follow our findings from the event study reported in chapter V.[4] We also calculated the portfolios using the target's average market capitalization in the year preceding the transaction, i.e. without any takeover premium; that left our results qualitatively unchanged. In what follows only the results for the 20% premium are reported. Thus, to be included as potential targets, listed firms must have a market capitalization two days prior to announcement day within the following interval at the time of the observed transaction, so as to allow again for a +/- 20 percent fluctuation margin:

$$\text{market capitalization} = \frac{\text{transaction value}}{1.2} \pm 20\%$$

With these restrictions there was at least one potential target available for more than 15,000 transactions. This results in a minimum portfolio size of two, since the actual target is included in the portfolio as well. Figure 5 displays the distribution of hypothetical portfolio sizes over time and industries. The SIC codes of the twenty most active industries are shown in the left half of figure 5, together with their average portfolio sizes and the number of observations per industry, i.e. the number of deals where at least one hypothetical deal has been identified. The right side of figure 5 displays the distribution of the average portfolio over time. Not surprisingly, the years with highest M&A activity – in the late nineties and the first years in the new century – display the highest average portfolio sizes.

[4] This is about half the value Gondhalekar et al. (2004) implicitly report in their study of cash offers for targets listed on NASDAQ between 1990 and 1999 with a premium of 41.6 percent (own calculation). Since these are cash offers, this marks the upper level of premiums.

**Figure 5**

## Average portfolio sizes over time and per industry

The left table reveals the average portfolio size of the 20 most active industries. On the right side the average portfolio size per year is shown. The observation figure represents the number of transactions with a portfolio size of at least two targets.

| *SIC* | *avg. Portfolio size* | *obs* |
|---|---|---|
| 6512 | 34.62 | 784 |
| 7372 | 34.37 | 1379 |
| 6022 | 21.49 | 751 |
| 7011 | 20.05 | 418 |
| 6035 | 16.36 | 511 |
| 6021 | 15.99 | 758 |
| 7375 | 13.46 | 451 |
| 7373 | 12.88 | 319 |
| 4832 | 10.53 | 313 |
| 1311 | 9.32 | 369 |
| 7389 | 8.45 | 234 |
| 4813 | 7.54 | 319 |
| 7371 | 7.00 | 214 |
| 6311 | 6.35 | 197 |
| 7379 | 5.33 | 163 |
| 8742 | 4.82 | 114 |
| 8011 | 4.52 | 136 |
| 6162 | 3.90 | 94 |
| 8748 | 3.78 | 82 |
| 6411 | 3.77 | 81 |

| *Year* | *avg. Portfolio size* | *obs* |
|---|---|---|
| 1990 | 4.25 | 115 |
| 1991 | 4.94 | 329 |
| 1992 | 5.99 | 572 |
| 1993 | 7.37 | 831 |
| 1994 | 9.34 | 1082 |
| 1995 | 10.11 | 1255 |
| 1996 | 11.58 | 1420 |
| 1997 | 14.95 | 1764 |
| 1998 | 16.77 | 1902 |
| 1999 | 14.62 | 1444 |
| 2000 | 15.10 | 1356 |
| 2001 | 13.65 | 880 |
| 2002 | 11.57 | 709 |
| 2003 | 10.28 | 621 |
| 2004* | 9.90 | 210 |

* first quarter only

For 601 transactions each acquirer could have chosen one out of over fifty hypothetical target companies that were traded within the conditions laid out above; 1633 acquirers faced a hypothetical portfolio of a minimum of 30 possible targets (see figure 6 below). When appropriate, we report the results for different portfolio sizes, although the results do not change qualitatively.

### B. The evidence

The home bias ($HB_i$) of each deal i is calculated in kilometers as the difference between the average distance to all ($n_i$-1) potential targets j of the portfolio i ($PTAD_{i,j}$) in the hypothetical portfolio plus the distance to the actual target on the one side and the actual distance between acquirer and target ($TAD_i$) on the other:

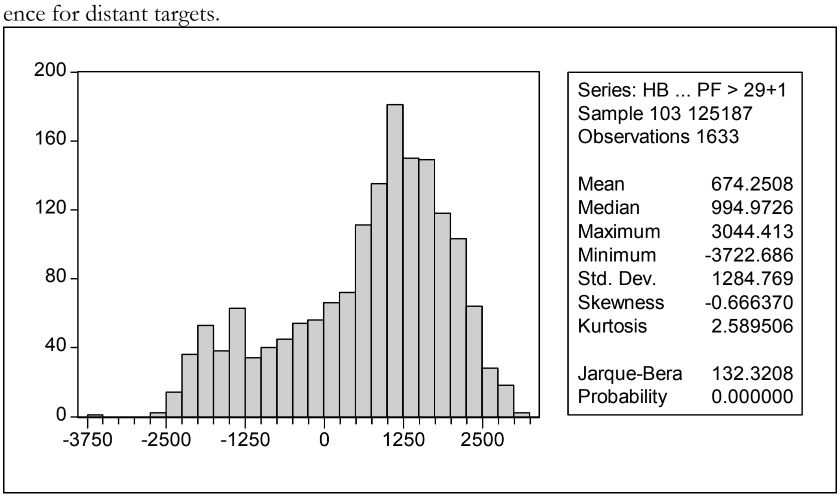
$$HB_i = \frac{TAD_i + \sum_{j=1}^{n_i - 1} PTAD_{i,j}}{n_i} - TAD_i$$

With this specification, $HB_i$ gives information about spatial proximity for every M&A transaction. A positive value for $HB_i$ means that the actual target was closer to the acquirer than the average of possible targets, i.e. the acquirer displayed a home bias. Negative values occur when the realized target is farer away from the buyer than the average hypothetical target. Summarizing all the deals, we would expect a mean value of zero when the choice of the buyer is spatially indifferent. Figure 6 shows the frequency distribution of $HB_i$ for a portfolio size of more than 30 targets, i.e. 29 potential targets and the actual target. In order to prevent a distortion by extreme values, the Federal States Alaska and Hawaii as well as Puerto Rico were excluded.

**Figure 6**

**Frequency Distribution of Home Bias**

This figure shows the frequency distribution of the Home Bias HBi for all domestic M&A transactions without AK, HI and PR at a portfolio size of a minimum of 29+1 targets. Positive values represent a preference for proximate and negative values a preference for distant targets.




The frequency distribution shows an asymmetrical shape with a mean home bias of 674 kilometers: On average, acquirers chose targets that are almost 674 kilometers closer to them than what could be expected when calculating the average distance to all the hypothetical portfolios. The median takes a value of 995 kilometers – half of the acquirers selected a target that was at least 995 kilometers closer to them than the average distance to the respective hypothetical portfolio.

Including the remote states do not alter the results qualitatively. Since the portfolio size – as the reference against which the home bias is measured – could influence our findings, we calculate the home bias with several portfolio sizes. There are more than 15000 deals for which we could find at least one hypothetical other target – and even here the average home bias displayed is 447 kilometers. 5270 portfolios with at least nine hypothetical targets could be found, 1633 with 29 hypothetical targets, and 601 acquirers could chose between 50 or more potential targets – all these portfolio sizes display roughly the same average home bias of 447 to 674 kilometers. For all portfolio sizes the home bias is significantly different from zero (one-sided test in figure 7).

**Figure 7**

**One-sided Hypothesis Test on Home Bias**

The null-hypothesis $H_0$ of the shown one-sided hypothesis test states that the mean of the Home Bias distribution equals zero. The alternative hypothesis postulates that the mean is strictly positive. As the results reveal, the null-hypothesis can be rejected in all cases.

*One sided hypothesis test*

$H_0: \varnothing \, HB = 0$

$H_1: \varnothing \, HB = 1$

| *portfolio size* | *n* | *mean* | *std. dev.* | *t-value* |
|---|---|---|---|---|
| *> 1+1* | 15042 | 447.40 | 1104.78 | 49.67 |
| *> 9+1* | 5270 | 664.95 | 1219.68 | 39.58 |
| *> 29+1* | 1633 | 674.25 | 1284.77 | 21.21 |
| *> 49+1* | 601 | 616.50 | 1363.05 | 11.09 |

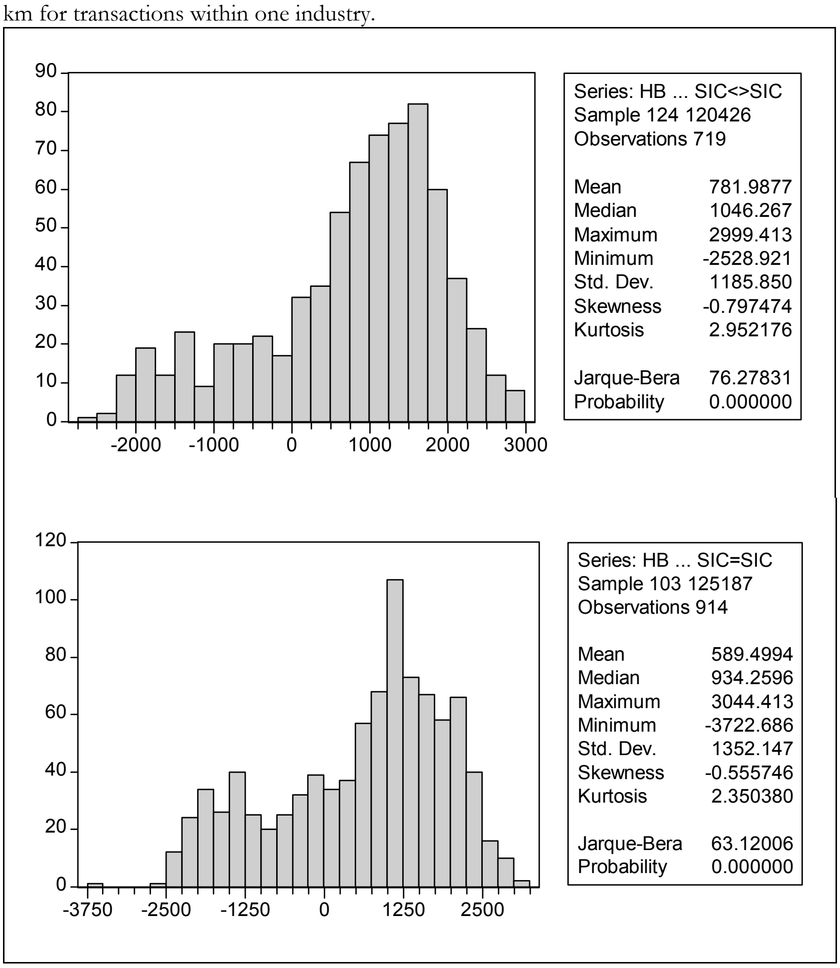
As stated above, four main reasons could be held responsible for the home bias in M&A transactions, i.e. higher synergies in connection with saving of integration costs, better monitoring after the deal, merging for local monopoly, and informational reasons. These reasons are not mutually exclusive and thus not easy to separate analytically. It should, however, be possible to distinguish informational reasons from those of local monopoly and integrations costs. When achieving a local monopoly – with arguably also the highest potential of cost savings – is the main motive for the observed home bias in M&A transactions, transactions that take place within an industry should display a stronger home bias: Merging with similar firms nearby saves more costs and leads to higher local monopoly power than merging with firms farer away. On the contrary, if the lack of (soft) information on firms further away is the main driver of the home bias, merging with firms within the same industry should display less home bias: Acquirer's knowledge of the target's business model is much higher when the target operates in the same industry as the acquirer does. Spatial proximity is less important in assessing a firm's value and understanding its risks and opportunities.

Figure 8 displays the frequency distribution of the home bias for deals where acquirer and target are in different industries (four-digit SIC) and the same for deals where acquirers and targets are in the same industry, again for a hypothetical portfolio of at least 30 potential targets. Acquirers are considered to be in the same industry when they have either their primary or any secondary SIC in the same SIC as the target's primary or secondary SICs, according to the Thomson Financial database. The upper graph in figure 8 shows a mean home bias of 782 kilometers (median 1046 kilometers) for acquirers that diversify into new industries. This contrasts with a mean home bias of 589 kilometers (median 934 kilometers) for acquirers that buy firms within the same industry, as shown in the lower graph in figure 8. Diversifying acquirers thus display a much stronger home bias, which is in line with the information hypothesis. The mean home bias for acquisitions within an industry is 193 kilometers – or about one third – smaller: We conclude that it is the lack of soft information about remote targets that drives the home bias in M&A transactions to a large extent. Since there is a home bias in all transactions, both industry-internal and in diversifying transactions, the other hypotheses hold also, but to a lesser extent.

## Figure 8

## Frequency Distributions of Home Bias within industry and for diversification

Every histogram shows the Home Bias frequencies with a portfolio size of at least 29+1 targets excluding the states AK, HI and PR. The upper graph shows a mean Home Bias of 782 km for diversifying transaction in contrast to the lower graph with a mean of 589 km for transactions within one industry.




## Figure 9

## A significant difference

The test for equality of means shows a highly significant inequality of the two means for varying portfolio sizes. As a result, transactions within one industry tend to show a significantly smaller home bias.

*Test for Equality of Means of $HB_i$*

| *portfolio size* | *> 1+1* | *> 9+1* | *> 29+1* | *> 49+1* |
|---|---|---|---|---|
| *t-value* | 4.45 | 5.09 | 3.01 | 2.98 |

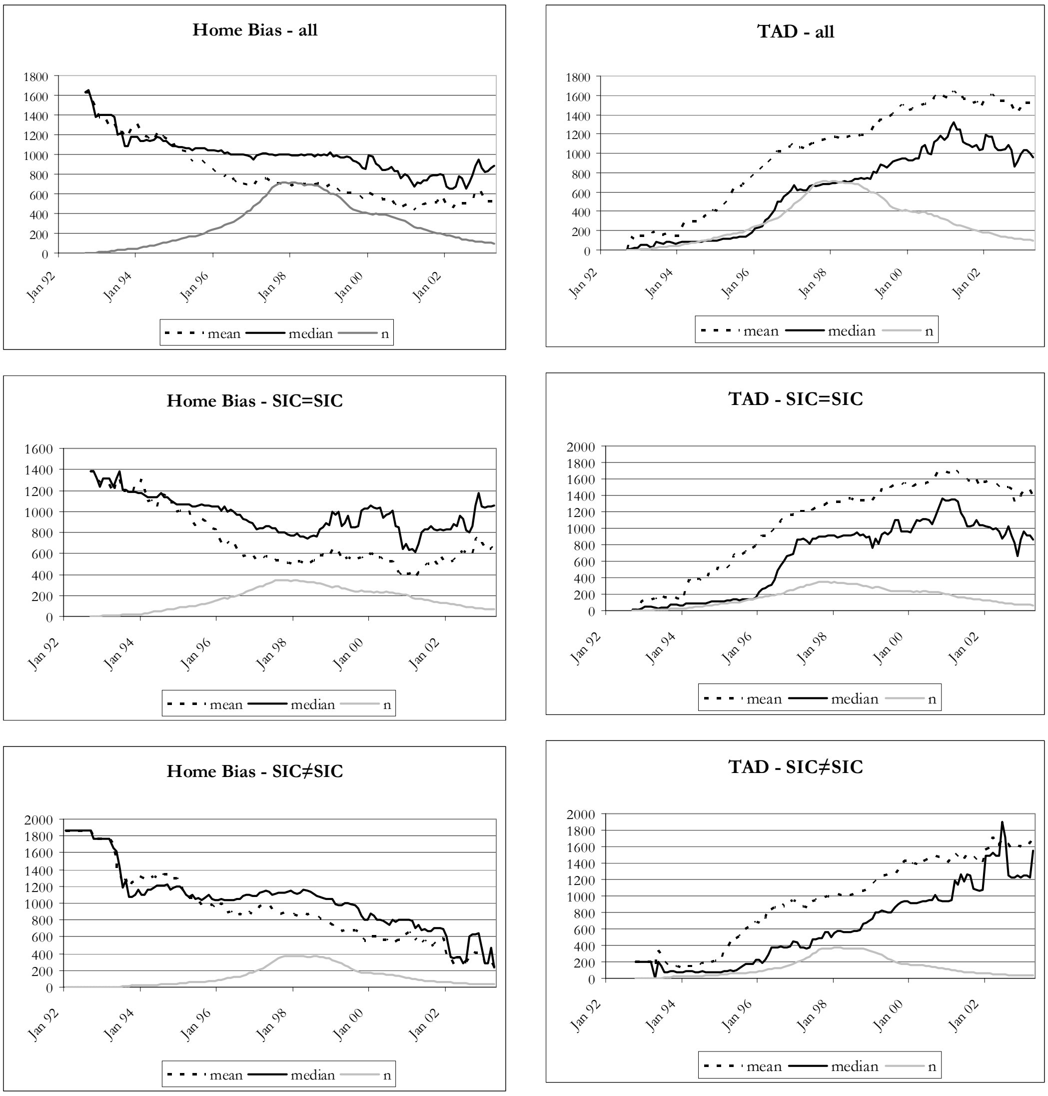
At all portfolio sizes transactions within one industry show a significantly lower home bias (at the 99%-level) than transactions that cross industry borders (see figure 9). This holds true also for many individual industries (tables not reported). We conclude that it is mainly informational asymmetries that are responsible for the home bias: Acquirers that already have a good understanding of the firm they are buying because they are in the same industry tend to buy firms farer away and display less home bias than acquirers that are buying into new business lines.

When availability of information about the target is the main driver of buying decisions, we would expect a declining home bias and increasing distance in the observed deals in time. Due to the spreading of information technology – notably the Internet during the 1990s – the availability of information has become ubiquitous. Petersen and Rajan (2002) report that bank's distance to lenders has increased with time and also attribute this to information technology and the emergence of specialized data vendors that now help to bridge spatial distance. The same might be true for M&A transactions and should yield also higher distances and presumably lower home bias. In figure 10 we look at the development of the home bias (left column) and the target acquirer distance (right column) over time for a minimum portfolio size of 30. We use a two-year moving average to smooth the graphs, the use of other averages does not change the picture much. The observations mostly start in 1993 because there are too few transactions before. Each frame in figure 10 shows three graphs, the mean, the median and the number of observations.

# Figure 10

## 2 year moving average
## home bias and target acquirer distance

The figure shows the moving average of home bias as well as the target-acquirer-distance TAD with a two year window around the date drawn [-1;+1]. We use a hypothetical portfolio size of a minimum of 30 transactions to calculate home bias and the target acquirer distances. The three values reported are the mean and median of the moving window, where n shows the number of transactions.



The first row displays the home bias and the target-acquirer distance (TAD) with all transactions included. We find a striking reduction of the home bias from the beginning of the 1990s from about 1500 kilometers to a median of below 1000 kilometers at the end of our (moving averaged) observation data, the beginning of 2003. A reduction in the home bias could have two explanations: Either industry locations got more dispersed over time or the target acquirer distance has gone up. We are interested only in the latter. The right column shows a dramatic increase of the mean and median target acquirer distance over time, which matches the decreasing home bias quite well. Starting from about 100 kilometers, the median distance between target and acquirer climbs up to more than 1000 kilometers in 2003. That increase is even more distinct when looking at the mean. This is in line with the information availability hypothesis and the findings of Petersen and Rajan (2002) for bank's distance to lenders. The same trend is also visible when looking at intra-industry deals (SIC=SIC) in the second row and for inter-industry deals (SIC≠SIC), third row. In line with the static findings displayed above, the trend for diversifying deals is decidedly stronger than for the deals within an industry. For the diversifying deals – where information asymmetries are playing a more important role – the decrease in the home bias is much stronger: from about 1400 kilometers down to about 400 kilometers as opposed to about 1400 kilometers down to about 1000 kilometers for intra-industry deals. Equivalently, the median distance between target and acquirer went up more strongly for diversifying deals. Information technology actually helps to bring information in. In the next chapter we examine this incident in more detail.

## IV. Drivers of home bias

### A. Methodology

In the following section we try to explore the phenomenon more deeply and to identify what drives the home bias. We set up a linear regression model where the dependent variable is the home bias $HB_i$. This variable shows the deviation of the observed transaction distance from the mean distance to each potential target, measured in kilometers. For example, if an acquirer shows an $HB_i$ of 300 kilometers it chose to buy a company that is 300 kilometers closer than the mean of all other potential targets. The theoretical interval of $HB_i$ shows values from about minus to plus 4700 kilometers which is determined by the absolute maximum in our sample – the coast-to-coast distance.

We are interested in the analysis of selected firm characteristics of the target and in general transaction characteristics regarding information flows. The coefficient of each regressor shows the impact of the variables for the explanation of acquirers' proximity preferences. Each linear coefficient serves as an indicator for the percentage change of home bias when the variable is increased by one percent.

For simplicity we use the ordinary least squares estimate for the following linear regressions. Due to volatile variances in the residuals we correct with the heteroscedastic consistent variance-covariance matrix of White. Having **HB** as (n x 1) vector of dependent variables and **X** as (n x k) matrix of the firm characteristics we generate a standard form of equation. As before, we include the log of the target's market value, the financial leverage, the return on assets as well as the price to book ratio in our analysis. Thus, the following regression model evolves:

$$\mathbf{HB} = \beta_1 \mathbf{ln(MV)} + \beta_2 \mathbf{Leverage} + \beta_3 \mathbf{RoA} + \beta_4 \mathbf{P/B} + \beta_0 + \varepsilon$$

The following tables show the results of the linear regressions with a portfolio size of at least 1+1 companies (the actual deal target as well as one hypothetical transaction target). The results stay robust if we exclude small portfolio sizes (e.g. $\geq$ 1+9) but also diminish the sample size. Although there is less distortion within large portfolios, we do not assume that all mismatches are spatially aiming in one direction. Therefore, we include all portfolio sizes.

As before, the full sample is then divided into sub-samples for different firm sizes. The smallest category builds the nano caps with a market capitalization of up to 50 million US dollars. The second frame contains the micro caps with at least 50 to 300 million and is followed by the small caps with up to 2 billion dollars. The second largest category includes the mid caps with a market capitalization between 2 and 10 billion dollars. As the last category the large caps embrace enterprises of up to 200 billion dollars.

After the firm size distinction we partition the full sample into two time frames with the first starting form 1990 until 1997 and the second from 1998 until the first quarter of 2004. To complete the analysis we distinguish transactions that take place within one industry (SIC=SIC) from deals that aim into a new industry (SIC $\neq$ SIC).

The top most regression contains the full sample of n = 2186 observations. Considering the total number of M&A transactions the sample size appears to be rather small. This is due to the fact that the regression includes only deals where all variables are known. As the majority of M&A transactions happens with small and medium sized enterprises SME there is very poor data availability especially on accounting data (e.g. leverage, RoA, P/b Ratio).

### B. Regression results

Figure 11 shows the results of the multivariate regression of the target's firm characteristics on the home bias. The full sample regression shows that both the company size and the leverage are statistically and economically significant. The regression equation exhibits that acquirer of large companies have a lower proximity preference. They tend to buy over greater distances than acquirer of small companies. The t-value of t *ln(MV)* = -6.28 manifests the significance level of 99 percent which means that with a probability of one percent the observed slope coefficient beta *ln(MV)* equals zero. This result is robust throughout an additive generation of the regression equation (table not reported). The coefficient's interpretation of a log variable describes the average proportional change (in hundred) of the endogenous variable, with a one per cent change of the exogenous variable. A $\beta_{ln(MV)}$ of -92.70 therefore shows an average decrease in home bias of 0.927 per cent if the log of market value is increased by one per cent. The significant negative influence is consistent with both the results of Coval and Moskowitz (1999) who find a similar investment behavior of US funds managers as well as Kang and Stulz (1997) who find similar results for foreign investors in Japan.

The next characteristic, leverage, is an indicator for the financial distress of the target company. Again the results in figure 11 show a highly significant coefficient $\beta$ = 677.35 at a 99 percent level. That means that the higher the leverage of a target the stronger the home bias of an acquirer. Quantitatively spoken, a one percent increase of leverage leads to an increase in home bias of 6.77 kilometers. Again, this is similar to the results of Coval and Moskowitz (1999) find that US fund managers have a preference for nearby highly levered companies. Also, a strong analogy to the results of Kang and Stulz (1997) persists which we will point out in the following sections.

## Figure 11

## Multivariate regression (firm characteristics)

The dependent variable in the following regression is the home bias $HB_j$. The main sample contains all M&A transactions with a portfolio size of at least 1+1 companies that provide data for all regressors (n = 2186). The exogenous variables consist primarily of target characteristics being the log of market value *ln(MV)*, leverage, Return-on-Assets *RoA*, Price-to-Book Ratio *P/B*. The sample is being divided into sub samples for the target size, time window and industry internal transactions *SIC=SIC* versus deals that aim into a new industry *SIC≠SIC*.

| *Sample* | *ln(MV)* | *Lev* | *RoA* | *P/B* | *C* | *n* | $R^2$ |
|---|---|---|---|---|---|---|---|
| **All** | **-92.70** | **677.35** | **3.168** | **-1.103** | **491.95** | **2186** | **0.056** |
| | -(6.28) | (7.89) | (1.92) | -(1.78) | (5.15) | | |
| Nano Cap | | 635.38 | 3.47 | -0.166 | 201.509 | 759 | 0.042 |
| | | (4.42) | (1.64) | -(0.51) | (1.86) | | |
| Micro Cap | | 715.02 | 0.450 | -0.969 | 117.22 | 940 | 0.038 |
| | | (5.82) | (0.15) | -(1.74) | (1.30) | | |
| Small Cap | | 687.03 | 4.136 | -1.482 | -212.77 | 392 | 0.033 |
| | | (3.01) | (0.82) | -(1.16) | -1.35 | | |
| Mid Cap | | 635.35 | 21.953 | -13.293 | -349.16 | 82 | 0.131 |
| | | (1.53) | (1.54) | -(0.71) | -1.17 | | |
| Large Cap | | 2519.31 | 90.404 | -38.265 | -2029.36 | 13 | 0.117 |
| | | (1.14) | (1.37) | -(0.22) | -1.31 | | |
| **1990 to 1997** | **-86.58** | **763.98** | **10.354** | **-0.372** | **387.18** | **867** | **0.072** |
| | -(3.98) | (6.02) | (3.53) | -(1.77) | (3.00) | | |
| **1998 to Q1/04** | **-91.07** | **685.14** | **1.088** | **-7.199** | **502.29** | **1319** | **0.059** |
| | -(4.54) | (5.83) | (0.55) | -(2.81) | (3.73) | | |
| **SIC = SIC** | **-67.88** | **526.93** | **2.937** | **-1.314** | **422.80** | **1230** | **0.032** |
| | -(3.46) | (4.34) | (1.27) | -(1.28) | (3.23) | | |
| SIC = SIC | -69.58 | 655.18 | 12.282 | -0.547 | 314.17 | 491 | 0.057 |
| 1990 to 1997 | -(2.46) | (3.65) | (3.30) | -(2.11) | (1.85) | | |
| SIC = SIC | -63.64 | 532.29 | 0.652 | -5.758 | 424.06 | 739 | 0.033 |
| 1998 to Q1/04 | -(2.32) | (3.19) | (0.23) | -(2.25) | (2.21) | | |
| **SIC ≠ SIC** | **-122.95** | **837.10** | **3.094** | **-0.983** | **571.12** | **956** | **0.092** |
| | -(5.20) | (7.02) | (1.44) | -(1.44) | (4.10) | | |
| SIC ≠ SIC | -91.78 | 850.37 | 7.676 | -0.420 | 429.82 | 376 | 0.087 |
| 1990 to 1997 | -(2.54) | (4.71) | (1.72) | -(1.14) | (2.15) | | |
| SIC ≠ SIC | -124.56 | 863.95 | 0.764 | -14.434 | 590.87 | 580 | 0.105 |
| 1998 to Q1/04 | -(4.12) | (5.38) | (0.31) | -(4.72) | (3.20) | | |

The target's *RoA* is significant in the comprising regression, but in the regressions separated by firm size and also not in most additive regression analyses (not reported here). On top of that, the industry specific analysis reveals both positive as well as negative slope coefficients. Altogether, there is no definite picture of the influence of *RoA* on the acquirer's home bias. Slightly opposing our findings, Coval and Moskowitz (1999) point to a weak but significant negative influence on the fund manager's home bias. They conclude 'that investors favor local firms with relatively poor accounting performance. However, this preference is not manifested in an economically important way' (Coval and Moskowitz 1999, p. 2064). The P/B ratio is, similarly to the RoA, not statistically significant. This finding is true also for industrial specific regressions (not shown here).

Since the size of target companies might affect the merging patterns that are obscured in the general picture, we partition our set into several sub-samples, according to size. The majority of M&A transactions takes place within the micro (n=940) and nano-cap (n=759) segment, where all private companies are placed. The large cap segment has too little observations for statistically significant findings and is mentioned here for informational reasons only. Figure 11 shows that the significance of leverage decreases with business size and is not significant in the mid cap segment or larger. This result is in line with the information hypothesis: For assessing highly indebted smaller firms physical proximity is helpful, but not needed for the large caps since those are more transparent. The Return-on-Assets (RoA) and the Price-book ratio (P/B) are not consistently significant. RoA has the expected positive sign when significant; a high return on asset ratio characterizes a profitable, opaque firm where presumably important assets are not recorded in the balance sheet. The higher the RoA, the more home bias could be observed – i.e., in the small- and mid-cap sector only. The P/B ratio is significant with a negative sign only in the mid cap sector and almost significant in the small cap sector: A high price-book ratio decreases the home bias. This is not in line with an information hypothesis with similar reasoning as before. The lack of significance could be due to the strong explanatory power of the leverage variable, with also captures firm distress and thus opaqueness (see Coval and Moskowitz 1999; Fama and French 1992).

We differentiate also between M&A transactions within the industry on a four-digit SIC level (SIC=SIC) from diversifying transactions (SIC≠SIC). For the most part, the coefficients and levels of significance remain largely unchanged. However, the coefficient for the size of the firm *ln(MV)* exerts a much stronger influence on the home bias in diversifying transactions. When buying into a new SIC, acquirers react more to the size of the target (with a coefficient of -122.95 as opposed to -67.88 in industry-internal transactions). This is in line with a story about information problems: Small firms in other industries are harder to evaluate than firms in a known industry, so size does matter more in diversifying transactions. Accordingly, in those transactions the coefficient for the leverage variable is larger.

The most striking changes occur when we split up the results in time. We create two sub-samples with transactions from 1990 to 1997 and from 1998 until the first quarter of 2004, the end of our dataset. The second half covers roughly two thirds of all transactions (n=1319). Both, the coefficient of the firm size *ln(MV)* and its significance slightly increase in the second period. Firm size plays a bigger role after 1997 in explaining the variance of the home bias.

Many of the findings for the two different periods are confirmed when we split the data into industry-internal and diversifying transactions within each time period. The leverage variable remains with a large positive coefficient and highly significant in all four sub-samples and the price-book ratio mostly has a negative sign but is not significant in any case; also not significant is the return-on-assets, with the exception of a significant positive coefficient in the early period when transactions occur within one industry. Looking at the industrial internal transactions, firm size has about the same negative coefficient in both periods, although the sub-samples both display a slightly lower t-value.

The same is not true for transactions crossing industries: As in the whole sample, firm size is not significant in the early period but highly significant in the later. A puzzle arises again from the private dummy. While not significant for the whole period, being a private target has a strong negative, significant coefficient in the early phase for both sub-samples and strong positive and highly significant coefficient in the later period, again for both samples.

Since we pool our data across industries, industry-specific characteristics may distort our findings. As a robustness check we run the same linear regression model with industry-normalized variables. The annual industry-specific means of each variable are calculated from the Compustat database. In some industries there have been only few observations in some years. We run two checks, one in which we include all observations and one where we only include industries of at least 30 observations per variable per year. Both tests lead to very similar results, so the latter is not reported here. We divided each value by its corresponding industry mean. The results are shown in figure 12. This demeaned model shows qualitatively the same results as the one without normalization. However, significance levels are slightly lower. Remarkably, the industry-specific model does not display stronger impacts or significance of *RoA* and *P/B* ratios. Still, market value shows a significant negative impact. The financial leverage has mainly positive coefficients, some significant. Only for intra-industry transactions there are negative but insignificant coefficients for leverage as opposed to positive and significant coefficients in the inter-industry fraction. This is in line with the information hypothesis: For acquiring firms that buy within their industry, targets' financial leverage does not play a role for the home bias. Firms that venture into new business lines across industries need more information and buy highly leveraged target firms only when they are in close distance.

## Figure 12

## Industry-normalized multivariate regression

The dependent variable in the following regression is the home bias $HB_i$. The main sample contains all M&A transactions with a portfolio size of at least 1+1 companies that provide data for all regressors (n = 1556). The exogenous variables consist of industry-normalized target characteristics market value *MV*, leverage, Return-on-Assets *RoA* and Price-to-Book Ratio *P/B*. Each firm-variable is divided by its annual industry-specific mean. The sample is being divided into sub samples for the target size, time window and industry internal transactions *SIC=SIC* versus deals that aim into a new industry *SIC≠SIC*.

| *Sample* | *MV* | *Lev* | *RoA* | *P/B* | *C* | *n* | $R^2$ |
|---|---|---|---|---|---|---|---|
| **All** | **-67.06**<br>-(2.92) | **128.23**<br>(1.49) | **-1.067**<br>-(0.48) | **-3.582**<br>-(1.70) | **297.23**<br>(3.92) | **1556** | **0.009** |
| Nano Cap | | 64.34<br>(0.45) | -0.95<br>-(0.11) | 6.924<br>(0.90) | 383.671<br>(2.92) | 488 | 0.001 |
| Micro Cap | | 56.28<br>(0.44) | -0.499<br>-(0.22) | -2.029<br>-(0.74) | 404.71<br>(3.76) | 679 | 0.001 |
| Small Cap | | 331.49<br>(1.50) | 14.357<br>(0.41) | -4.219<br>-(1.08) | -125.37<br>-0.66 | 314 | 0.013 |
| Mid Cap | | 266.36<br>(0.70) | -101.272<br>-(1.72) | -71.936<br>-(1.18) | -187.93<br>-0.51 | 65 | 0.105 |
| Large Cap | | -46.01<br>-(0.03) | -292.539<br>-(0.44) | 113.999<br>(1.06) | -491.35<br>-0.42 | 10 | 0.223 |
| **1990 to 1997** | **-23.54**<br>-(0.70) | **191.33**<br>(1.29) | **-1.784**<br>-(0.25) | **0.084**<br>(0.12) | **245.02**<br>(1.88) | **522** | **0.004** |
| **1998 to Q1/04** | **-90.13**<br>-(2.87) | **100.54**<br>(0.95) | **-0.660**<br>-(0.31) | **-10.871**<br>-(2.79) | **321.61**<br>(3.45) | **1034** | **0.018** |
| **SIC = SIC** | **-47.24**<br>-(1.59) | **-142.59**<br>-(1.20) | **-1.201**<br>-(0.37) | **-2.846**<br>-(1.29) | **395.01**<br>(3.97) | **872** | **0.006** |
| SIC = SIC<br>1990 to 1997 | -12.51<br>-(0.31) | -66.33<br>-(0.33) | -0.093<br>-(0.02) | -0.178<br>-(0.25) | 295.65<br>(1.77) | 299 | 0.001 |
| SIC = SIC<br>1998 to Q1/04 | -85.32<br>-(1.94) | -165.06<br>-(1.11) | -1.651<br>-(0.45) | -7.992<br>-(1.55) | 444.24<br>(3.56) | 573 | 0.012 |
| **SIC ≠ SIC** | **-87.30**<br>-(2.39) | **416.66**<br>(3.33) | **-3.339**<br>-(1.47) | **-4.691**<br>-(1.58) | **193.42**<br>(1.67) | **684** | **0.032** |
| SIC ≠ SIC<br>1990 to 1997 | -24.72<br>-(0.37) | 374.78<br>(1.60) | -13.198<br>-(0.59) | -0.812<br>-(0.52) | 272.11<br>(1.26) | 223 | 0.016 |
| SIC ≠ SIC<br>1998 to Q1/04 | -98.03<br>-(2.26) | 397.99<br>(2.69) | -2.276<br>-(1.33) | -12.447<br>-(2.32) | 177.14<br>(1.29) | 461 | 0.044 |

## V. Economic Significance

### A. Data and methodology

With the stated home bias in M&A transactions it is of interest whether tendency to merge with firms nearby has any economic significance – i.e., are firms doing better when buying firms nearby. We conduct a short-term event study of the weighted total stock price reactions of acquirer and target within a three-day window [-1; +1] around announcement date of the respective transactions, implying relatively efficient capital markets. While undoubtedly there are reactions before and presumably afterwards, the three-day window is commonly used in merger studies (see Andrade et al., 2001, for an overview).

In this study, we use the same dataset as before and complement it with daily share prices from the CRSP database. Since capital market reactions from both, acquirer and target are needed our sample decreases to 1758 M&A deals from 1990 to the first quarter of 2004. The large reduction is mainly due to the fact that most transactions recorded by SDC Thomson Financial involve at least one private firm and thus are not eligible. Additionally, we exclude from the analysis any transaction that involves the acquisition of less than 50 percent of the target company. As before, we do not distinguish between mergers and acquisitions. The total success of a transaction is measured as the three-day abnormal return of acquirer and target weighted by their respective market capitalizations two trading days before announcement date. The expected normal return is calculated by the CAPM, with the daily beta taken from a period [-250;-50] trading days against the CRSP all share index, which is also used as benchmark index during the event. On average, targets gain about 21.6% during the three day window, acquirers lose about 1.5%, and the average total abnormal return for target and acquirer combined is 1.0%, roughly in line with the Andrade et al. 2001 results and others. Since we consider only deals where both, acquirer and target are listed companies the results for acquirers are slightly worse than reported in other studies.

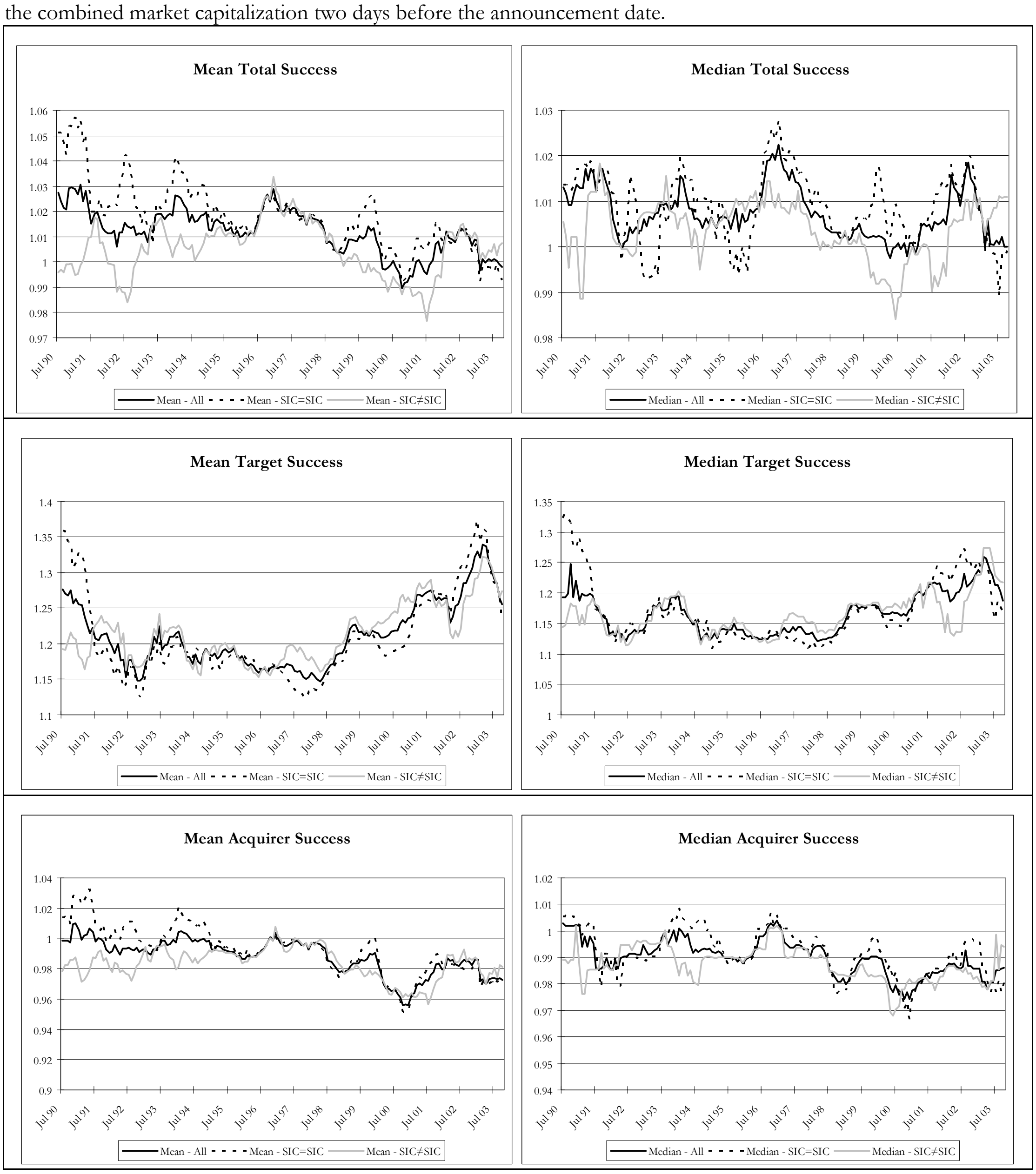
The frames in figure 13 report the success of M&A transactions measured by the cumulated abnormal return in a three-day window [-1;+1] around announcement date. The graphs in figure 13 show the data as a 12-month moving average [-6;+6]. In each frame, the success for all deals, the success for deals within one industry (SIC=SIC) and for diversifying deals (SIC≠SIC) are displayed. The total success of M&A transactions decreases during our observation period. Especially the mean total success of transactions within one industry (SIC=SIC) reveals a strong movement from roughly +3.5 percent in the first half of the nineties to around zero.

The targets' abnormal returns are firmly positive during the whole period. The U-shaped graph of mean and median reveal a slight but steady upward movement from 1992 onwards. In contrast, acquirers' success (mean and median) show a downward movement through the whole observation period. Starting from a mean of around zero percent abnormal return (i.e. 100% or 1.0 of market capitalization two days before announcement) in 1990 the median acquirer success hardly shows positive results over the entire period. In total, acquirers' share prices show a positive return in only 40 percent of all transactions.

## Figure 13

## Mean and median abnormal return

This table reports the success of M&A transactions measured by the cumulated abnormal return in a three-day window [-1;+1] around announcement date. The total success is computed by the abnormal returns of target and acquirer weighted by their market capitalization. The graphs below show the data with a moving average of +6 and -6 months. In each frame, the success for all deals, the success for deals within one industry (SIC=SIC) and for diversifying deals (SIC ≠ SIC) are displayed. The vertical axis shows the market capitalization one day after the announcement relative to the combined market capitalization two days before the announcement date.



In general, M&A deals involve a lot of idiosyncrasy with a few stylized facts emerging from the data: On average, the total success measured by differences in the weighted share price of acquirer and target is modestly positive. However, more is happening beneath. Whereas the acquirer does not gain much if at all, the target's share price – usually a smaller firm – increases a lot. Diversifying deals are less successful than transactions within one industry. The terms of payments are important, i.e. cash payments are more successful than hybrid payments and paying for the acquisitions with shares only usually means a drop in share prices for the acquirer. Tender offers and leveraged transactions tend to be more successful than others, as is buying large firms. To our knowledge the influence of distance in domestic M&A transactions has not been tested so far.

We are using the above mentioned stylized facts about the success of M&A transactions as control variables. Thus, we expect the abnormal returns to be correlated with home bias, market value of the target, leverage of the target, whether the transaction is a leveraged buyout, and the payment method (only cash, only shares, hybrid payment). The basic model specification is given by:

$$\mathbf{R} = \beta_1 \mathbf{BIAS} + \beta_2 \mathbf{ln(MV)} + \beta_3 \mathbf{Leverage} + \beta_{4,j} \mathbf{Dummy}_j + \beta_0 + \varepsilon$$

Where R refers to the cumulative abnormal return; $\beta_0$ is the intercept; home bias, *ln(MV)* and leverage have the same specifications as in the regressions before. We use five different binary variables as separate dummies for the indication of specific transaction characteristics: For deals that were highly debt financed (indication taken from the Thomson Financial data set) the dummy *lbo* takes the value of 1. For deals where a tender offer was launched for the target the dummy *tender* takes the value of 1. And finally, to control for the way of payment we use the dummies *cash, shares, hybrid* representing the corresponding type.

## B. Regression results

The first section of figure 14 shows the results for the whole dataset. Our study reproduces the general findings in the literature quite well: The extended use of debt financing of the acquisition (*lbo*) increases the success, as do tender offers and payment with cash. Payment of target shareholders by shares only reduces the total success; hybrid payments (both cash and shares) are not significant. The size of the firm, measured by the log of the market value *ln(MV)*, has a negative sign and is highly significant – the larger the target, the less successful the transaction. The same holds true for leverage, the more leveraged the target, the less successful the transaction. As displayed in the lower parts of figure 14, the results remain qualitatively unchanged between deals within an industry (SIC=SIC) and across industries (SIC≠SIC), although most coefficients are lower and less significant in the latter case (with the exception of market value).

We are most interested in the home bias coefficient, which in the full sample is showing a positive sign throughout the specifications and is mostly significant with t-values ranging from 1.20 to 1.87: The lower the acquirer's home bias, the worse the success of the deal measured by abnormal share price differences during the event. The coefficient is close to zero and thus the influence of distance is in general not economically relevant: A stronger home bias does not change the combined abnormal return of both participants a lot – which is surprising. That is to say, merging with a firm closer by does on average not improve the results either. Most of the theoretical arguments mentioned in the beginning – less integration costs, local monopoly power, better monitoring afterwards – do not lead to higher pay offs for shareholders of the combined firm!

We get qualitatively unchanged results when regressing with the target-acquirer distance instead of home bias (table not reported). This underscores the above findings.

## Figure 14 a

## Multivariate Regression on Cumulated Abnormal Return

The dependent variable in the shown regression is the total success of the transaction measured by the cumulative abnormal return. The explanatory variables are home bias, log of market value and leverage as in the regressions before. We use five different binary variables as separate dummies for the indication of specific transaction characteristics: For deals that were highly debt financed (indication taken from the Thomson Financial data set) *lbo* takes the value of 1. For deals where a tender offer was launched for the target *tender* takes the value of 1. And finally, to control for the way of payment we use *cash, shares, hybrid* representing the corresponding type.

| *Sample* | *bias* | *ln(MV)* | *leverage* | *lbo* | *tender* | *cash* | *shares* | *hybrid* | *c* | *n* | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| All | 0.000229 | -0.500727 | -0.002333 | 1.869 | | | | | 103.387 | 1758 | 0.016 |
| | (1.23) | -(4.64) | -(4.85) | (8.53) | | | | | (181.02) | | |
| | 0.000353 | -0.488455 | -0.001564 | | 2.971 | | | | 102.778 | 1758 | 0.040 |
| | (1.87) | -(4.56) | -(2.98) | | (6.35) | | | | (177.79) | | |
| | 0.000338 | -0.368951 | -0.001717 | | | 2.792 | | | 101.936 | 1758 | 0.045 |
| | (1.81) | -(3.42) | -(3.35) | | | (7.37) | | | (171.20) | | |
| | 0.000311 | -0.441870 | -0.000810 | | | | -2.739 | | 104.382 | 1758 | 0.052 |
| | (1.69) | -(4.15) | -(1.52) | | | | -(8.20) | | (178.94) | | |
| | 0.000225 | -0.513709 | -0.002189 | | | | | 0.489 | 103.350 | 1758 | 0.017 |
| | (1.20) | -(4.71) | -(4.36) | | | | | (1.20) | (181.57) | | |
| **SIC = SIC** | 0.000422 | -0.476764 | -0.002145 | | 3.285 | | | | 103.159 | 983 | 0.043 |
| | (1.67) | -(3.22) | -(3.46) | | (4.93) | | | | (123.57) | | |
| | 0.000424 | -0.345469 | -0.002089 | | | 3.507 | | | 102.052 | 983 | 0.059 |
| | (1.70) | -(2.36) | -(3.37) | | | (6.64) | | | (121.52) | | |
| | 0.000375 | -0.426616 | -0.000957 | | | | -3.313 | | 104.925 | 983 | 0.064 |
| | (1.52) | -(2.94) | -(1.44) | | | | -(6.99) | | (127.63) | | |
| | 0.000328 | -0.524187 | -0.002681 | | | | | 0.3171 | 103.895 | 983 | 0.018 |
| | (1.30) | -(3.50) | -(4.27) | | | | | (0.56) | (127.38) | | |

**Figure 14 b**

## Multivariate Regression on Cumulated Abnormal Return (continued)

(Repeated) The dependent variable in the shown regression is the total success of the transaction measured by the cumulative abnormal return. The explanatory variables are home bias, log of market value and leverage as in the regressions before. We use five different binary variables as separate dummies for the indication of specific transaction characteristics: For deals that were highly debt financed (indication taken from the Thomson Financial data set) *lbo* takes the value of 1. For deals where a tender offer was launched for the target *tender* takes the value of 1. And finally, to control for the way of payment we use *cash, shares, hybrid* representing the corresponding type.

| *Sample* | *bias* | *ln(MV)* | *leverage* | *lbo* | *tender* | *cash* | *shares* | *hybrid* | *c* | *n* | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **SIC ≠ SIC** | 0.000057 | -0.585664 | 0.758078 | 2.452 | | | | | 102.753 | 775 | 0.022 |
| | (0.19) | -(3.83) | (1.05) | (7.96) | | | | | (116.48) | | |
| | 0.000186 | -0.618703 | 1.263568 | | 2.831 | | | | 102.037 | 775 | 0.048 |
| | (0.64) | -(4.08) | (1.66) | | (4.28) | | | | (112.18) | | |
| | 0.000132 | -0.500932 | 1.080429 | | | 1.872 | | | 101.623 | 775 | 0.037 |
| | (0.45) | -(3.22) | (1.43) | | | (3.43) | | | (102.25) | | |
| | 0.000129 | -0.549493 | 0.983241 | | | | -1.884 | | 103.405 | 775 | 0.042 |
| | (0.44) | -(3.58) | (1.34) | | | | -(3.97) | | (117.71) | | |
| | 0.000053 | -0.602335 | 0.716393 | | | | | 0.543 | 102.762 | 775 | 0.023 |
| | (0.18) | -(3.89) | (1.00) | | | | | (0.99) | (116.73) | | |

**C. Time**

To test whether the observed phenomena are stable in time we split the sample into two sub-samples, an early phase from 1990 to 1997 and a later phase from 1998 to the first quarter of 2004 (see figure 15). Without changing qualitatively, most control variable coefficients are lower and show also lower – but predominantly still significant – t-values in the early phase. Surprisingly, both market value and home bias are not significant drivers of success in the early phase. While market value looses its significance but still has the expected negative sign, the home bias coefficient becomes even negative, but not significant. Proximity as a driver of success became important only in the later phase, starting in 1998. Recall that during the observation period the home bias went down while, at the same time, the average distance between target and acquirer increased significantly. From these two observations the following picture emerges: During the early phase, when home bias is high and the average distance to the target is low, distance does not yield significant explanatory power for the success of M&A transactions. In the later phase, however, with a strongly decreasing home bias and strongly increasing distances to the targets, the home bias variable becomes significant. The stronger the home bias the more successful the deal is. Since proximity never becomes an economically relevant factor, we do not pursue the analysis further at this point. This is however, an important hint for future research.

In the full sample, home bias is not an important driver of the success of an M&A-transaction (neither is distance, the results are not reported here). This is, in fact, puzzling: Although many theoretical arguments are in favor of better results for proximate transactions, this is not reflected in our event study. The main reason for choosing proximate targets may just be a familiarity argument along the lines of Huberman (2001). Managers are predominantly more familiar with firms close by – but that does not necessarily mean that they have better information about them. Indeed, if the theoretical arguments above would hold (and we cannot rule this out), i.e. lower integration costs, better monitoring afterwards and local monopoly in the case of proximate targets, there seems to be almost an adverse selection process: Since success is influenced only to a very small extent by the distance between the partners, acquirers might miss the best opportunities by predominantly choosing firms that are located close by.

## Figure 15

## Multivariate Regression on Cumulated Abnormal Return through time

(Repeated) The dependent variable in the shown regression is the total success of the transaction measured by the cumulative abnormal return. The explanatory variables are home bias, log of market value and leverage as in the regressions before. We use five different binary variables as separate dummies for the indication of specific transaction characteristics: For deals that were highly debt financed (indication taken from the Thomson Financial data set) *lbo* takes the value of 1. For deals where a tender offer was launched for the target *tender* takes the value of 1. And finally, to control for the way of payment we use *cash, shares, hybrid* representing the corresponding type.

| *Sample* | *bias* | *ln(MV)* | *leverage* | *lbo* | *tender* | *cash* | *shares* | *hybrid* | *c* | *n* | $R^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1990 to 1997 | -0.000261<br>-(1.07) | -0.299102<br>-(1.68) | 0.566414<br>(0.71) | | 3.710<br>(5.21) | | | | 102.451<br>(90.63) | 731 | 0.050 |
| 1998 to Q1/04 | 0.000644<br>(2.55) | -0.502894<br>-(3.60) | -0.000750<br>-(1.23) | | 2.357<br>(3.81) | | | | 102.302<br>(127.16) | 1027 | 0.039 |
| 1990 to 1997 | -0.000364<br>-(1.48) | -0.157260<br>-(0.89) | 0.281576<br>(0.36) | | | 2.487<br>(4.33) | | | 101.966<br>(89.55) | 731 | 0.034 |
| 1998 to Q1/04 | 0.000696<br>(2.78) | -0.368641<br>-(2.59) | -0.000607<br>-(0.99) | | | 3.093<br>(6.07) | | | 101.150<br>(119.21) | 1027 | 0.057 |
| 1990 to 1997 | -0.000377<br>-(1.57) | -0.217095<br>-(1.22) | 0.151536<br>(0.20) | | | | -2.419<br>-(5.02) | | 104.206<br>(94.56) | 731 | 0.040 |
| 1998 to Q1/04 | 0.000665<br>(2.70) | -0.451248<br>-(3.28) | 0.000447<br>(0.67) | | | | -3.058<br>-(6.70) | | 103.865<br>(131.62) | 1027 | 0.066 |
| 1990 to 1997 | -0.000418<br>-(1.66) | -0.259811<br>-(1.44) | -0.017464<br>-(0.02) | | | | | 0.279<br>(0.47) | 103.282<br>(91.53) | 731 | 0.006 |
| 1998 to Q1/04 | 0.000553<br>(2.23) | -0.558696<br>-(3.95) | -0.000982<br>-(1.57) | | | | | 0.784<br>(1.45) | 102.833<br>(133.17) | 1027 | 0.027 |

### D. Best and worst deciles

Do the results so far mean that distance does not play an important role for the success of M&A-transactions at all? To see whether distance has an impact, we compare the most successful (again in terms of combined abnormal return for buyer and target) ten percent of the deals with the lowest ten percent with regard to their respective average distances and home biases. This comparison yields some interesting results (see figure 16), which are also visible – though less pronounced – when comparing the highest quartile with the lowest one (not reported).

**Figure 16**

**Best and worst deciles**

To see whether distance has an impact, we compare the most successful (again in terms of combined abnormal return for buyer and target) ten percent of the deals with the lowest ten percent with regard to their respective average distances and home biases. This comparison yields some interesting results, which are also visible – though less pronounced – when comparing the highest quartile with the lowest one (not reported).

| | All (n=116 each) | | SIC=SIC (n=66 each) | | SIC≠SIC (n=50 each) | |
|---|---|---|---|---|---|---|
| | 10 percent highest abnormal returns | 10 percent lowest abnormal returns | 10 percent highest abnormal returns | 10 percent lowest abnormal returns | 10 percent highest abnormal returns | 10 percent lowest abnormal returns |
| Total abnormal return, mean | 13.6% | -11.6% | 14.5% | -12.5% | 12.2% | -10.1% |
| Distance, mean | 1136 | 1740 | 1169 | 1777 | 1166 | 1721 |
| Distance, median | 588 | 1412 | 682 | 1516 | 439 | 1412 |
| Home bias, mean | 421 | 51 | 369 | -122 | 476 | 268 |
| Home bias, median | 437 | 160 | 361 | 66 | 565 | 343 |

The mean total abnormal return – reported in the first row – for the best performing 10 percent (116 firms in our sample) is 13.6%, compared to -11.6% for the worst ten percent. When looking only at deals within one industry (SIC=SIC), the returns of the best decile are slightly higher (14.5%) and of the lowest slightly lower (-12.5%). Not surprisingly, the average abnormal return in the best diversifying deals is lower at 12.2%; however, the worst decile of diversifying deals is performing better than the others at -10.1%.

The median distance of the best performing deals is 588 kilometers, as opposed to the median 1412 kilometers of the worst performing deals. The difference is less distinct when looking at the respective means (1136 vs. 1740) but still visible. Clearly, the best performing deals have a lower distance between acquirer and target than the worst performing deals. However, it is not only the distance that matters – in that case we would conclude that it's indeed mainly post-transaction costs or the building of local monopolies that are responsible for the better results. Also, the home bias is strikingly higher in the group of the best performing deals, with a median home bias of 437 kilometers (mean 421) in contrast to a small home bias of 160 kilometers (mean 51) in the worst performing group. While the best performing firms chose on average target firms that were 421 kilometers closer to them than other possible targets, in the badly performing transactions acquirers chose target firms that had about the average distance to them as their respective portfolios of possible targets. We take this as evidence that information availability is better for firms closer by and that it might indeed transform into better deals.

When comparing the best deals where acquirer and target are in the same industry (column 2) with those where they are in different industries (column 3), the difference in the median distances stand out: The best deals within in the industry show a median distance of 682 kilometers whereas the best deals in diversifying deals show a median distance of only 439 kilometers. This corresponds with a smaller median home bias in deals within an industry of 361 kilometers compared to 565 kilometers in diversifying deals: When crossing industry borders, the best performing deals display a lower distance between acquirer and target and a larger home bias. This again is in line with the information availability hypothesis as acquirers that have knowledge from operating in the same industry as the target do need less tacit information about the target for assessment; distance is less important in these cases. A stronger home bias (and slightly lower distances) is also observed when comparing the worst performing deals crossing industries to those within one industry. In the former, a median home bias of 343 kilometers is observed (as opposed to 66 kilometers in deals within one industry). We interpret this again as a manifestation of differences in information availability; however, choosing targets closer by than the average target seems to merely a necessary but not sufficient condition for success.

## VI. Conclusion

Using data of US domestic mergers and acquisitions transactions, this paper shows that acquirers have a preference for geographically proximate target companies. We measure the 'home bias' against benchmark portfolios of hypothetical deals where the potential targets consist of firms of similar size in the same four-digit SIC code that have been targets in other transactions at about the same time or firms that have been listed at a stock exchange at that time. There is a strong and consistent home bias for M&A transactions in the US, which is significantly declining during the observation period, i.e. between 1990 and 2004. At the same time, the average distances between target and acquirer increase articulately. The home bias is stronger for small target companies, relatively opaque companies and when acquirers diversify into new business lines, suggesting that local information is the decisive factor in explaining the results. With an event study we show that investors react relatively better to proximate acquisitions than to distant ones. That reaction is more important and becomes significant in times when the average distance between target and acquirer becomes larger, but never becomes economically significant. We interpret this as evidence for the familiarity hypothesis brought forward by Huberman (2001): Acquirers know about the existence of proximate targets and are more likely to merge with them without necessarily being better informed. However, when comparing the best and the worst deals, we are able to show a dramatic difference in distances and home bias: The most successful deals display on average a much stronger home bias and distinctively smaller distance between acquirer and target than the least successful deals. Proximity in M&A transactions therefore is a necessary but not sufficient condition for success. The paper contributes to the growing literature on the role of distance in financial decisions.

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