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From China with Love: The Role of FDI from Third Countries on EU Competition and R&D Activities

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From China with Love: The Role of FDI from Third Countries on EU Competition and R&D Activities

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Abstract

This report presents empirical analysis on the linkage between mergers and acquisition FDI and acquirer innovation efforts. The data indicates that acquisitions tend to result in a spike in research in the two following years. This impact, however, is contingent on industrial linkages between target and acquirer. In particular, non-manufacturing targets appear to have the largest impact. Further investigation using input-output linkages finds that acquirer R&D increases more when the target is a primary source of inputs for the acquirer. These effects, however, are smaller for Chinese acquirers, suggesting that concerns over whether acquisition of foreign technology is spurring faster Chinese technological growth may be misguided. Finally, these effects are smaller in more concentrated industries, suggesting the need to consider industry concentration when projecting the R&D implications of cross-border mergers.

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1 Introduction

Since Helpman, Melitz, and Yeaple (2004), a large body of literature has arisen documenting that multinational enterprises (MNEs) are more productive that exporters, who are themselves more productive than purely domestic firms.[1] In the theory, this occurs via selection where, in the first stage firms pay a fixed cost to determine their productivity with only the most productive firms choosing foreign direct investment (FDI). Oftentimes, this initial stage is described as a "research and development" (R&D) phase wherein successfully innovating firms go on to become global. As such, innovation drives the FDI. A second approach to the innovation/FDI link is that FDI itself can give rise to increased innovation. A commonly discussed motivation for this is the fact that most FDI occurs via mergers and acquisitions (M&As).[2] This is because when obtaining control of a target, the acquiring parent firm gains control of the innovations and future R&D path of the affiliate. This presents several possible changes in innovation across the two. For example, if the integration of the two parts of the MNE unleashes innovative synergies, R&D in both can rise. Similarly, due to the larger market access of the combined entity, the potential payoff from uncertain innovation can rise, leading to more R&D spending.[3] On the other hand, if innovative activities across the two substitute for one another, innovation may fall in one while rising in the other with the direction of this shift depending on local comparative advantages. Finally, if the two were engaged in an R&D race with one another, then the elimination of this competition can see innovation in both fall.

Ultimately, one must rely on the data to determine which, and under what circumstances, certain effects dominate. A review of the literature shows that, as one might expect given the breadth of possibilities mentioned above, no clear consensus emerges for what FDI via acquisition does to innovation in the MNE. In an attempt to resolve these differences, the literature has turned to examining granular effects in which the impact can vary according to the target and acquirer's characteristics. Examples here include

This is where our contribution lies. Specifically, we examine how the acquirer's R&D spending changes post-acquisition depending on features such as the industrial relatedness of the target and acquirer (that is, their connection via an input-output table), the concentration of the acquirer's industry (which matters in theory for the decision to innovate to "remain on top" or catch up to the leader), and the origin of the acquirer (with a particular eye on Chinese acquirers given the fast growth of their acquisitions). Using data from ORBIS that combines firm information with their acquisitions and data on those targets (including their industry and R&D spending) for investment within the European Union, China, and the US from 2009-2016, we find that more acquisitions leads to more acquirer innovation. This effect, however, is contingent on industrial linkages, with the strongest impacts when the target is in a non-manufacturing sector. Furthermore, we find that acquiring a high

[1] Examples include Davies and Jeppesen (2015), Bloom, et. al (2012), Harrison and Rodriguez-Clare (2010), and Criscuolo and Martin (2009).

[2] Although as discussed by Davies, Desbordes, and Ray (forthcoming) in terms of numbers most FDI now occurs via greenfield, when discussing the value of the investment, M&As still dominate the landscape. That said, Nocke and Yeaple (2007, 2008) provide theoretic frameworks for the choice between greenfield and M&A driven in part by innovation issuess.

[3] This can also feature for greenfield FDI.

R&D target increases acquirer innovation more when the target is a major source of inputs. These effects, however, are significantly smaller for Chinese firms, suggesting less concern for whether Chinese acquisitions of R&D intensive acquisitions may result in a Chinese overtaking of the research marketplace. Finally, industry concentration tends to result in smaller effects.

In further robustness checks, to control for potential endogeneity of targeting, we follow Blonigen and Pierce (2016), Stiebale (2016), and others by using a matching algorithm. This is particularly necessary given the work of Bena and Li (2014), Guadalupe, Kuzmina, and Thomas (2012), and others which finds "cherry-picking", that is, that more innovative firms are more likely to be targets. Our results point towards this indeed being the case as, after matching, while we find that acquirers undertake more R&D, this difference is not statistically significant at the standard levels. This may be due to the fact that, because of some controls needed to examine how the R&D measures are constructed, we are forced to match within the set of acquirers. This points to the need for future work which may focus on alternative measures of innovation.

Understanding these effects is important for policy along several dimensions. First, because post-acquisition innovation activity varies across deals, this can be a useful factor for competition authorities deciding whether or not to permit a given acquisition to take place. Second, assuming that a primary goal of providing government funds to support research is to boost technological growth, understanding the innovative activities of MNEs can make a difference when decided to whom those funds should be allocated. In particular, it suggests that there may be value in promoting acquisition of non-manufacturing targets by firms in less concentrated industries.

In the next section, we provide a brief overview of the existing literature disussing FDI and innovation. Section 3 presents our data and methodology. Our baseline results are found in Section 4 alongside a battery of robustness checks. Finally, Section 5 concludes.

2 Existing literature

The literature on FDI is as large and wide-ranging as the activity of multinationals themselves, covering determinants of FDI, the impacts of MNEs on home and host economies, and government policies used to influence these firms.[4] Even within the narrow area of FDI and innovation, as illustrated by the survey of Castellani and Zanfei (2006), there is a great deal of existing work. Rather than attempt to exhaustively cover even this narrow slice of the literature, here we provide an overview of that specifically linking cross-border acquisitions and innovation.[5]

As mentioned above this literature has two main approaches: one in which acquisitions drive R&D (where our work lies) and one in which R&D predicts the pattern of acquisitions.[6] Beginning with the first, primary question is how innovation in the target or acquirer changes

[4] Blonigen and Piger (2014) and Barba-Navaretti and Venables (2004) provide surveys of the literature.

[5] Thus, we are setting aside work such as Arnold and Javorcik (2009) which examines productivity post-acquisition, and Bertrand and Zuniga (2006), who compare the innovation effects of domestic versus international acquisitions.

[6] While we focus on the work aiming to establish causality, this does not deny the useful contributions made exploring more basic correlations between FDI and innovation, e.g. Criscuolo, Slaughter, and Haskel

in response to the acquisition. The answer to this depends on which of several conflicting effect dominates. On the optimistic side, one can envision a scenario where innovative activity is complementary across the two parts of the MNE due to, for example, unleashed synergies in the knowledge held by the two initially unaffiliated firms. Alternatively, FDI in both could rise because of the increased the market size the expanded MNE can serve post-acquisition. With a larger market over which to spread the fixed costs of innovation, this can make further R&D expenditures profitable (at least in expected terms). Note that this increased market size could arise due to avoidance of trade costs (as in the horizontal model (Markusen, 1984) or its expanded export platform version (Ekholm, Markusen, and Forslid, 2007) or because the acquisition eliminates competitors (such as in Neary (2007) or Head and Ries (2008)).

On the other hand, innovation can fall post-acquisition. This can happen if innovation in the different parts of the MNE are substitutes, where one would expect that, post-acquisition the MNE might shift innovation towards its headquarters and/or to locations that have a comparative advantage in skill-intensive activities such as R&D. Thus in this case, one might observe that R&D in either the acquirer or the target rises even as the reverse happens on the other side of the acquisition deal. Furthermore, when firms are in competition with one another pre-acquisition, the reduction in competition can affect innovation in a variety of ways with cooperation leading to more or less R&D, often depending on parameter values.[7]

Thus, in general, the expected impact of an acquisition is ambiguous and depends on whether one looks at the acquirer (as we do) or the target as well as the conditions surrounding the deal, making this ultimately an empirical question. To provide answers, the standard framework utilizes some measure of innovative activity such as R&D spending (which is ours), patenting, or the implementation of product or process innovation and examines how, controlling for other factors, this changes post-acquisition. Perhaps unsurprisingly, the results are somewhat mixed. Bertrand (2009), for example, finds that R&D spending rises post-acquisition for his sample of French targets. A similar result is found in Guadalupe, Kuzmina, and Thomas (2012) using Spanish data, where they are able to employ a number of measures of innovation such as product innovation, process innovation, and the installation of new machines. Using a dummy variable for whether or not a firm does R&D, Girma, et. al (2012) find that, post-acquisition, Chinese targets are more likely to innovate.

In contrast, using data on cross-border European investments, Stiebale (2016) finds that although innovation for the firm as a whole goes up post-acquisition, this is driven by increased acquirer activity with target activity falling. Szücs (2014) finds a similar pattern, although he is careful to point out that some measures of innovation such as R&D intensity (R&D expenditures relative to sales) of acquirers falls post-acquisition not due to a decline in R&D but because of the rise in sales following the acquisition. Confounding the issue further, Desyllas and Hughes (2010) find that acquirer R&D intensity moves non-monotonically post-acquisition, initially falling then rising.

In an attempt to resolve such conflicting results, the literature has turned towards es-

(2005), which shows that, as with dimensions such as productivity and profitability, more globally active firms are more innovative ones.

[7] See for example Davies and Ellis (2007), Doraszelsi (2003), or D'Aspremont and Jacquemin (1988).

timating granular effects, that is, how such movements may differ across acquisitions. For example, Garcia-Vega, Hoffmann, and Kneller (2012) find that the impact on the target depends on whether the acquirer comes from a country with a higher or lower level of technology. Similarly, Stiebale (2016) meanwhile shows that the the impact varies with the pre-existing stock of patents in the acquirer. Thus, this reflects the notion that the change in the target depends on how much it can learn from the acquirer. In the mirror image of this, Cloodt, Hagedoorn, and van Kranenburg (2006) show that the impact of an acquisition on the acquirer's innovation depends on the knowledge base of the target. Hou and Mohnen (2013) show that the impact of Chinese firms' acquisitions varies with firm size, perhaps indicative of the need for absorptive capacity to benefit from the foreign knowledge.

This is where our work contributes by examining how acquirer R&D activity is affected by the characteristics of the target and in particular, industrial overlap as measured by linkages via input-output tables. This complements the work of Bena and Li (2014) who show that when there is greater technological overlap between the acquirer and target, measured as the technology class overlap of their patents, that this increases the post-acquisition boost in acquirer innovation. It also builds off of the contribution of Javorcik (2004) which shows that the productivity spillovers of FDI to local firms varies with industrial linkages, with the most significant effects found via backwards linkages, that is, for those firms supplying to the MNE's industry. This is where our work contributes by examining how acquirer R&D activity is affected by the characteristics of the target and in particular, industrial overlap as measured by linkages via input-output tables.[8] This complements the work of Bena and Li (2014) who show that when there is greater technological overlap between the acquirer and target, measured as the technology class overlap of their patents, that this increases the post-acquisition boost in acquirer innovation. It also builds off of the contribution of Javorcik (2004) which shows that the productivity spillovers of FDI to local firms varies with industrial linkages, with the most significant effects found via backwards linkages, that is, for those firms supplying to the MNE's industry.

Second, we examine how the impact varies with the degree of competition in the acquirer's sector. As as long been acknowledged, the relationship between competition and R&D is generally ambiguous, with the same model capable of producing a non-monotonic relationship (e.g. Bloom, et. al, 2004) and evidence supporting such a relationship (e.g. Peneder and Wörter (2015) and Tingvall and Poldahl (2006)). Finally, similar to Garcia-Vega, Hoffmann, and Kneller (2012) we allow the affect to vary by origin of the acquirer. In particular, we consider how the post-acquisition varies with whether the acquirer is Chinese. We do this both in response to the swift growth in Chinese acquisitions (as discussed in the next section) and the work of Hou and Mohnen (2013) who find that acquisition of foreign technology via Chinese acquisitions is both a prime motivator for investments as well as a significant determinant of parent firm innovation post-acquisition. [9] Finally, similar to

[8]Note that this is different from Javorcik as she analyzes the impact of FDI on the productivity of unrelated firms as it depends on linkages; we consider the impact of FDI on innovation of the firm undertaking the investment as it relates to those some linkages.

[9]This is therefore a complement to the work of, e.g., Bloom, Draca, and van Reenen (2016), who examine the effect of Chinese import competition on innovation in Europe, finding that higher competition increases average innovation, with innovation being skewed towards more advanced local firms. It also complements the work of Cheung and Lin (2004), Liu, Hodgkinson, andChuang (2014), and Wang and Wang (2015) who

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The second main theme of the literature turns this first on its head to ask how innovation affects the decision to undertake FDI.[11] Similar to the above story, if the acquisition is made to exploit synergies, then those firms initially successful in research may be more apt to acquire or be acquired. On the other hand, technologically lagging firms may seek to catch up by acquiring advanced targets (the "make or buy" comparison). An early contribution here is Blonigen and Taylor (2000) who examine the determinants of acquisitions in the American electronic and electrical equipment sector and find that firms which innovate more are less likely to acquire another. Comparable results are found by Bena and Li (2014) and Higgins and Rodriguez (2006) who use event study methodologies rather than estimating the probability of acquisition. Turning to the target, in general the literature finds that more innovative firms are more likely to be targets (e.g. Bena and Li (2014), Guadalupe, Kuzmina, and Thomas (2012), and Bertrand (2009)). This thus suggests that acquirers tend to "pick cherries".[12] Finally, there is a small literature which examines the matching between acquirer and target, e.g. Hall (1987) and Guadalupe, Kuzmina, and Thomas (2012), where it is commonly found that more similar firms are more likely to be parties to an acquisition deal. Although this side of the literature is not our focus, it is critical to recognize that it points to the likelihood that acquisitions are not random but depend themselves on innovation. As such, this raises the concern over biases in the estimates. We will follow the examples of Blonigen and Pierce (2016), Stiebale (2016), Girma, et. al (2012), and others by using propensity score matching techniques to examine such biases.

3 Data and Empirical Methodology

Our primary data set draws from the Bureau van Dijk's Orbis (which provides firm characteristics) and Zephyr (which provides information on acquistions) datasets.[13] From Orbis, for the period 2009-2017, we are able to obtain a number of firm characteristics including year of incorporation (used to construct firm age), turnover, size (proxied by the number of employees), the sector of a firm (measured at the two digit NACE Rev2 level for both

examine the impact of imports and FDI into China on Chinese innovation.

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[11]See Xie, Reddy, and Liang (2017) and Haleblian, et al. (2009) for surveys of literature on the determinants of cross-border M&As.

[12]Norbäck and Persson (2012) present a model where targets innovate partly in order to become sought-after cherries.

[13]These can be found at `www.bvdinfo.com`.

acquirer and target), the country of the target and acquirer, the year of the acquisition, and most importantly, R&D expenditures as well as information on patents held in 2018.[14] This is then matched with the Zephyr data on cross-border acquisitions to form a final dataset where for each firm i that is not acquired itself during the period, we have its own characteristics in a year t as well as the characteristics of the targets it acquired during year t. To determine whether a controlling acquisition has taken place, we impose the international standard 10% rule where control is assumed when a given individual has acquired at least a 10% equity stake in the target. Thus, we identify a deal in the Zephyr data as an acquisition if the deal results in 10% or more ownership in t whereas prior ownership was less than 10% (i.e. a shift from a non-controlling stake to a controlling one), leaving us with 1,875 acquisitions for which our controls were available. Note that in our data, only 7 acquisitions started with a positive initial stake. As reported in Table 1, these 1,875 acquisitions were spread across 1,501 acquirers, with 53.5% of the firms in our sample making a single acquisition during the sample period. Note that although our data covers only Orbis-listed firms that make an acquisition during 1999-2017, 23.9% of them do not make an acquisition during 2008-2016 (since we use lagged controls, only those occurring during this period are used). The 22.6% of firms with more than one acquisition, however, make up 57.2% of the acquisitions in our sample, highlighting the concentration of cross border M&A activity.

Our dependent variable is R&D intensity, $RD_{i,t}$ which is measured as the log of expenditures relative to employment (or revenues in robustness checks).[15] In the raw data, missing observations for R&D expenditures were common. To improve on this, we replaced any missing observation where the listed number of patents was zero with a zero, i.e. we assumed that non-patenting firms did no R&D unless otherwise reported. As we use logged intensity, we replaced those observations with the minimum value of expenditures for those firm-years where we had our other controls (-5.7323 in our data). In addition, we then constructed a dummy variable $Fake0_{i,t}$ when this was the case, something true of roughly half of the observations (which then motivates some of our exploratory results below). Finally, $FakeShare0_{i,t}$ is the share of such replaced logged intensity variables for a given acquirer-target combination.

We then use this to estimate:

$$RD_{i,t} = X_{i,t}\beta + \alpha Targets_{i,t-1} + F_{i,t} + \epsilon_{i,t} \tag{1}$$

$X_{i,t}$ is a vector of firm characteristics, $Target_{i,t-1}$ is information on the targets the firm acquired in that period, $F_{i,t}$ is a vector of fixed effects (acquirer country, acquirer two-digit NACE code, and year), and $\epsilon_{i,t}$ is the error term. For our firm characteristics, we include a lagged dependent variable $RD_{i,t-1}$, logged revenues in $t-1$, the firm's age in t, and the two above described dummies indicating whether $RD_{i,t}$ was constructed and what share of those for i are constructed.[16] In all specifications, we use robust standard errors clustered by acquirer.

[14]This time frame is used because prior to 2008, there is a marked dropoff in the number of listed firms available in Orbis. To eliminate concerns over sample selection driven by that, we restrict it to this time period.

[15]Compare this to Bertrand (2009) who uses expenditures or Stiebale (2016) who uses the number of patent applications and the number of citations.

[16]In unreported results, we also included lagged employment. This was not often significant and, as it forms the denominator in our dependent variable, we omit it here to reduce endogeneity concerns.

For the information on targets, we use three alternatives. First, we use a simple indicator equal to 1 if i acquired a target in $t-1$, regardless of the number of those targets. As this loses information for those acquirers who have acquired more than one target in a year, we alternatively use the number of acquisitions. We next proceed by using the R&D intensity of the target in $t-1$ with the idea that targets which spend more on innovation have a greater impact on the acquirer.[17] For targets with multiple acquisitions in a given year, this is the sum of the R&D intensity of the targets.[18]

In addition, following Javorcik (2004), we construct three R&D measures based on the industrial linkages between the acquirer and the target, a horizontal linkage, an output linkage, and an input linkage. The first of these is a dummy variable when the acquirer and target are in the same two-digit NACE industry. The output and input linkages are derived from the WIOD input-output matrix which provides sales between sectors broken down by country pairs and years.[19] We aggregate across country pairs to generate global input-output shares and then aggregate over the period 2009-2014 (the last year in the WIOD data). We do this for two reasons. First, as there may be random fluctuations in trade in a given year, this hopefully reduces such noise in the measure. Second, this aggregation my reduce biases introduced if trade moves precisely because an acquisition has taken place. Finally, note that while Orbis gives us four-digit NACE Rev2 codes, WIOD instead follows the a slightly more aggregated classification. We therefore map from the NACE to the WIOD classification and use the appropriate input-output shares. Each of these is then interacted with the $Target_{i,t-1}$ variable and then summed across acquisitions in a given year (for those acquirers with multiple acquisitions in a year).

The notion behind these three measures is that the closer the linkage between the industries of the acquirer and its targets, the greater the potential for interactions in the R&D of the two. For horizontal effects, these could be positive (if there are synergies) or negative (if either the two R&Ds are substitutes). For backwards linkages, substitution seems less of an issue as the innovation in one industry may have fewer applications in the other excepting through the lower cost and better quality inputs provided by the target. Thus here we generally anticipate postiche effects if acquiring a target increases the flow of superior inputs to the acquirer, spurring them to increase their own innovation to take better advantage of this. Similarly, we would typically expect positive forward linkages since acquiring a more innovative target which can better use improved inputs from the acquirer might encourage them to push further in this direction via more R&D spending.

Following on from these, we introduce further alternatives including decompositions of acquisitions according to the sector (manufacturing and non-manufacturing) as discussed below.

3.1 An Overview of the Data

Before moving on to our regression analysis, it is useful to to provide a basic overview of the data. Table 2 presents the share of acquirers and targets for the countries in our

[17]We follow the same procedure for dealing with missing/zero values of the target's R&D expenditures.

[18]Note that this is the sum of logs, not the log of sums.

[19]This can be found at `http://www.wiod.org`. For details on their construction, see Dietzenbacher, et. al (2013).

sample. Here, there are two things worth noting. First, US acquirers make up over half of the sample, with the UK a distant second. Second, China occupies the third position, having made just under 8% of the acquisitions in our sample. This large share is the result of China's remarkable acquisition growth, which rose from just one acquisition in 2010 to 25 in 2016. Table 3 presents the number of acquisition deals by year. Consistent with the findings of Davies, Desbordes, and Ray (forthcoming), M&A activity during the crisis years of 2008-2010 were lower relative to other years. The data also indicates a decline in acquisitions during 2016. This is potentially the result censoring in the Orbis data due to delays between reporting and data entry.[20] Table 4 lists the number of acquisitions for a given acquirer-year dyad for years in which an acquisition took place. Given that most acquirers made one or no acquisitions during the sample, it is natural that most dyads have no acquisition. Overall, just under 2% of the observations have more than one acquisition in an acquirer-year, something worth noting given the summations used in construction of the industry-linkage variables.

Table 5 presents information on the industries of acquirers. Of these, 51.1% are in manufacturing industries.[21] Figure 1 presents a representation of the industry relationship between targets and acquirers. The size of a circle indicates the number of deals. Although the figure is too overpopulated to be of much real use, it makes one point very clear – although a fair number of deals are horizontal (with 42.8% where the acquirer and target share the same industry) many are not. As reported in Table 6, 39.8% of acquisitions are when both the target and acquirer are in manufacturing; 41.4% are when both are in services. Acquisitions across this divide (which by definition cannot be horizontal), however, are less common, with 14.6% of deals between a manufacturing acquirer and a non-manufacturing target with the last 4.2% comprised of a non-manufacturing acquirer purchasing a manufacturing target. Given the prevalence of within-manufacturing and within-non-manufacturing deals, Figure 2 repeats Figure 1 for the within-manufacturing subsample whereas Figure 3 does so for non-manufacturing. As shown in Table 6, the number of non-horizontal deals even within these groups is a significant share of M&A activity.

Table 6 also presents some summary statistics for the average input and output shares of a deal, breaking this down into our four industry categories and between acquisitions that are horizontal and those that are non-horizontal. From this, three things become apparent. First, horizontal linkages are much stronger in terms of both input and output shares, i.e. the largest sources of inputs and destination of sales are for those deals where acquirer and target share an industry. This suggests that it is important to account for the horizontal nature of a deal in addition to the input-output linkages since they are correlated. Second, for horizontal deals, input-output linkages are roughly two to three times higher when the acquirer and target are in manufacturing than when not. Finally, within broad industry group deals (the first two rows) have noticeably stronger non-horizontal input linkages than do those across groups.

Summary statistics for our controls can be found in Table 7.

[20] In unreported results omitting 2017, results were comparable.

[21] Manufacturing industries are those from NACE 10 to NACE 37, inclusive.

4 Results

We begin our exploration in Table 8. In column 1, we only include our non-acquisition controls. As one might expect, the lagged R&D intensity is positive and highly significant. It is worth noting that we are able to rule out a unit root in R&D intensity. Firms that have higher revenues, and are younger are spend more on R&D per workers. The two variables addressing the replacement of undefined logged R&D intensity are both significant, suggesting that these replaced values may follow a different distribution, something we delve into more deeply below.

In column 2, we introduce lagged acquisitions measured as a dummy variable equal to one for any positive number of acquisitions in $t-1$. As can be seen, this is insignificant. Column 3 replaces this simple dummy with the number of acquisitions an acquirer purchases in a given year where again it is insignificant. This suggests an important difference between the majority of acquirer-years where a single acquisition occurs and the minority of "superstar" firms that have multiple acquisitions within a single year.[22] This specification, however, treats the acquirer's response the same regardless of whether it acquires a target in manufacturing or non-manufacturing. Column 4 relaxes this restriction. Here, we now find a significant coefficient, but only when the acquisition is in non-manufacturing. Column 5 controls for both the number of acquisitions and the number of those that are within the same industry, that is, the horizontal acquisitions. Neither is significant. Finally, columns 6 and 7 alters the dependent variable to be R&D expenditures relative to revenues.[23] In column 6, we find that the total number of acquisitions is now positively correlated with this altered measure of research intensity. In column 7, we again see that this is driven by acquisitions in non-manufacturing.

Prompted by the difference between manufacturing and non-manufacturing, in Table 9 we expand on the idea by allowing the impact to vary according to whether the acquirer and target are both in manufacturing (MM), only the acquirer is (MN), only the target is (NM), or neither (NN). Again, these are the sum of acquisitions within a year for each of the four groups. Here, we see that again, the significant coefficients are driven by non-manufacturing acquisitions, something true for both manufacturing and non-manufacturing acquirers. When using expenditures per employee, both manufacturing acquirers and non-manufacturing ones see higher intensity post-acquisition, with the average impact of another non-manufacturing acquisition leading to an 8% increase in R&D per worker. When using expenditures relative to revenues, this is true only for non-manufacturing acquirers. In neither case does controlling for horizontal acquisitions matter.

In Figure 4, we illustrate the acquisition within the MN category. As can be seen, unlike the NN category in Figure 3, there are three spikes in target industries: 42 (wholesale trade, except of motor vehicles and motorcycles), 62 (computer programming, consultancy and related activities), and 72 (scientific research and development). In particular, these latter two are likely quite related to innovative activity. For NACE 62, this is reminiscent of the notion of integrated manufacturing and "the internet of things", that is, the increasing integration

[22] See Freund and Pierola (2015) for discussion on superstars in trade and Davies, Siedschlag, and Studnicka (2016) for additional discussion on superstars in FDI.

[23] Since revenues were missing less than employment, this actually gives a slight rise in the number of observations.

of software with other products. According to Xu (2012) cloud computing is one of the major enablers for the manufacturing industry revolution, as "it can transform the traditional manufacturing business model, help it to align product innovation with business strategy, and create intelligent factory networks that encourage effective collaboration." Further, according to Mourtzis et al. (2016) and Low et al. (2011), the adoption of the internet of things in manufacturing is the driving force behind the transition of tradition manufacturing systems into modern digitalized ones, which will generates economic opportunities. Bradley et al. (2013) estimate the the internet of things will generate 14.4 trillion US dollars in value worldwide, of which more than half will be shared by four industries: manufacturing; retail trade; information services, finance and insurance. Therefore it is notable that we find evidence of this in acquirer innovation.

In Table 10 we introduce the input/output weighted sum of acquisitions both on their own (in columns 1 and 4) and alongside the number of acquisitions (in total and broken down by the four groups in Table 9). In short, these variables are not significant; however their inclusion does result in a positive and significant effect from the number of acquisitions even when using expenditures relative to employment. Again, however, the impact from the number of acquisitions appears to be largely driven by acquisitions in non-manufacturing.

Table 11 takes columns 2 and 5 of Table 10 and examines how much the results change as we leave out acquirers where missing R&D intensity values were set to the minimum level. In column 1 and 4, we omit those acquirers where all the expenditures were reset in this fashion. Despite the large drop in the number of observations, this has little impact. In columns 2 and 5, we leave out all where at least half of the years were reset. This is enough to eliminate significance for the revenue measure, but not the employment one. Finally, columns 3 and 6 use only those acquirers where no values were reset, resulting in patterns comparable to columns 2 and 5. Thus, it appears that the employment measure is particularly robust to this treatment of the data.

One possibility is that, by looking only at acquisitions in the year prior, we are missing critical interactions that require time to manifest. With this in mind, Table 12 extends acquisition information back two $t-2$ and $t-3$. The main difference this generates is that, whereas we did not find effects in $t-1$ on expenditures per employee when not including industrial linkages, we do find significant effects for $t-2$ with a comparable specification. Again, these seem driven by non-manufacturing targets. Adding in information on $t-3$ acquisitions, however, reveals little additional information. Table 13 does this for the expenditures relative to revenue measure. Here, while we find some impact of the $t-2$ acquisitions on intensity in t, the effect is less pronounced. In any case, the overall pattern again points to a positive effect of recent acquisitions on current R&D intensity, with the effects being driven by non-manufacturing acquisitions.

4.1 Target R&D Intensity

To this point, we have focused on the number of acquisitions while ignoring the actual R&D done by the target. In Table 14, we change this by considering the R&D intensity of the targets in the year of acquisition. In column 1, we only include this, where it has no significant impact. Column 2 also includes the number of acquisitions, i.e. including an extensive as well as an intensive margin of acquisition. Now, both this and target intensity are significantly positive. Column 3 replaces the number of acquisitions with the number of horizontal acquisitions and input/output weighted acquisition totals. These are not significant, nevertheless the intensity of targets remains significantly positive.

Column 4 is where we find much more nuanced results. Here, as elsewhere, we find that more acquisitions are correlated to higher acquirer expenditures per employee post acquisition. Now, however, we find significant variation across industrial linkages. The positive effect of the number of acquisitions is higher when those acquisitions are horizontal. This effect, however, is smaller, when the target purchases larger shares of inputs from the acquirer's industry. The reverse is true when the acquirer relies on the target's industry for a higher share of its inputs. Higher target R&D intensity, is similarly negatively correlated with acquirer R&D post-acquisition when the acquirer is a major supplier to the target. The reverse, however, is true for backwards linkages, with higher target supplies to the acquirer reinforcing more acquirer R&D per worker. Together, these suggest a shift of R&D to the downstream part of the merged entity. Table 15 repeats this process using expenditures relative to revenue. Unlike the employment measure, here we see little of significance. Given the potential sensitivity of this measure to the reset intensity values (recall that this was done for both acquirer and target) found in Table 11, this may again reflect that difference across measures.

4.2 China and Concentration

Overall, more and more attention has been given to cross-border acquisitions, with two features in particular garnering attention. First, acquisitions by Chinese-owned firms have been rising rapidly as illustrated in Figure 5. In 2009, Chinese acquisitions made up 6% of the sample, by 2016 this had more than tripled. In particular, there is the concern that, if these acquisitions give Chinese firms an edge in global markets boosted by their access to low-cost labour, that this has potential negative implications for growth elsewhere. Second, regardless of the nationality of the acquirers, there is a concern that such mergers may be increasing industry concentration leading to negative effects for consumers via both higher prices and potentially less innovation in a more complacent industry.

Given the attention received by the rapid expansion in Chinese acquisitions abroad, in Table 16, we interact our acquisition variables with a dummy equal to one when the acquirer is Chinese.[24] Columns 1 and 2 consider just the number of acquisitions; 3 and 4 expand it to target intensity (using expenditures per employee throughout).[25] Looking across the results, two difference stand out. First, looking at the total number of acquisitions, the increases post-acquisition are essentially non-existent for Chinese acquirers. Further, the input/output variation from target intensity found in Table 14 are non-existent for the Chinese. These differences may arise from their lower absorptive capacity which makes them less able to expand research following the acquisition of an R&D intensive target. Alternatively, this may be due to the lack of non-manufacturing targets by Chinese acquirers. Since Table 9 found that these targets were the greatest source of R&D growth, the focus on manufacturing

[24]Here, we report only the results when using R&D relative to employment; the results for R&D relative to revenues are available on request.

[25]Note that due to perfect colinearity with the R&D weighted share, the forward weighted number of acquisitions is dropped from the regression.

targets for Chinese firms prior to 2015 may well have something to do with the lack of evidence for post-acquisition R&D growth. Thus, it appears that concerns over Chinese acquisitions leading to a Chinese takeover in global innovation may be unfounded.

Table 17 turns to the issue of concentration.[26] With this in mind, we construct a Herfindahl index for each acquirer's country, industry, and year. We then include this $HHI_{i,t}$ measure on its own and interacted with the acquisition variables. From the theory, it is unclear what we should expect since concentration can encourage more innovation as there is less leakage of consumers and science to competitors while more concentration can reduce the intensity of R&D competition. With that in mind, across the three specifications we find a strong negative correlation between concentration and R&D intensity. Looking to the acquisition interactions, we find a consistent pattern in which the acquisition effects are dampened (that is closer to zero in absolute value) when the acquirer's market is more concentrated even if the coefficients are not always statistically significant. As such, if there is concern over concentration increasing prices post-merger, our evidence does not indicate that there is an offsetting R&D effect that would balance out those worries.

4.3 Matching

One clear concern with the above results is that the pattern of acquistion may not be random, that is, an acquirer's choice to acquire in a given year may be driven by other factors that also affect R&D intensity, opening up the acquisition variables to endogeneity. We have attempted to deal with this in part by using lagged control variables. However, it is still possible that the unobserved factor driving acquisitions in $t-1$ still affects innovation in year t separately from its affect on innovation in $t-1$. As an attempt to deal with this possibility, we use a propensity score matching estimator. With this approach, the goal is to estimate:

$$\tau_{ATT} = R\&D_{ACQ=1,p(X)}(E(R\&D(1)|_{ACQ=1,p(X)}) - E(R\&D(0)|_{ACQ=1,p(X)})) \tag{2}$$

which is the difference in R&D intensity E (here, the R&D intensity in t) when the firm has an acquisition in $t-1$ (i.e. is treated) versus when it does not, holding the probability of the firm acquirering constant (see Caliendo and Kopeinig, 2008).[27] As any remaining differences in the R&D intensity of the matched sample of acquirers and non-acquirers is attributed to the treatment, it is paramount to ensure that all observable factors influencing the firm's selection into a given treatment as well as the firm's R&D intensity are controlled for. This, however, comes at the cost of the number of firms for which a match could be found, resulting in 1,711 treated and 8,509 untreated acquirer-years for which there was common support (i.e. a large majority of the sample).[28]

As shown in Panel A of Table 18, after matching we find no significant difference between acquirers and those that do not acquire, although the t-statistic is not far off the typical

[26] This uses R&D relative to employment; results for revenue intensity available on request.

[27] Note that we continue to control for acquirer country, acquirer sector, and year dummies in this.

[28] In this, we also attempted to include firms in Orbis that never acquire, i.e. those that are not in Zephyr. However, as we did not have patent data on these firms, they had many missing observations and we did not have the ability to construct the $Fake0_{i,t}$ and $MeanFake_i$ measures. As such, acquirers were only being matched to other firms appearing in Zephyr. This only results in one off support treated observation.

threshold level for significance. Panel B shows that this is not a function of poor matching. It may, however, result from the fact that we are matching across acquirer-years, i.e. all firms in our sample acquire at *some point*. As such, the timing of acquisition may be less important than the act of acquisition over a longer window, suggesting value in adding data on those that (according to Zephyr) never engage in acquisitions.

5 Conclusion and Policy Recommendations

The above results find that cross-border acquisitions have the potential to spur acquirer innovation, but that such effects are contingent on factors including industrial linkages and industry concentration. This granularity has two key implications. First, when considering the innovation effects of a proposed merger, one should be very cognizant of the industrial mix of the joined entity. In particular, non-manufacturing targets tend to increase acquirer innovation. When considering target R&D intensity, targets with strong input linkages to the acquirer have the greatest innovation effects. Thus, when comparing the social welfare of an acquisition, this may be grounds to tip the scale towards some acquisitions rather than others. Second, allowing mergers when the acquirer is in a concentrated industry may have smaller innovation effects as compared to a more competitive one. Together, these point to a "one size does *not* fit all" result, pointing out the need for a nuanced approach to merger policy. Finally, it must be recalled that this study looks at research activities only. In practice there are other gains and losses from cross-border acquisitions such as price changes, productivity synergies, and more. Thus, the present results must be considered in a broader context for policy development.

One way to implement policies along these lines would be to simply exercise the competition authority's power to halt or permit a given acquisition. Alternatives, however, exist. For example the rise of knowledge or patent boxes which provide tax reductions for income earned via innovations can spur overall R&D and further enhance the increases derived from acquisition. Other types of subsidies would have a similar effect. Both of these, however, should be operated with caution so as not to run afoul of, for example, prohibitions against state aid within the European Union. A further option would be to offer broad-based support for firms looking to acquire. For example, by gathering information on the availability of non-manufacturing targets (especially those in information technology and/or research and development industries) might serve to make such acquisitions more profitable and therefore spur higher innovation by acquirers. In any case, one must always be cognizent of the limitations of any data analysis when developing policy recommendations. Here, the potential for sample selection suggests a need for expanding the net of firms under consideration, including those who never acquire (which likely requires the search for alternative proxies for innovation) and/or within-country acquisitions. Such caveats not withstanding, this paper provides a step in the direction of incorporating industrial linkages into our understanding of the relationship between acquisition and innovation.

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Figure 1: Industry Pairs

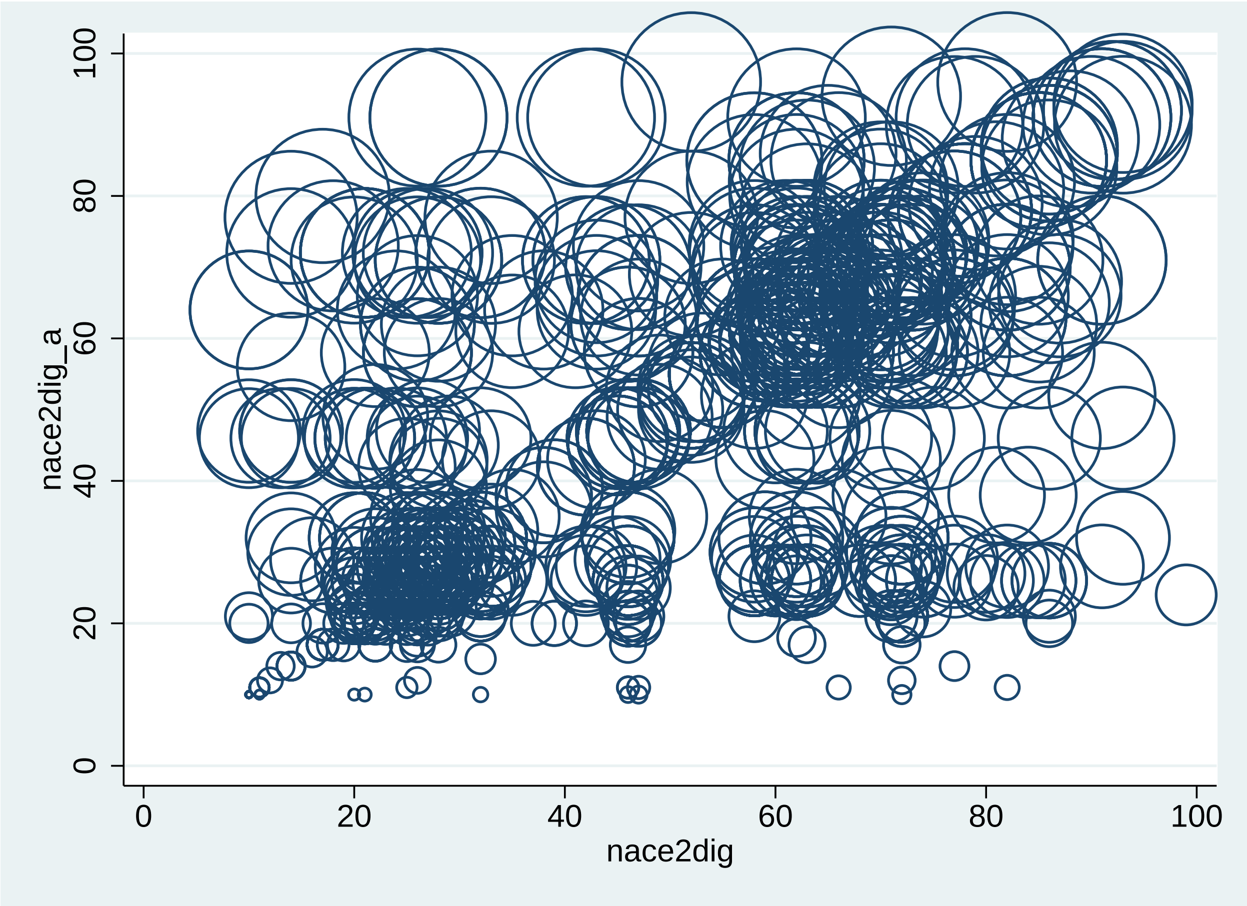

Figure 2: Industry Pairs - Within Manufacturing

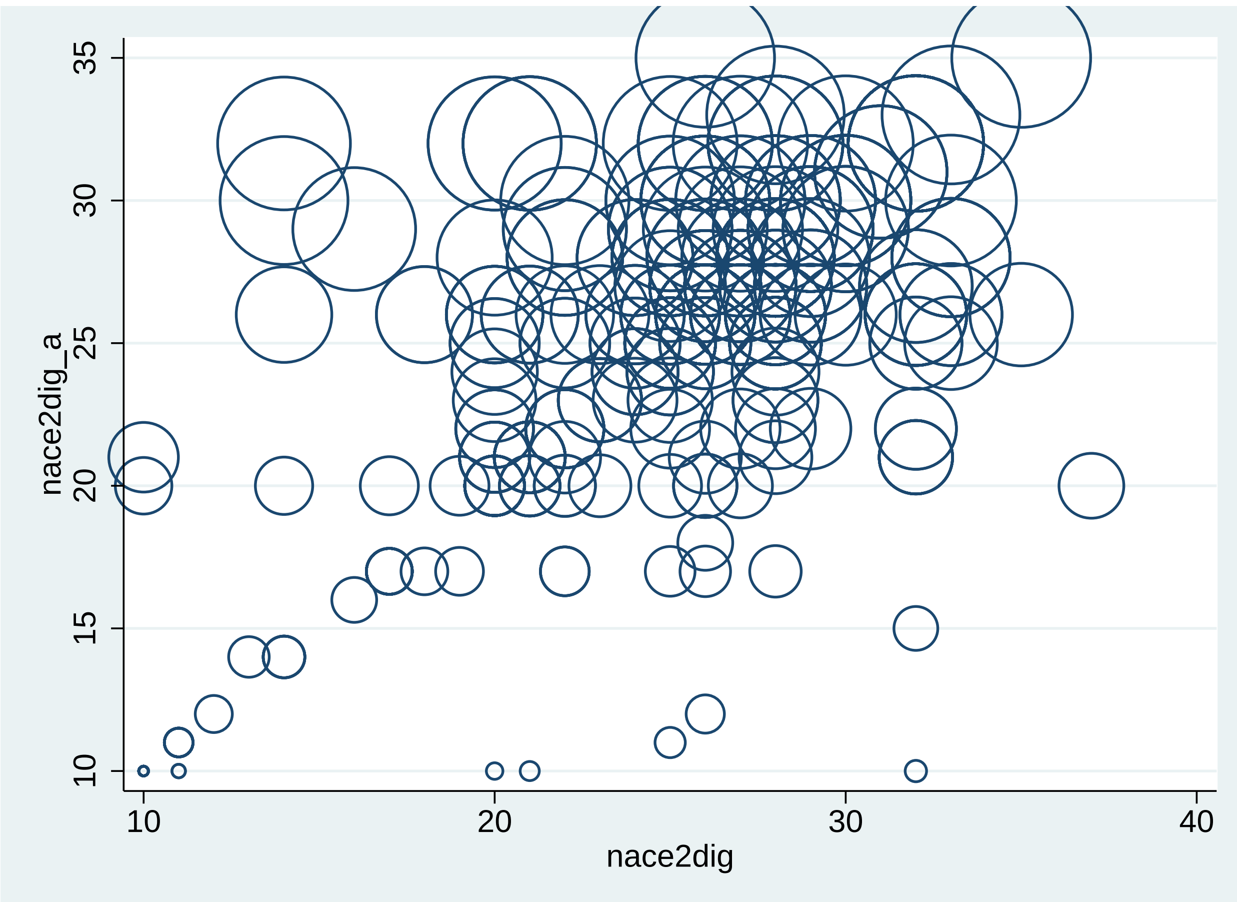

Figure 3: Industry Pairs - Within Non-Manufacturing

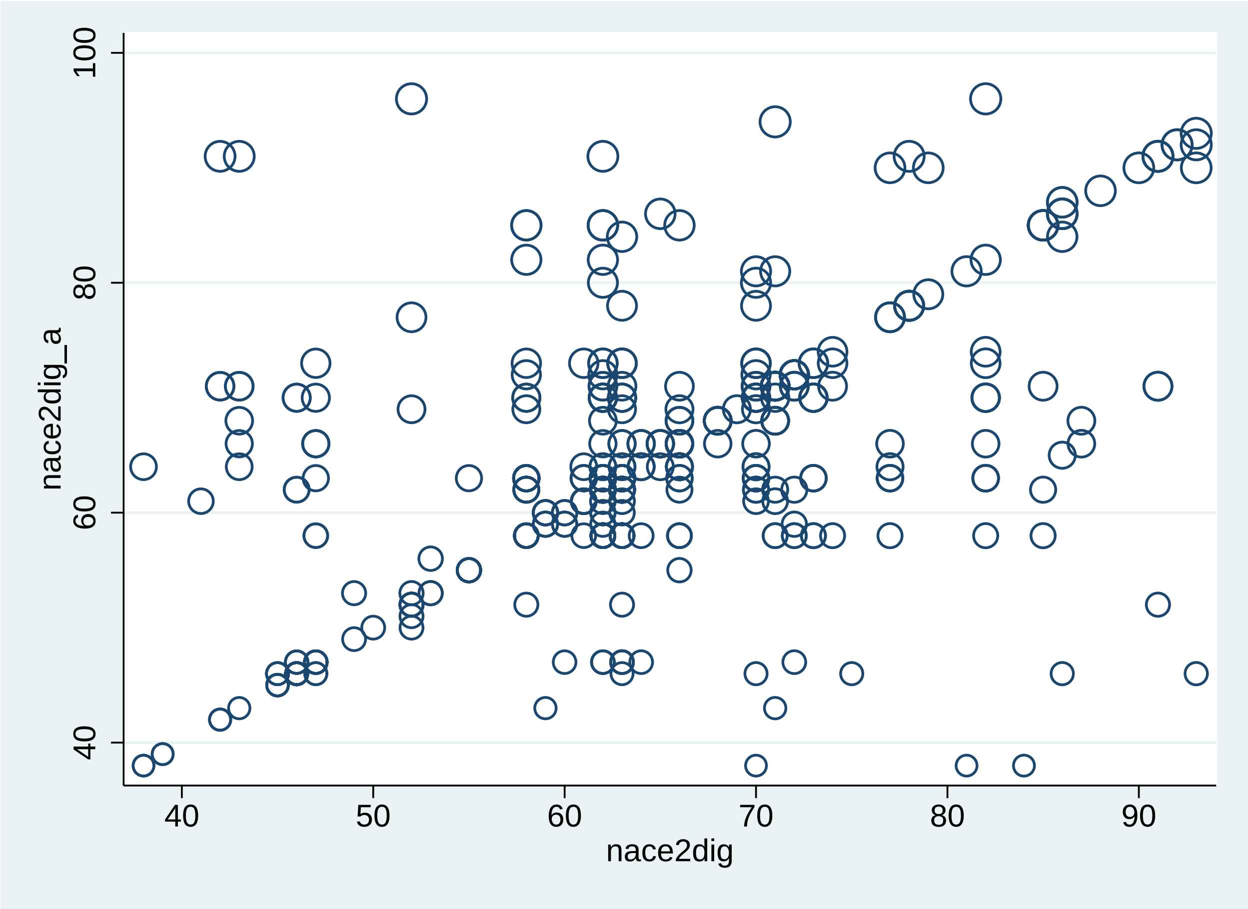

Figure 4: Industry Pairs - Within Non-Manufacturing

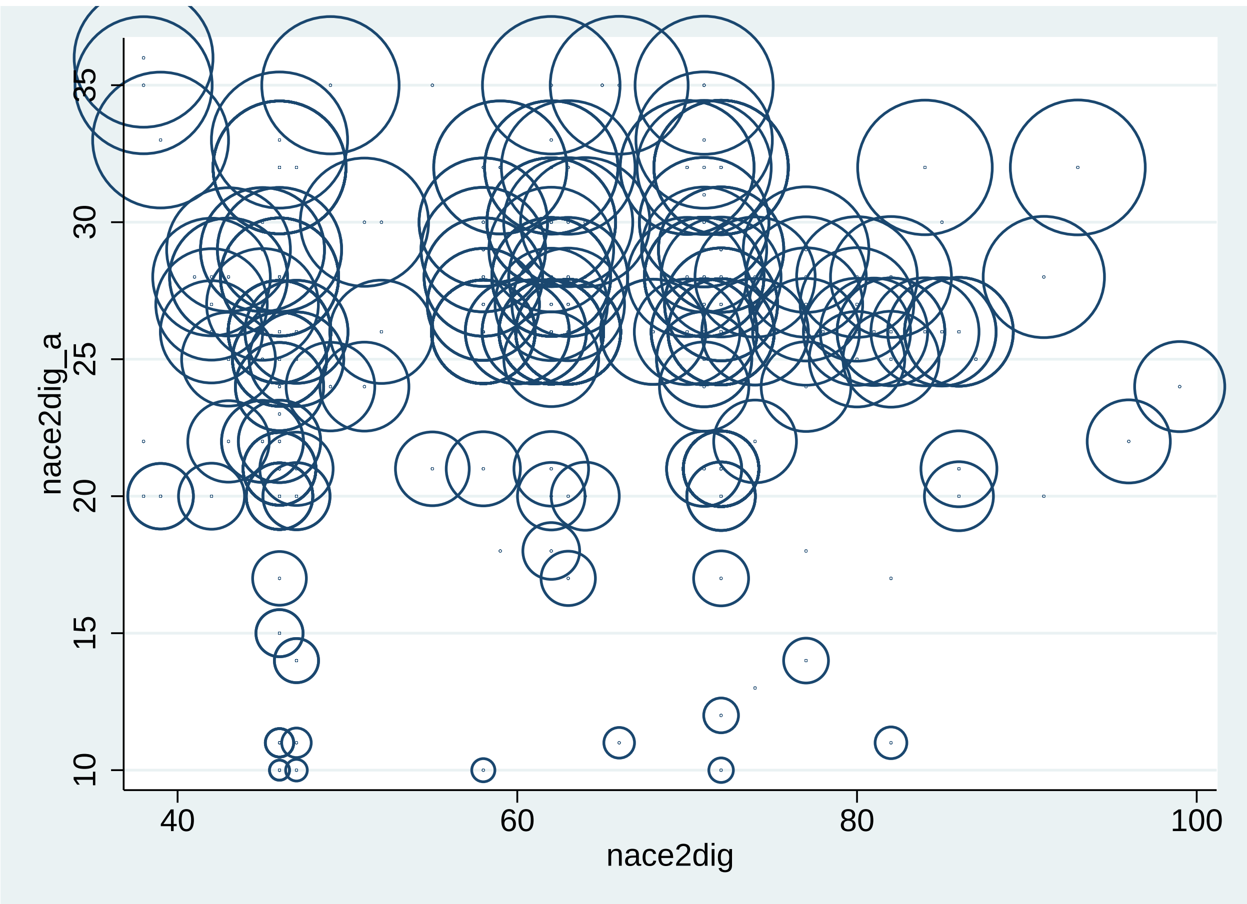

Figure 5: Chinese Acquisitions

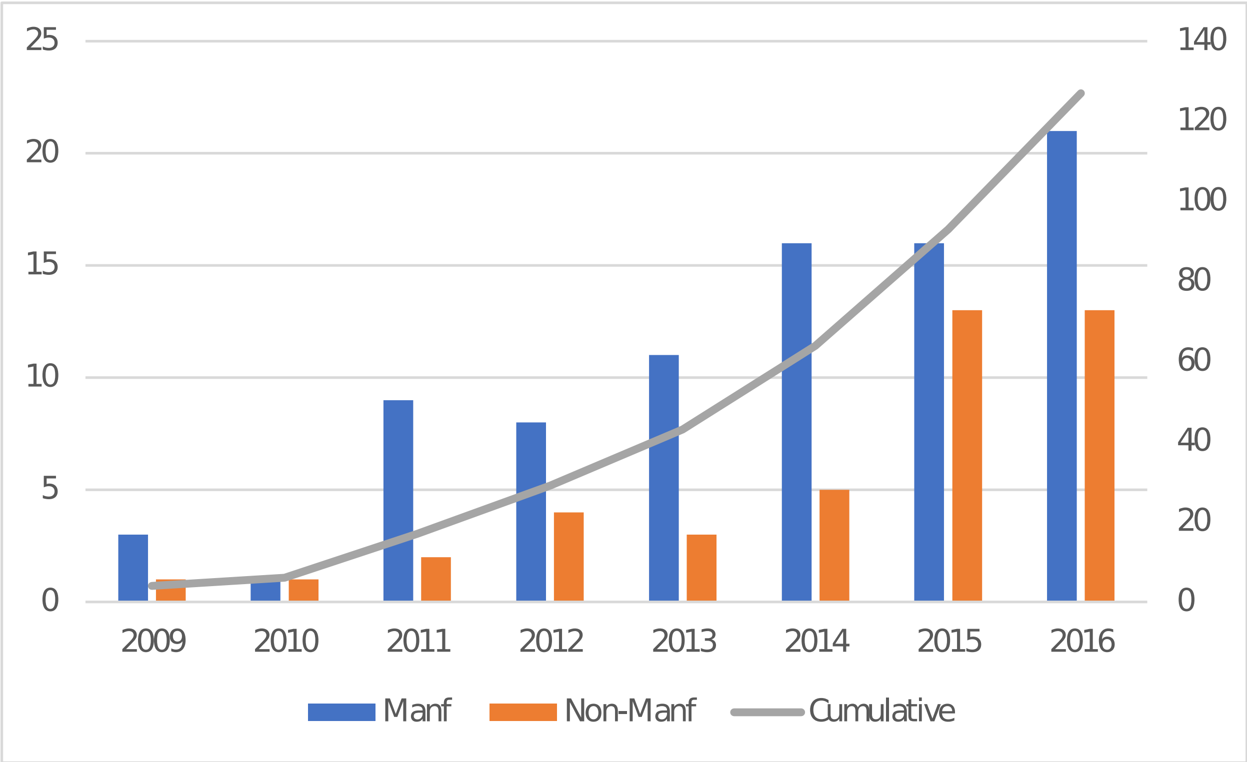

Table 1: Acquisitions per Acquirer

Num. of Acquisitions	Num.of Acquirers	Share of Acquirers	Share of Acquisitions
0	359	23.92	0
1	803	53.5	42.83
2	190	12.66	20.27
3	66	4.4	10.56
4	37	2.47	7.89
5	10	0.67	2.67
6	11	0.73	3.52
7	5	0.33	1.87
8	6	0.4	2.56
9	5	0.33	2.4
10	3	0.2	1.6
11	4	0.27	2.35
13	1	0.07	0.69
15	1	0.07	0.8
Total	1875	1501	

The number of acquisitions is the total number of acquisitions made by a single acquirer during 2008-2016.

Table 2: Countries

Acquirer Country	Num. of Acquirers	Share of Acquirers
AT	5	0.33
BE	18	1.2
CN	117	7.79
CZ	1	0.07
DE	89	5.93
DK	18	1.2
ES	34	2.27
FI	14	0.93
FR	96	6.4
GB	251	16.72
GR	1	0.07
HK	9	0.6
HR	4	0.27
HU	1	0.07
IE	30	2
IT	28	1.87
LU	12	0.8
LV	1	0.07
NL	47	3.13
PL	2	0.13
SE	49	3.26
US	674	44.9
Total	1,501	100

Table 3: Acquisitions in $t-1$ by Year

	Obs.	Num. of Acq. in $t-1$
2009	1149	66
2010	1194	106
2011	1236	197
2012	1256	258
2013	1288	238
2014	1311	245
2015	1297	331
2016	1271	320
2017	699	180

The number of acquisitions reported for year t are those in $t-1$ since that is what is used in the estimation.

Table 4: Acquisitions by a Single Acquirer in a Given Year

Num of Acquisitions	Num of Acquirer-Years	Share of Acquirer-Years
0	9,076	84.81
1	1,432	13.38
2	150	1.4
3	35	0.33
4	5	0.05
5	1	0.01
6	1	0.01
7	1	0.01
Total	10,701	100

The number of acquisitions is that made by a given acquirer in a given year.

Table 5: Industry of Acquirers

Acquirer Industry	Num. of Acquirers	Share	Acquirer Industry	Num. of Acquirers	Share
10	36	2.4	55	9	0.6
11	18	1.2	56	4	0.27
12	6	0.4	58	84	5.6
13	3	0.2	59	13	0.87
14	10	0.67	60	5	0.33
15	1	0.07	61	20	1.33
16	2	0.13	62	74	4.93
17	11	0.73	63	114	7.59
18	3	0.2	64	38	2.53
20	62	4.13	65	5	0.33
21	66	4.4	66	44	2.93
22	17	1.13	68	7	0.47
23	11	0.73	69	3	0.2
24	18	1.2	70	40	2.66
25	43	2.86	71	41	2.73
26	182	12.13	72	31	2.07
27	38	2.53	73	14	0.93
28	102	6.8	74	3	0.2
29	31	2.07	77	9	0.6
30	28	1.87	78	6	0.4
31	6	0.4	79	1	0.07
32	56	3.73	80	4	0.27
33	4	0.27	81	4	0.27
35	11	0.73	82	14	0.93
36	2	0.13	84	2	0.13
38	2	0.13	85	6	0.4
39	4	0.27	86	5	0.33
42	8	0.53	87	1	0.07
43	6	0.4	88	1	0.07
45	7	0.47	90	3	0.2
46	42	2.8	91	6	0.4
47	18	1.2	92	3	0.2
49	6	0.4	93	2	0.13
50	3	0.2	94	1	0.07
51	2	0.13	96	3	0.2
52	10	0.67	99	1	0.07
53	5	0.33			
			Total	1,501	100

Table 6: Manufacturing vs. Non-Manufacturing

Acquirer in:	Manf	Non-Manf	Manf	Non-Manf
Target in:	Manf	Non-Manf	Non-Manf	Manf
Num. Deals	747	776	273	79
% of Deals	39.84	41.39	14.56	4.21
% Hor	64.66	47.04	0	0
Hor Input	0.3259	0.1517	-	-
Hor Output	0.3631	0.1251	-	-
Non-Hor Input	0.0438	0.0623	0.0189	0.0184
Non-Hor Output	0.0404	0.0559	0.0129	0.0226

Table 7: Summary Statistics

	Obs.	Mean	Std. Dev	Min	Max
$RD_{i,t}$	10,701	-1.3823	4.114	-5.7323	7.5042
$Revenue_{i,t}$	10,701	13.2333	2.4911	0.5858	19.9287
$Age_{i,t}$	10,701	55.3077	37.6455	12	372
$Fake0_{i,t}$	10,701	0.4509	0.4976	0	1
$MeanFake0_i$	10,701	0.4626	0.4725	0	1
$Acq_{i,t}^{Dummy}$	10,701	0.1519	0.3589	0	1
$Acq_{i,t}$	10,701	0.1752	0.4543	0	7
$Acq_{i,t}^{Man}$	10,701	0.0772	0.2974	0	7
$Acq_{i,t}^{Non}$	10,701	0.098	0.3483	0	6
$Acq_{i,t}^{Hor}$	10,701	0.075	0.2946	0	7
$Acq_{i,t}^{Back}$	10,701	0.0228	0.0863	0	2.0381
$Acq_{i,t}^{For}$	10,701	0.023	0.0927	0	2.1302
$RD_{i,t-1}^{Target}$	10,701	-0.9624	2.5988	-41.0909	7.715
$Acq_{i,t}^{MM}$	10,701	0.0698	0.2856	0	7
$Acq_{i,t}^{MN}$	10,701	0.0255	0.1772	0	4
$Acq_{i,t}^{NM}$	10,701	0.0074	0.0888	0	2
$Acq_{i,t}^{NN}$	10,701	0.0725	0.3057	0	6
$hhi_{i,t}$	10,701	0.6267	0.3426	0	1
$Fake0_{i,t}^{Target}$	10,701	0.0027	0.047	0	1

Table 8: Baseline Estimates

R&D to	(1) Emp	(2) Emp	(3) Emp	(4) Emp	(5) Emp	(6) Rev	(7) Rev
$Acq^{Dummy}_{i,t-1}$		0.0189					
		(0.0182)					
$Acq_{i,t-1}$			0.0207		0.0199	0.0212**	
			(0.0145)		(0.0222)	(0.00882)	
$Acq^{M}_{i,t-1}$				-0.0305			0.00855
				(0.0218)			(0.0114)
$Acq^{N}_{i,t-1}$				0.0580***			0.0303**
				(0.0196)			(0.0129)
$Acq^{Hor}_{i,t-1}$					0.00186		
					(0.0317)		
$RD_{i,t-1}$	0.547***	0.547***	0.547***	0.546***	0.547***	0.856***	0.856***
	(0.0242)	(0.0242)	(0.0242)	(0.0242)	(0.0242)	(0.0145)	(0.0146)
$Revenue_{i,t-1}$	-0.0150***	-0.0152***	-0.0153***	-0.0156***	-0.0153***	-0.00335	-0.00344
	(0.00576)	(0.00576)	(0.00575)	(0.00573)	(0.00575)	(0.00258)	(0.00259)
$Age_{i,t}$	-0.000705*	-0.000705*	-0.000705*	-0.000692*	-0.000705*	-0.000129	-0.000126
	(0.000383)	(0.000383)	(0.000383)	(0.000383)	(0.000383)	(0.000119)	(0.000119)
$Fake0_{i,t}$	-4.583***	-4.583***	-4.584***	-4.586***	-4.584***	0.597***	0.597***
	(0.188)	(0.188)	(0.188)	(0.188)	(0.188)	(0.108)	(0.108)
$MeanFake0_{i,t}$	1.072***	1.072***	1.073***	1.070***	1.073***	-0.575***	-0.575***
	(0.135)	(0.135)	(0.135)	(0.135)	(0.135)	(0.108)	(0.108)
Constant	1.009***	1.009***	1.011***	1.021***	1.011***	-0.581***	-0.579***
	(0.141)	(0.141)	(0.140)	(0.140)	(0.140)	(0.0815)	(0.0815)
Observations	10,701	10,701	10,701	10,701	10,701	10,982	10,982
Adjusted R-squared	0.972	0.972	0.972	0.972	0.972	0.854	0.854

Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 9: Decomposition by Industry Pairs

R&D to	(1) Emp	(2) Emp	(3) Rev	(4) Rev
$Acq^{MM}_{i,t-1}$	-0.0349	-0.0655**	0.00459	0.0152
	(0.0232)	(0.0314)	(0.0114)	(0.0177)
$Acq^{MN}_{i,t-1}$	0.117***	0.119***	0.00584	0.00540
	(0.0397)	(0.0396)	(0.0137)	(0.0137)
$Acq^{NM}_{i,t-1}$	0.00379	0.00211	0.0512	0.0518
	(0.0547)	(0.0549)	(0.0545)	(0.0544)
$Acq^{NN}_{i,t-1}$	0.0370*	0.0129	0.0388**	0.0471**
	(0.0214)	(0.0297)	(0.0167)	(0.0213)
$Acq^{Hor}_{i,t-1}$		0.0510		-0.0177
		(0.0343)		(0.0207)
$RD_{i,t-1}$	0.546***	0.546***	0.856***	0.856***
	(0.0242)	(0.0242)	(0.0145)	(0.0145)
$Revenue_{i,t-1}$	-0.0157***	-0.0157***	-0.00335	-0.00337
	(0.00573)	(0.00572)	(0.00259)	(0.00259)
$Age_{i,t}$	-0.000687*	-0.000690*	-0.000126	-0.000125
	(0.000383)	(0.000383)	(0.000119)	(0.000119)
$Fake0_{i,t}$	-4.587***	-4.587***	0.597***	0.597***
	(0.188)	(0.188)	(0.108)	(0.108)
$MeanFake0_i$	1.068***	1.068***	-0.576***	-0.575***
	(0.135)	(0.135)	(0.108)	(0.108)
Constant	1.023***	1.020***	-0.580***	-0.579***
	(0.140)	(0.140)	(0.0814)	(0.0815)
Observations	10,701	10,701	10,982	10,982
Adjusted R-squared	0.972	0.972	0.854	0.854

Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 10: Forward and Backward Linkages

R&D to	(1) Emp	(2) Emp	(3) Emp	(4) Rev	(5) Rev	(6) Rev
$Acq^{For}_{i,t-1}$	-0.00603	0.00510	0.139	-0.137	-0.130	-0.0865
	(0.238)	(0.238)	(0.259)	(0.134)	(0.134)	(0.137)
$Acq^{Back}_{i,t-1}$	-0.0271	-0.186	-0.153	0.189	0.0937	0.0672
	(0.257)	(0.271)	(0.279)	(0.140)	(0.134)	(0.135)
$Acq_{i,t-1}$		0.0433**			0.0258**	
		(0.0208)			(0.0103)	
$Acq^{MM}_{i,t-1}$			-0.0348			0.0103
			(0.0338)			(0.0171)
$Acq^{MN}_{i,t-1}$			0.118***			0.00551
			(0.0399)			(0.0137)
$Acq^{NM}_{i,t-1}$			0.00342			0.0519
			(0.0547)			(0.0544)
$Acq^{NN}_{i,t-1}$			0.0405			0.0395**
			(0.0263)			(0.0167)
$RD_{i,t-1}$	0.547***	0.546***	0.546***	0.856***	0.856***	0.856***
	(0.0242)	(0.0242)	(0.0242)	(0.0145)	(0.0145)	(0.0145)
$Revenue_{i,t-1}$	-0.0149***	-0.0154***	-0.0157***	-0.00310	-0.00340	-0.00337
	(0.00577)	(0.00575)	(0.00573)	(0.00257)	(0.00258)	(0.00259)
$Age_{i,t}$	-0.000704*	-0.000700*	-0.000688*	-0.000128	-0.000126	-0.000126
	(0.000383)	(0.000383)	(0.000383)	(0.000119)	(0.000119)	(0.000119)
$Fake0_{i,t}$	-4.583***	-4.584***	-4.587***	0.598***	0.597***	0.597***
	(0.188)	(0.188)	(0.188)	(0.108)	(0.108)	(0.108)
$MeanFake0_i$	1.071***	1.072***	1.068***	-0.576***	-0.575***	-0.576***
	(0.135)	(0.135)	(0.135)	(0.108)	(0.108)	(0.108)
Constant	1.010***	1.015***	1.020***	-0.580***	-0.578***	-0.578***
	(0.141)	(0.141)	(0.140)	(0.0814)	(0.0814)	(0.0814)
Observations	10,701	10,701	10,701	10,982	10,982	10,982
Adjusted R-squared	0.972	0.972	0.972	0.854	0.854	0.854

Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 11: Impact of Reset Acquirer R&D Intensity

	(1)	(2)	(3)	(4)	(5)	(6)
R&D to	Emp	Emp	Emp	Rev	Rev	Rev
$Acq_{i,t-1}$	0.0611*	0.0713***	0.0226*	0.0422**	0.0164	0.0163
	(0.0317)	(0.0268)	(0.0133)	(0.0168)	(0.0117)	(0.0108)
$Acq^{Hor}_{i,t-1}$	0.160**	0.118**	0.0142	0.000121	-0.0161	-0.00265
	(0.0635)	(0.0495)	(0.0246)	(0.0446)	(0.0294)	(0.0258)
$Acq^{For}_{i,t-1}$	-0.00980	0.0304	-0.0940	-0.226	-0.120	-0.131
	(0.512)	(0.534)	(0.163)	(0.288)	(0.222)	(0.146)
$Acq^{Back}_{i,t-1}$	-0.670	-0.584	0.0424	0.153	0.108	0.0915
	(0.564)	(0.603)	(0.173)	(0.309)	(0.244)	(0.158)
$RD_{i,t-1}$	0.498***	0.612***	0.953***	0.826***	0.878***	0.918***
	(0.0252)	(0.0297)	(0.0108)	(0.0179)	(0.0151)	(0.0166)
$Revenue_{i,t-1}$	-0.0226*	-0.0165*	0.00200	-0.00775	0.00324	0.00812**
	(0.0119)	(0.00996)	(0.00250)	(0.00551)	(0.00411)	(0.00394)
$Age_{i,t}$	-0.00122**	-0.00103**	-4.45e-05	-0.000173	-0.000106	-9.68e-05
	(0.000541)	(0.000442)	(0.000105)	(0.000182)	(0.000143)	(0.000118)
$Fake0_{i,t}$	-4.766***	-4.282***		0.621***	0.539***	
	(0.188)	(0.281)		(0.110)	(0.119)	
$MeanFake0_i$	0.627***	0.616**		-0.617***	-0.392***	
	(0.195)	(0.296)		(0.124)	(0.137)	
Constant	0.895***	0.715***	-0.161***	-0.847***	-0.767***	-0.571***
	(0.215)	(0.229)	(0.0527)	(0.121)	(0.118)	(0.103)
Observations	6,396	5,780	4,902	6,677	6,027	5,054
Adjusted R-squared	0.897	0.859	0.955	0.858	0.909	0.945

Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 12: Longer Lags: Expenditures Relative to Employment

	(1)	(2)	(3)	(4)	(5)
$Acq_{i,t-1}$	0.0177	0.0165		0.0126	0.0110
	(0.0135)	(0.0133)		(0.0128)	(0.0127)
$Acq_{i,t-2}$	0.0308**	0.0585***		0.0206	0.0447**
	(0.0142)	(0.0206)		(0.0129)	(0.0181)
$Acq_{i,t-3}$				0.0104	0.00919
				(0.0149)	(0.0213)
$Acq_{i,t-1}^{MM}$			-0.0398*		
			(0.0218)		
$Acq_{i,t-1}^{MN}$			0.0888***		
			(0.0317)		
$Acq_{i,t-1}^{NM}$			0.0125		
			(0.0584)		
$Acq_{i,t-1}^{NN}$			0.0389*		
			(0.0202)		
$Acq_{i,t-2}^{MM}$			-0.0359		
			(0.0238)		
$Acq_{i,t-2}^{MN}$			0.110***		
			(0.0340)		
$Acq_{i,t-2}^{NM}$			0.0785		
			(0.0724)		
$Acq_{i,t-2}^{NN}$			0.0552***		
			(0.0208)		
$Acq_{i,t-2}^{Hor}$		0.0295			0.0282
		(0.0389)			(0.0362)
$Acq_{i,t-2}^{For}$		-0.312			-0.274
		(0.195)			(0.197)
$Acq_{i,t-2}^{Back}$		-0.00849			-0.0143
		(0.235)			(0.234)
$Acq_{i,t-3}^{Hor}$					0.0874**
					(0.0396)
$Acq_{i,t-3}^{For}$					-0.353
					(0.229)
$Acq_{i,t-3}^{Back}$					0.0755
					(0.271)
$RD_{i,t-1}$	0.396***	0.396***	0.395***	0.382***	0.382***
	(0.0246)	(0.0245)	(0.0245)	(0.0262)	(0.0262)
$RD_{i,t-2}$	0.180***	0.180***	0.180***	0.0920***	0.0919***
	(0.0182)	(0.0182)	(0.0182)	(0.0208)	(0.0208)
$RD_{i,t-3}$				0.153***	0.153***
				(0.0145)	(0.0145)
$Revenue_{i,t-1}$	-0.0160***	-0.0162***	-0.0167***	-0.0140***	-0.0144***
	(0.00569)	(0.00569)	(0.00567)	(0.00527)	(0.00527)
$Age_{i,t}$	-0.000556	-0.000550	-0.000515	-0.000276	-0.000270
	(0.000371)	(0.000371)	(0.000370)	(0.000355)	(0.000354)
$Fake0_{i,t}$	-4.926***	-4.925***	-4.930***	-5.349***	-5.349***
	(0.188)	(0.188)	(0.189)	(0.201)	(0.200)
$MeanFake0_i$	1.643***	1.640***	1.632***	2.469***	2.461***
	(0.172)	(0.172)	(0.172)	(0.215)	(0.215)
Constant	0.970***	0.981***	0.994***	1.013***	1.031***
	(0.131)	(0.131)	(0.131)	(0.128)	(0.129)
Observations	9,944	9,944	9,944	8,801	8,801
Adjusted R-squared	0.974	0.974	0.974	0.976	0.976

Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 13: Longer Lags: Expenditures Relative to Revenue

	(1)	(2)	(3)	(4)	(5)
$Acq_{i,t-1}$	0.0217**	0.0213**		0.0214***	0.0206**
	(0.00844)	(0.00846)		(0.00829)	(0.00832)
$Acq_{i,t-2}$	0.00511	0.0127		0.00878	0.0170
	(0.00828)	(0.0118)		(0.00823)	(0.0115)
$Acq_{i,t-3}$				-0.0111	-0.00398
				(0.00839)	(0.0121)
$Acq^{MM}_{i,t-1}$			0.00777		
			(0.0103)		
$Acq^{MN}_{i,t-1}$			0.00152		
			(0.0154)		
$Acq^{NM}_{i,t-1}$			0.0614		
			(0.0521)		
$Acq^{NN}_{i,t-1}$			0.0386**		
			(0.0164)		
$Acq^{MM}_{i,t-2}$			0.00283		
			(0.0134)		
$Acq^{MN}_{i,t-2}$			0.00568		
			(0.0187)		
$Acq^{NM}_{i,t-2}$			0.146		
			(0.0898)		
$Acq^{NN}_{i,t-2}$			-0.00591		
			(0.0116)		
$Acq^{Hor}_{i,t-2}$		0.0148			0.0113
		(0.0265)			(0.0263)
$Acq^{For}_{i,t-2}$		-0.0200			0.00735
		(0.0865)			(0.0860)
$Acq^{Back}_{i,t-2}$		-0.0916			-0.114
		(0.112)			(0.111)
$Acq^{Hor}_{i,t-3}$					0.0404
					(0.0251)
$Acq^{For}_{i,t-3}$					-0.143
					(0.114)
$Acq^{Back}_{i,t-3}$					-0.0446
					(0.135)
$RD_{i,t-1}$	0.701***	0.701***	0.700***	0.685***	0.685***
	(0.0435)	(0.0435)	(0.0436)	(0.0454)	(0.0454)
$RD_{i,t-2}$	0.177***	0.177***	0.177***	0.130*	0.130*
	(0.0442)	(0.0442)	(0.0443)	(0.0727)	(0.0728)
$RD_{i,t-3}$				0.0774**	0.0774**
				(0.0390)	(0.0390)
$Revenue_{i,t-1}$	-0.00407	-0.00408	-0.00396	-0.00663***	-0.00672***
	(0.00260)	(0.00260)	(0.00258)	(0.00253)	(0.00254)
$Age_{i,t}$	-0.000116	-0.000115	-0.000112	-0.000103	-0.000100
	(0.000113)	(0.000113)	(0.000113)	(0.000116)	(0.000116)
$Fake0_{i,t}$	0.660***	0.661***	0.661***	0.745***	0.746***
	(0.121)	(0.121)	(0.121)	(0.135)	(0.135)
$MeanFake0_i$	-0.645***	-0.645***	-0.645***	-0.743***	-0.745***
	(0.122)	(0.122)	(0.122)	(0.137)	(0.137)
Constant	-0.564***	-0.563***	-0.563***	-0.464***	-0.461***
	(0.0827)	(0.0825)	(0.0826)	(0.0805)	(0.0806)
Observations	10,273	10,273	10,273	9,147	9,147
Adjusted R-squared	0.854	0.854	0.854	0.857	0.857

Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 14: Target Intensity: Expenditures Relative to Employment

	(1)	(2)	(3)	(4)
$Acq_{i,t-1}$		0.146***		0.123*
		(0.0447)		(0.0691)
$Acq^{Hor}_{i,t-1}$				0.246**
				(0.112)
$Acq^{For}_{i,t-1}$				-1.765**
				(0.736)
$Acq^{Back}_{i,t-1}$				1.190
				(0.823)
$RD^{Target}_{i,t-1}$	-0.00125	0.0229***	0.0198**	0.0166
	(0.00245)	(0.00759)	(0.00808)	(0.0117)
$RD^{Target,Hor}_{i,t-1}$			-0.0105	0.0304
			(0.00673)	(0.0190)
$RD^{Target,For}_{i,t-1}$			-0.00812	-0.306**
			(0.0400)	(0.123)
$RD^{Target,Back}_{i,t-1}$			0.0637	0.268*
			(0.0494)	(0.138)
$RD_{i,t-1}$	0.547***	0.546***	0.546***	0.546***
	(0.0242)	(0.0242)	(0.0242)	(0.0242)
$Revenue_{i,t-1}$	-0.0151***	-0.0156***	-0.0157***	-0.0157***
	(0.00575)	(0.00574)	(0.00574)	(0.00573)
$Age_{i,t}$	-0.000699*	-0.000696*	-0.000696*	-0.000702*
	(0.000383)	(0.000382)	(0.000382)	(0.000382)
$Fake0_{i,t}$	-4.584***	-4.586***	-4.586***	-4.587***
	(0.188)	(0.188)	(0.188)	(0.188)
$MeanFake0_{i,t}$	1.072***	1.073***	1.072***	1.071***
	(0.135)	(0.135)	(0.135)	(0.135)
$MeanFake0^{Target}_{i,t}$	0.172	0.164	0.164	0.154
	(0.106)	(0.107)	(0.107)	(0.110)
Constant	1.011***	1.016***	1.017***	1.019***
	(0.141)	(0.140)	(0.141)	(0.141)
Observations	10,701	10,701	10,701	10,701
Adjusted R-squared	0.972	0.972	0.972	0.972

Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 15: Target Intensity: Expenditures Relative to Revenue

	(1)	(2)	(3)	(4)
$Acq_{i,t-1}$		0.0389**		0.0486
		(0.0177)		(0.0307)
$Acq^{Hor}_{i,t-1}$				0.0324
				(0.0479)
$Acq^{For}_{i,t-1}$				-0.232
				(0.233)
$Acq^{Back}_{i,t-1}$				0.0757
				(0.267)
$RD^{Target}_{i,t-1}$	-0.00320**	0.00325	0.00226	0.00393
	(0.00155)	(0.00315)	(0.00345)	(0.00546)
$RD^{Target,Hor}_{i,t-1}$			0.00259	0.00790
			(0.00460)	(0.00883)
$RD^{Target,For}_{i,t-1}$			0.0198	-0.0192
			(0.0230)	(0.0433)
$RD^{Target,Back}_{i,t-1}$			-0.0215	-0.00784
			(0.0267)	(0.0494)
$RD_{i,t-1}$	0.856***	0.856***	0.856***	0.856***
	(0.0145)	(0.0145)	(0.0145)	(0.0145)
$Revenue_{i,t-1}$	-0.00325	-0.00341	-0.00345	-0.00347
	(0.00258)	(0.00258)	(0.00258)	(0.00258)
$Age_{i,t}$	-0.000128	-0.000127	-0.000123	-0.000124
	(0.000119)	(0.000119)	(0.000120)	(0.000120)
$Fake0_{i,t}$	0.597***	0.597***	0.597***	0.597***
	(0.108)	(0.108)	(0.108)	(0.108)
$MeanFake0_{i,t}$	-0.576***	-0.575***	-0.575***	-0.575***
	(0.108)	(0.108)	(0.108)	(0.108)
$MeanFake0^{Target}_{i,t}$	0.0563	0.0540	0.0537	0.0522
	(0.0479)	(0.0482)	(0.0481)	(0.0484)
Constant	-0.581***	-0.581***	-0.577***	-0.577***
	(0.0816)	(0.0814)	(0.0814)	(0.0815)
Observations	10,982	10,982	10,982	10,982
Adjusted R-squared	0.854	0.854	0.854	0.854

Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 16: Chinese Acquirers

	(1)	(2)	(3)	(4)
$Acq_{i,t-1}$	0.0318**	0.0508**	0.158***	0.131*
	(0.0148)	(0.0229)	(0.0453)	(0.0705)
$Acq_{i,t-1^{China}}$	-0.269***	-0.364**	-0.342***	-0.233***
	(0.102)	(0.152)	(0.122)	(0.0900)
$Acq^{Hor}_{i,t-1}$		0.0641*		0.232**
		(0.0385)		(0.113)
$Acq^{China,Hor}_{i,t-1}$		0.0398		-2.990***
		(0.459)		(1.025)
$Acq^{For}_{i,t-1}$		0.103		-2.032**
		(0.239)		(0.792)
$Acq^{China,For}_{i,t-1}$		-0.920		5.520***
		(0.969)		(1.785)
$Acq^{Back}_{i,t-1}$		-0.474		1.514*
		(0.290)		(0.870)
$Acq^{China,Back}_{i,t-1}$		1.931		.
		(1.918)		.
$RD^{Target}_{i,t-1}$			0.0231***	0.0148
			(0.00768)	(0.0119)
$RD^{China,Target}_{i,t-1}$			-0.0136	0.0225
			(0.0242)	(0.0252)
$RD^{Target,Hor}_{i,t-1}$				0.0299
				(0.0191)
$RD^{China,Target,Hor}_{i,t-1}$				-0.512**
				(0.214)
$RD^{Target,For}_{i,t-1}$				-0.375***
				(0.132)
$RD^{China,Target,For}_{i,t-1}$				1.133***
				(0.305)
$RD^{Target,Back}_{i,t-1}$				0.350**
				(0.145)
$RD^{China,Target,Back}_{i,t-1}$				-0.406
				(0.346)
$RD_{i,t-1}$	0.548***	0.548***	0.548***	0.547***
	(0.0239)	(0.0239)	(0.0239)	(0.0239)
$Revenue_{i,t-1}$	-0.0177***	-0.0178***	-0.0180***	-0.0181***
	(0.00570)	(0.00570)	(0.00569)	(0.00569)
$Age_{i,t}$	-0.000633*	-0.000631*	-0.000624	-0.000629*
	(0.000381)	(0.000381)	(0.000380)	(0.000380)
$Fake0_{i,t}$	-4.521***	-4.522***	-4.523***	-4.525***
	(0.180)	(0.180)	(0.180)	(0.180)
$MeanFake0_{i,t}$	1.014***	1.013***	1.014***	1.013***
	(0.122)	(0.123)	(0.123)	(0.123)
$MeanFake0^{Target}_{i,t}$			0.167	0.159
			(0.108)	(0.111)
Constant	0.762*	0.764*	0.763*	0.765*
	(0.410)	(0.411)	(0.410)	(0.411)
Observations	11,610	11,610	11,610	11,610
Adjusted R-squared	0.972	0.972	0.972	0.972

Dependent variable is R&D relative to employment. Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 17: Concentration

	(1)	(2)	(3)
$Acq_{i,t-1}$	0.0747**	0.107**	0.201**
	(0.0301)	(0.0472)	(0.0964)
$Acq_{i,t-1}HHI_{i,t}$	-0.0848**	-0.125*	-0.106
	(0.0407)	(0.0659)	(0.163)
$Acq^{Hor}_{i,t-1}$		0.0177	
		(0.0824)	
$Acq^{Hor}_{i,t-1}HHI_{i,t}$		0.110	
		(0.112)	
$Acq^{For}_{i,t-1}$		-1.000**	
		(0.501)	
$Acq^{For}_{i,t-1}HHI_{i,t}$		1.400**	
		(0.704)	
$Acq^{Back}_{i,t-1}$		0.725	
		(0.602)	
$Acq^{Back}_{i,t-1}HHI_{i,t}$		-1.591*	
		(0.888)	
$RD^{Target}_{i,t-1}$			0.0242
			(0.0162)
$RD^{Target}_{i,t-1}HHI_{i,t}$			-0.00536
			(0.0273)
$HHI_{i,t}$	-0.157***	-0.155***	-0.157***
	(0.0513)	(0.0511)	(0.0513)
$RD_{i,t-1}$	0.546***	0.546***	0.546***
	(0.0238)	(0.0238)	(0.0238)
$Revenue_{i,t-1}$	-0.0163***	-0.0162***	-0.0165***
	(0.00575)	(0.00574)	(0.00574)
$Age_{i,t}$	-0.000629	-0.000638*	-0.000622
	(0.000382)	(0.000382)	(0.000381)
$Fake0_{i,t}$	-4.522***	-4.524***	-4.524***
	(0.181)	(0.180)	(0.181)
$MeanFake0_{i,t}$	1.007***	1.005***	1.008***
	(0.123)	(0.123)	(0.123)
$MeanFake0^{Target}_{i,t}$			0.141
			(0.108)
Constant	0.986**	0.991**	0.986**
	(0.400)	(0.400)	(0.400)
Observations	11,610	11,610	11,610
Adjusted R-squared	0.972	0.972	0.972

Dependent variable is R&D relative to employment. Robust standard errors clustered by acquirer in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All specifications include acquirer country, acquirer 2-digit NACE, and year fixed effects.

Table 18: Propensity Score Matching

Panel A: Selection

Sample	Treated	Controls	Difference	S.E.	T-stat
Unmatched	-1.13805093	-1.73166702	0.593616093	0.109278249	5.43
ATT	-1.13962143	-1.34263576	0.20301433	0.153257474	1.32

Panel B: Sensitivity Test

Variable		Treated	Control	T stat	Prob. Val.
$RD_{i,t-1}$	U	-1.1861	-1.8147	5.78	0
	M	-1.1875	-1.3169	0.92	0.357
$Revenue_{i,t-1}$	U	13.723	13.06	9.72	0
	M	13.721	13.695	0.32	0.752
$Age-i,t$	U	57.484	54.445	3.08	0.002
	M	57.505	58.608	-0.82	0.413
$Fake0_{iI,t}$	U	0.42757	0.49512	-5.11	0
	M	0.42782	0.45003	-1.31	0.191
$MeanFake0_i$	U	0.44044	0.51248	-5.73	0
	M	0.44064	0.45459	-0.85	0.393

Sample	Pseudo R^2	LR χ^2	$p > \chi^2$
Unmatched	0.038	349.33	2
Matched	0.013	60.85	2.1

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