

**Chinese and Indian Multinationals:
A Firm-Level Analysis of their Investments in Europe**

Vito Amendolagine

Dipartimento di Scienze Politiche Sociali - Università di Pavia

vito.amendolagine@unipv.it

Claudio Cozza

Dipartimento di Scienze Economiche, Aziendali, Matematiche e Statistiche - Università di Trieste

claudio.cozza@me.com

Roberta Rabellotti

(corresponding author)

Dipartimento di Scienze Politiche Sociali - Università di Pavia

roberta.rabellotti@unipv.it

Abstract

This paper contributes to the literature on Chinese and Indian multinationals investing in Europe through an empirical investigation about their identity, their characteristics and the association between their features and their international strategies. The investigation exploits a database at the level of the investing firms. In relation to the mode of entry, we find that greenfield investments are a more likely option for large-sized companies. Moreover a high propensity for innovation is associated with a high probability to enter with an acquisition and with technological asset-seeking investments. Finally, high profitability is needed to invest in the core EU countries.

Key Words: Multinationals; China; India; Europe

JEL Classification: F21; F23

1. Introduction

Over the last years, foreign direct investments (FDI) undertaken by developing country multinational enterprises (MNEs) have been continuously increasing, and in 2013 they have reached a record level of US\$460 billion, representing 39% of global direct investment outflows (UNCTAD, 2014).

Among MNEs from developing countries, Chinese and Indian companies are particularly active in their outward FDI. In the eleven years between 2001 and 2012, FDI flows from China and India have dramatically increased: from US\$6.9 billion to US\$84.2 billion for China, and from US\$1.4 billion to US\$8.6 billion for India. Within the same time span, outward FDI stocks have risen from US\$34.6 billion to US\$ 509 billion in the case of China, and from US\$2.5 billion to US\$ 118.2 billion in the case of India (UNCTAD 2014). If we consider overall investments made by the BRICS (Brazil, Russian, India, China, South Africa), we find that in 2012, 42% of their outward FDI stock was in developed economies, with Europe accounting for 35% of the total (UNCTAD 2013).¹

China and India, together with Russia, account for the lion's share of investments in Europe and their increasing presence is generating considerable interest, concern, and controversy. Their rapid expansion is viewed with a mix of optimism and fear: on the one hand inputs of fresh capital are welcomed by the host countries, especially in the current period of low growth, while on the other hand, there are fears that these foreign investments might be an attempt to gain control over strategic assets and infrastructures, and could lead to the loss of key technological capabilities. These mixed sentiments are often based on anecdotal empirical evidence and personal interpretations of a few well known cases of leading multinationals such as Lenovo, Haier, and Huawei from China, and Tata and Mittal from India. So far, relatively little is known about the characteristics of the Chinese and Indian firms engaging in FDI, and how these features are related to their internationalization strategies.

In the academic literature there is clearly a growing interest in Emerging Market MNEs (EMNEs); about the adequacy of the existing MNE theories to study the behavior of EMNEs. Some scholars consider EMNEs to be a new type of MNEs, requiring a new theory (Mathews 2002); others think still valid the standard MNE theories (Narula, 2006). The former group considers that EMNEs count on different advantages with respect to Advanced Country MNEs (AMNEs), which rely mainly on ownership of key assets such as technologies, brands, and other intellectual property. Ramamurti (2012) shows that the reality is somewhere in between these two positions, and that

¹ The shares of China and India in the stock of BRICS outward FDI are respectively 36% and 10% (UNCTAD 2014).

there are aspects of EMNEs that are similar to AMNEs and others which are not. On the basis of a large number of case studies, Ramamurti and Singh (2009) conclude that EMNEs are a heterogeneous group exhibiting a variety of internationalization strategies, which the authors categorize according to *host country-specific* (natural resources, cheap factors of production, and cultural factors) and *firm-specific* (product/process technologies, brands, marketing and commercial skills) advantages, and which differ according to their target markets (other developing or emerging countries or advanced economies).

Empirically, Chinese and Indian FDI's have been mainly investigated using aggregate official FDI data (among others see Buckley et al. 2007; Chang 2014; Kolstad and Wiig 2012). Furthermore, as said before there are many case studies on individual companies at the level of the investing firm, mostly focusing on the same well-known multinationals and providing useful anecdotal evidence but do not allowing any generalization (Fan et al. 2012; Zhang and Filippov 2009; Zhang et al. 2011).

In this paper, we add to the empirical literature on Chinese and Indian multinationals by focusing on their investments in Europe and providing a detailed picture about who these firms are, their characteristics, and how these features are associated with their international business strategies. The novelty of our empirical exercise derives from two main features: the availability of a new database and the use of an innovative, in this field, statistical instrument.

The database, named EMENDATA (Emerging Multinationals' Events and Networks DATAbase), contains information on greenfield investments and mergers and acquisitions (M&A) in the period 2003-2011. The data are derived from commercial sources and associate information at the level of the deal with information about the firm undertaking the investment. Specifically, each cross-border deal is associated with information available in BvD's *Orbis* on the investing company; this allows an investigation of the foreign expansion strategies of Chinese and Indian multinationals at firm level (Amighini et al. 2014). Sutherland and Anderson (2014) have recently stressed the importance of using commercial databases, such as those at the basis of EMENDATA, to overcome some geographical and sectorial biases in official FDI data because the flows going to and passing thorough tax havens and fiscal paradises are not adequately dealt in them. So far, there are a few studies using firm level data from these databases but they are either on greenfield FDI (Amighini & Franco 2013; Amighini et al. 2013a and b; De Beule and van de Bulcke 2012) or on M&As (Bhabra and Huang 2013). The main advantage of EMENDATA, used in this paper, is the merging of greenfield investments and M&As at the level of the investing firm as a unit of analysis.

In the empirical analysis we adopt classification trees, a data mining nonparametric technique, commonly used in botany and in medical decision making processes but, as far as we know not frequent in economic and business studies, to select from among a large number of variables those that are the most important for determining the outcome variable to be explained. In the case of Chinese and Indian investors in Europe, we investigate which of their several characteristics (i.e. size, factor intensity, innovation propensity, leverage capacity, profitability) is most likely to be associated with their internationalization strategies in terms of mode of entry, destination, motivation, and replication of investments. In other words, classification trees allow us to segment the population of investing firms into meaningful subsets, including companies, characterized by similar characteristics, and more likely to choose similar internationalization strategies.

For the mode of entry, we find that greenfield investments are more likely to be chosen by large-sized EMNEs. We also find that a high propensity for innovation is associated with a high probability of opting for M&A strategy and strongly related with technological asset-seeking FDI. Furthermore, a high level of profitability is needed to invest in the core EU countries. Finally, very large size characterizes companies investing in more than one country.

The paper is organized as follows. Section 2 describes the database and provides a descriptive picture of Chinese and Indian investments in Europe. Section 3 discusses the methodology and the variables which are selected on the basis of the existing literature. Section 4 presents the empirical findings. Section 5 concludes.

2. Chinese and Indian FDI: some descriptive evidence

2.1. The EMENDATA database

The Emerging Multinationals' Events and Networks DATAbase (EMENDATA) includes greenfield investments, M&As, and other minority investments by emerging multinationals between 2003 and 2011. We match three data sources: *fDiMarkets* (Financial Times Group) for greenfield investments; *Zephyr* (Bureau van Dijk's - BvD) and *SDC Platinum* (Thomson Reuter) for M&A and other minority investments (corresponding to an ownership share of less than 50%).²

The three sources are built in different ways: *fDiMarkets* reports each investment resulting in a wholly-owned subsidiary established at a certain date by an investing firm; Bureau van Dijk's

² Bureau van Dijk's *Zephyr* and Thomson Reuters' *SDC Platinum* are recognized as comprehensive sources of data on M&As and most existing empirical analyses are based on one or the other of them. Merging these two sources provides us with more complete information. 41% of the deals in EMENDATA are both in *Zephyr* and *SDC Platinum*, 28% are only reported in *Zephyr* and 31% are only in *SDC Platinum*. Therefore, EMENDATA has better coverage of M&As than either single data source.

Zephyr and Thomson Reuters' *SDC Platinum* are firm-level databases, reporting the ownership relationships between any parent firm and its affiliates. Given the very different nature of these data sources, the main effort undertaken in EMENDATA is their harmonization, which involves intensive manual work.

In the current paper, we focus on the deals undertaken by Chinese and Indian investors in the EU27 countries; this represents a total of 1,790 deals, 841 undertaken by 495 Chinese companies, and 949 by 432 Indian investors.³ The available information on individual deals includes: location of the investment⁴, mode of entry (greenfield, M&A, or minority), industry specialization of the investing company and the subsidiary, the activity (e.g. R&D, production, sales) undertaken in the case of greenfield investments. In addition, for each investing company we have information on size, ownership structure, and consolidated and unconsolidated balance indicators.

2.2. *Chinese and Indian deals in the EU-27*

Table 1 shows that in the period 2003-2011 for both Indian and Chinese firms, greenfield investment is the favorite mode of entry and accounts for 80% of Chinese deals and 55% of Indian deals. Taking into account trends (Figure 1), greenfield investments are increasing all along the period, especially those undertaken by Chinese firms. M&As show a less clear trend: Indian M&As increased up to 2008 when they have reached the level of greenfield investments in absolute value and then dropped sharply; Chinese M&As have increased continuously but at a slower pace.

With regard to destinations, Chinese and Indian FDI in the EU27 countries represent respectively 30% and 10% of their global investments, with most (89% and 90% respectively of Chinese and Indian deals) going to the EU-15.⁵ The top destination countries for China and India differ: Indian firms mostly target the United Kingdom, while Chinese firms mainly invest in Germany. In both cases, the top destination country is the recipient of more than one-third of the total deals (Table 1).

³ When investigating the internationalization strategies of multinationals the number of deals is a more appropriate unit of analysis than the value of the investment because the choice to invest in a specific country and the motivation of the investment might be largely independent of the amount of capital invested. Moreover, investment size varies widely across sectors, with resource-intensive sectors receiving larger average investments than consumer goods sectors or services. For this reason several empirical studies take number of deals (not investment size) as the unit of analysis (Amighini et al.2014).

⁴ Concerning the role of financial centers and fiscal havens stressed by Sutherland and Anderson (2014), information at deal level allows identification of the location of both the direct acquirer and the ultimate owner and whether transit via a fiscal haven is involved, thus assessing the relative importance of fiscal havens as location choices. We have checked whether deals directed to EU-27 originating from fiscal havens could ultimately be attributed to a Chinese or an Indian companies and could be considered Chinese or Indian investments. This allowed us to add further deals increasing the coverage of EMENDATA.

⁵ EU15 includes Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, and United Kingdom. EU12 includes the countries having joined the EU in 2004 or later, i.e. Bulgaria, Cyprus, Czech Republic, Estonia, Hungary Lithuania, Latvia, Malta Poland, Romania, Slovenia, and Slovakia.

Chinese and Indian FDI in Europe are very concentrated in terms not only of destination countries but also of target sectors (Table 2). In both cases, around half of the deals are concentrated in four sectors, which are different for the two investing countries. Chinese firms invest mainly in manufacturing: electronics, industrial machinery, communication, and automotive; Indian MNEs invest in the service and pharmaceuticals sectors.

[FIGURE 1 HERE]

Notable in the number of investments undertaken by individual companies is that a large majority of Chinese (80%) and Indian (65%) MNEs were involved in one deal during the period investigated, evidence of still sporadic investments in Europe (Table 3). Most Chinese firms' investment (68%) was via greenfield, while Indian MNEs were involved in a mix of greenfield (33%) and M&A (32%). Finally, Indian firms show a greater propensity to invest in more than one country than their Chinese counterparts.

If we consider the top investors in the EU-27 (Table 4), we observe that more Indian groups are involved in at least ten deals than Chinese MNEs. Also, investment strategies based on multiple modes of entry, i.e. greenfield and M&As, tend to be concentrated in the capital and knowledge intensive manufacturing sectors, such as automotive (SAIC, Tata Group, Mahindra Group), chemicals (China National Chemical), and energy (Reliance, Suzlon Energy). Investors in the service sector (e.g. finance, communications, software) and in the electronics industry tend to rely on greenfield entry (see the cases of Huawei, ZTE, ICBC, State Bank of India, ICICI Bank).

(Tables 3 and 4 HERE)

3. The empirical analysis

3.1. The classification trees

Breiman et al.'s (1984) seminal paper introduced the notion of classification trees, belonging to the family of decision trees⁶ and based on a recursive procedure which allows partitioning a set of n statistical units (i.e. investing firms) into groups that are homogeneous with respect to a discrete or categorical output variable (i.e. modes of entry - greenfield or M&As, or motivations) (see the Appendix for a detailed description of the statistical procedure). The premise of the investigation is fairly simple – given factors $x_1, x_2, x_3, \dots, x_n$ (in our case firm characteristics: size, factor intensity, innovation propensity, leverage capacity, and profitability) we want to predict an outcome Y (in our case for instance greenfield or M&A, or location in the core or the periphery of the EU).

⁶ There are two types of decision trees: classification trees, which are used if the output variable can take a finite set of values (as in our case), and regression trees used when the output variable is continuous.

Classification trees allow identifying which of the various characteristics of the multinationals plays a statistically significant role in the decisions related to some key aspects of their internationalization strategy. Note that each single characteristic may not be a strong predictor of a given outcome, but together they may be important. In addition to identifying which variables matter to predict a given output, this technique also provides precise variable thresholds below/above that a certain international business strategy is more likely.

Compared to a simple linear regression model, classification trees have several advantages. First, they provide easily understandable predictions about which variables are important to classify the sample units with respect to a certain outcome, without introducing distribution assumptions and treating the data generation process as unknown. Second, they are extremely useful if the variables affecting the output interact in complicated and nonlinear ways. In such cases, defining a simple global model for the entire sample can be hard, and non-parametric smoothers such as classification trees, are helpful because they try to fit the model within smaller parts of the sample.⁷

3.2. *Internationalization strategies*

We apply classification trees to categorize Chinese and Indian multinationals investing in the EU27 and making a 1-0 decision with regard to i) mode of entry, ii) location, iii) motivation, and iv) decision to invest in more than one country.

(i) *Mode of entry: Greenfield vs. Mergers & Acquisitions.*

Although traditionally most outward FDI by EMNEs (especially Chinese MNEs) was in the form of greenfield investments, EMNEs have recently been exploiting M&As in order to expand abroad (Ramamurti 2012). M&As guarantee rapid entry into a foreign country, relatively easy control over specific and strategic assets such as reputation, brands and distribution networks, knowledge and technologies of the acquired firm, and access to local markets (Makino et al. 2002, Meyer et al. 2009a, b). Acquisitions can support EMNEs' catch up strategies through the development of new skills and competences, and organizational and technological learning (Piscitello et al. 2014; Vermeulen and Barkema 2001).

(ii) *Location: EU-core (EU-15) vs. EU-periphery (EU-12)*⁸

The literature on MNEs explains the location decision based on investment motive(s) and the characteristics of the host economy (Dunning and Lundan 2008): market seeking investments are

⁷For other examples see Durlauf and Johnson (1995), Minier (1998) and Sheridan (2014) adopting regression trees to investigate macroeconomic issues implying non-linear effects.

⁸ See Footnote 6 for the list of countries included.

attracted by large and growing markets; strategic resource seeking investments search for locations well-endowed with specialized knowledge assets; efficiency seeking investments favor low labor cost destinations. In the case of Chinese and Indian MNEs, there are several empirical studies that investigate the effect of some host country characteristics for explaining their location choices (Pradhan 2011; De Beule and Duanmu 2012, Kolstad and Wiig 2012). In particular, focusing on the EU-27, Brienen et al. (2010) show that the quality of the labor market is an important aspect of the decision to invest in a particular region.

(iii) *Motivation: Technology driven FDI (TFDI) vs. other FDI*

One of the motivations for EMNE investment in advanced countries is the existence of technological assets which give access to advanced knowledge and capabilities to improve the MNE's technological and innovative capabilities (Makino et al. 2002; Luo and Tung 2007, Deng 2009; Chen et al. 2012). In the case of Indian MNEs, Pradhan (2008) shows how their motivations have evolved from market seeking in the pre-liberalization phase (when investments were mostly directed to other developing countries), to resource seeking and asset seeking in more recent times, with investments shifting to developed countries.

In this paper, TFDI are identified in two different ways based on the information available in EMENDATA:

- for greenfield investments, *fDiMarkets* provides information on the activity undertaken with the investment, accordingly we define as TFDI the investments undertaking: “Research and Development”, “Design, Development & Testing”, and “Education & Training” activities;
- for acquisitions, BvD's Orbis provide information for intangible (fixed) assets including expenditure on training, and research and development expenses. We define as TFDI the investments where the target company has a value of intangible assets larger than zero.

(i) *Number of deals/countries: one deal vs. more than one deal in more than one country*

In a recent paper, Kalasin et al. (2014) suggest that the capacity to focus on the core business and cope with managerial and financial resources constraints is associated with EMNEs' ability to invest in several advanced markets, because of the high costs involved in undertaking investments in different countries.

3.3. *Firm level characteristics*

In the empirical analysis we investigate which of several characteristics of the investing companies are most likely to explain the modalities of the international business strategies discussed above. One of the difficulties related to the selection of appropriate variables to measure different structural characteristics of the EMNEs is the very high number of missing values. Our selected firm variables, all taken from BvD's Orbis database, are aimed at encompassing several structural aspects, at the same time minimizing sample reduction. The variables considered, taken in the same year of the deal, are the following ones:

- a) Total revenues as a measure of size in US\$ (**Y**) (Contractor et al. 2007);
- b) Ratio of total capital assets to number of employees as a measure of capital intensity in US\$ (**KL**);
- c) Ratio of intangible assets to total assets as a proxy for the propensity to innovate (**INN**) (Montresor et al. 2014);⁹
- d) Percentage of shareholders' assets with respect to total assets, i.e. the solvency ratio (**SOLV**), intended as a measure of negative leverage (Desai et al. 2008);
- e) Percentage of profits earned by the firm in relation to its total assets (**ROA**), as a measure of profitability (Contractor et al. 2007, Kalasin et al. 2014).

Table 5 provides the summary statistics for the variables employed in the empirical analysis,¹⁰ and shows some differences between Chinese and Indian investors. In terms of total revenues, Indian MNEs have a larger median value than Chinese MNEs, while the mean value is larger for Chinese companies due to the inclusion in the sample of some very large-sized companies (i.e. the 90th percentile value for Chinese companies is much larger than for Indian companies). With regard to innovation propensity, Indian MNEs have a larger mean value due to some outliers on the right side of the value distribution. Also, Indian companies have higher profitability, and higher solvency ratios and ROA values with respect to Chinese investors for both the mean and median values. Finally, Chinese MNEs, on average, are more capitalized than Indian companies, as shown by larger median values for the capital/labor ratio.

(Table 5 HERE)

4. Associating firm characteristics and international business strategies

⁹ Focusing on Innobarometer 2013, a survey about attitudes and activities related to innovation policy in the EU countries, Montresor, Perani and Pezzani (2014) find that a high level of intangible assets is associated with companies giving high priority to the development of new products/processes. The ratio of number of patents to total revenues was also used as a measure of innovation propensity in our econometric tests but the results were not statistically significant.

¹⁰ Appendix Table A1 presents the correlation matrix of the variables.

The output of the econometric tests is a tree which identifies groups of Chinese and Indian MNEs that are homogeneous in terms of their investment strategies in Europe.¹¹ In each tree we investigate an alternative choice of investment strategy: e.g. in Figure 2 the choice is between greenfield (1) or M&A (0) as a mode of entry. Each tree provides the following pieces of information. First, it reveals the firm characteristics significantly associated to each alternative choice (e.g. in Figure 3 INN, KL, Y, and ROA).¹² Second, each node offers a quantitative threshold (e.g. the first node in Figure 3: a ratio of intangible assets to total assets lower than 0.012) and the probability that companies satisfying this condition will choose a greenfield (93%) or an M&A (7%) investment. Third, the tree also reports the size of each sub-group of companies (in our example 77 companies). It is worth adding that the firm characteristics relevant to each alternative choice should be considered together to predict a given outcome. In what follows we explain the four estimated trees in detail.

Mode of entry: Greenfield vs. M&A

The choice is between greenfield (1) and M&A (0) (Figure 2). The largest homogeneous group of companies (216) with 87.8% probability of choosing a greenfield investment is characterized by a) $INN > 0.012$; b) $K/L > US\$ 47234$ and c) $Y >$ than US\$ 1 billion. The second largest homogeneous group includes 77 companies, characterized by $INN < 0.012$, with 93% probability of undertaking a greenfield investment.

For entry via M&A (72% of probability), the largest group includes 36 companies characterized by a) $INN > 0.012$, b) $K/L > US \$47234$, c) $Y <$ than US\$ 1 billion and d) $ROA < 14.6 \%$.

[FIGURE 2 HERE]

Destination: EU-core vs. EU-periphery

Figure 3 depicts the alternative decision between a EU15 region destination (1) and investment in the EU12 (0). For location choice, the relevant firm characteristic is profitability. We find that a very large group of 303 companies with $ROA > 5.81\%$ chose to locate in the EU core.

Motivation: TFDI vs. other FDI

In the case of motivation we consider the alternative between TFDI (1) and all the other FDI (0). INN is the main characteristic influencing the decision of the investors to undertake TFDI. In a group of 315 firms, there is a 20% probability of TFDI from companies with $INN > 0.015$ (Figure 4).

¹¹ The econometric tests were undertaken on a sample of 423 companies (253 from China and 170 from India), for which financial information is available in Orbis database, involving a total of 706 deals. In each test, we have dropped companies with more than one investment following different strategies. For instance, in the test for mode of entry we have excluded companies involved both in greenfield and M&A.

¹² Firm level characteristics were selected following the recursive procedure described in the Appendix.

Number of deals: One deal vs. more than one deal in more than one country

The choice is between undertaking more than one investment in more than one country (1) and making a single investment (0). The largest probability of undertaking investments in more than one country (58%) is linked to MNEs with revenues > US\$2.7 billion. This result is confirmed by another large group of companies (162) having 87% probability of undertaking a single investment and showing revenues < US\$2.7 billion and (Figure 5).

[FIGURE 3 HERE]

[FIGURE 4 and 5 HERE]

4.1. Discussion of the findings

Classification trees allow identifying the main characteristics of Chinese and Indian MNEs investing in Europe and associating them with some specific elements of their international business strategies. With regard to the mode of entry, large size facilitates investments in foreign markets through greenfield, which is a strategy involving high fixed entry costs (Eicher and Kang 2005). A greater propensity for innovation is associated with investments via M&A, while lower innovation propensities are associated to large probabilities to undertake greenfield investments. This result is confirmed by Zhou et al. (2014) who found that Chinese companies, especially in technology-intensive industries, acquire other companies in order to access technologically advanced assets not available at home. Besides small size and high innovation propensity, the group of companies with the highest probability of undertaking M&A investments is also characterized by low profitability (Aybar and Ficici 2009).¹³

High profitability characterizes a very large group of companies investing in the EU-core. This may be explained by the need for high performance to take part in large and competitive markets such as those of the EU-15 (Amiti 1998, 1999). The characteristics of the group of companies with the highest probability to invest into the EU-periphery include low ROA values, high solvency ratio values, and low innovation propensity. On the one hand greater financial stability can be helpful for investors interested in more volatile and riskier markets such as those in the EU12 (Desai et al. 2008). On the other hand, since the EU12 countries are less skills-abundant (Brulhart 1998) and less knowledge-oriented (Kottaridi 2007) than the core, they are likely to attract investments from companies with a lower innovation propensity.

¹³ They are also characterized by large capital intensity. However, this also applies to the group of companies with a high probability of choosing greenfield investments, so we found no clear direction in the relationship between capital/labour ratio and mode of entry.

Larger values of innovation propensity are associated with the group of investors with the largest probability of involvement in TFDI. This is in line with Lu et al. (2011), who find that asset-seeking investments are more likely to be undertaken by MNEs relying on technology-based competitive advantages.

Size matters for investing in more than one country. In fact, large size can be crucial for investors operating in multiple markets, given the very high fixed entry costs they have to deal with. Bernard et al. (2007) show that firms exporting to multiple destinations are much larger than those exporting to a single destination. Indeed, we can expect that the variables affecting the choice to export to multiple markets are similar to those affecting the strategy of investing into multiple countries.¹⁴ Taking a comparative perspective and also going back to the descriptive evidence presented in Section 2, Table 6 summarizes the main characteristics of Chinese and Indian FDIs. We find a clear difference between Chinese and Indian investors with respect to the mode of entry: greenfield investments are the preferred strategy for Chinese MNEs (80%), while both modes of entry are favored equally by Indian firms. If we take into account firm characteristics, this difference could be explained by the average larger and higher capital intensiveness of Chinese MNEs with respect to Indian investors (Table 5), confirmed by the classification tree depicted in Figure 3 identifying a large group of companies with a high probability of choosing greenfield entry that are both capital-intensive and large-sized.

(Table 6 HERE)

Finally, Chinese multinationals shows a median value of intangible assets share (0.017 as in Table 5) larger than the threshold value for TFDI in Figure 5 (0.015). This result implies that Chinese investors are more likely to undertake TFDI with respect to their Indian counterparts. Indeed, the identity of the largest Chinese investor in Europe (Huawei) and some of the top sectors targeted by Chinese deals (such as Electronics and Automotive) confirm their technological nature of them.

5. Concluding remarks

This paper provides new empirical evidence on Chinese and Indian investors in the EU27 countries. The study is motivated by the increasing amount of Chinese and Indian outward FDI in Europe in recent years, and the need for a more comprehensive understanding of their behavior based on firm level data.

We shed new light on Chinese and Indian international business strategies in the EU27 by looking at the decisions that investors are required to make: the alternative between different modes of

¹⁴ E.g., Helpman et al. (2004) study export and FDI within a common firm-level theoretical framework.

entry, location choice, motivations, and determination to replicate their investments in several countries. With classification we associate these aspects to key firm-level characteristics such as size, capital intensity, innovation propensity, leverage capacity, profitability, and efficiency. The empirical analysis is based on EMENDATA, a new database that includes all FDI (i.e. greenfield and M&A) made by Chinese and Indian MNEs between 2003 and 2011.

Our empirical analysis shows that size of the investing firm influences the choice of entry mode and the decision to undertake several investments in different countries. The propensity to innovate is a determinant of the mode of entry, the location decision and it motivates technology driven investments. Profitability and financial stability play a significant role in the decision to invest in a core or a peripheral country in Europe.

These results provide an empirically based picture representing how Chinese and Indian multinationals are investing in Europe, and goes beyond case studies of specific companies. It also highlights directions for future research and provides indications of some key firm level determinants that influence the mode of entry, the location decision, and the investment motivation. We plan to exploit EMENDATA to explore these indications further in future empirical work.

Acknowledgments

We would like to thank Silvia Figini for her collaboration in the statistical analysis. The Riksbankens Jubileumsfond is gratefully acknowledged for its financial contribution.

References

- Amighini A., Rabellotti R. and Sanfilippo M. (2013a) China's outward FDI: An industry-level analysis of host-country determinants, *Frontiers of Economics in China*, 8, pp. 903-936.
- Amighini A., Rabellotti R. and Sanfilippo M. (2013b) Do Chinese State-Owned and private Enterprises Differ in their Internationalization Strategies? *China Economic Review*, 27, pp. 312-235.
- Amighini A. and Franco C. (2013) A sector perspective on Chinese outward FDI: The automotive case, *China Economic Review*, [27](#), pp. 148–161.
- Amighini A., Cozza C., Rabellotti R. and Sanfilippo M. (2014) Chinese Outward FDI: What Can Be Done with Firm-level Data?, *China and the World Economy*, 22(6), pp. 44-63.
- Amiti M. (1998) New trade theories and industrial location in the EU: a survey of evidence, *Oxford Review of Economic Policy*, 7(2), pp-45-53.
- Amiti M. (1999) Specialization Patterns in Europe, *Weltwirtschaftliches Archiv*, 135, pp. 573-593.
- Aybar B. and Ficici A. (2009) Cross-border acquisitions and firm value: An analysis of emerging-market multinationals, *Journal of International Business Studies*, 40, pp.1317-1338.
- Bhabra, H.S. and Huang, (2013) An empirical investigation of mergers and acquisitions by Chinese listed companies, 1997–2007, *Journal of Multinational Financial Management*, 23, pp. 186-207.
- Bernard A. B., Jensen J. B., Redding S. J. and Schott P. K. (2007) Firms in international trade. *Journal of Economic Perspectives*, 21, pp. 105-130.
- Breiman, L., Friedman, J. H., Olshen, R. A. and Stone, C. J. (1984) *Classification and Regression Trees*. New York: Chapman & Hall / CRC Press.
- Brienen M. J., Burger M. J. and van Oort F. G. (2010) The Geography of Chinese and Indian Greenfield Investments in Europe, *Eurasian Geography and Economics*, 51 (2), pp. 254–273.
- Brulhart M. (1998) Trading Places: Industrial Specialisation in the European Union', *Journal of Common Market Studies*, 36, pp. 319-346.
- Buckley P. J., Clegg L. J., Cross A. R., Liu X., Voss H. and Zheng, P. (2007) The determinants of Chinese outward foreign direct investment, *Journal of International Business Studies*, 38, pp. 499–518.

- Chang S.C. (2014) The Determinants and Motivations of China's Foreign Direct Investment: A Spatial Gravity Model Approach, *Global Economic Review*, Vol.43 (3), pp. 248-268.
- Chen V.Z., Li J. and Shapiro D.M. (2012) International reverse spillover effects on parent firms: Evidences from emerging-market MNEs in developed markets. *European Management Journal*, 30 (3), pp. 204-218.
- Contractor F. J., Kumar V. and Kunder S. K. (2007) Nature of the relationship between international expansion and performance: the case of emerging market firms, *Journal of World Business*, 42, pp. 401-417.
- De Beule F. and Duanmu J.-L (2012) Locational determinants of internationalization: A firm-level analysis of Chinese and Indian Acquisitions. *European Management Journal*, 30, pp. 264– 277
- De Beule, F. and Van Den Bulcke D. (2012) Locational determinants of outward foreign direct investment: an analysis of Chinese and Indian greenfield investments, *Transnational Corporations*, 21, pp. 1-34.
- Deng P. (2009) Why do Chinese firms tend to acquire strategic assets in international expansion? *Journal of World Business*, 44 (1), pp. 74–84.
- Desai M. A., Foley C. F. and Hines J. R. Jr. (2008) Capital structure with risky foreign investments, *Journal of Financial Economics*, 88, pp. 534-553.
- Di F., Zhu C. J. and Nyland C. (2012) Factors affecting global integration of Chinese multinationals in Australia: A qualitative analysis, *International Business Review*, 21, pp. 13-26.
- Dunning J. H. and Lundan S. M. (2008) Institutions and the OLI paradigm of the multinational enterprise, *Asia Pacific Journal of Management*, 25, pp. 573-593.
- Durlauf, S. N. and Johnson, P.H. (1995) Multiple regimes and cross-country growth behavior, *Journal of Applied Econometrics*, 10, pp. 365-384.
- Eicher, T. and Kang, J. W. (2005) Trade, foreign direct investment or acquisition: Optimal entry modes for multinationals, *Journal of Development Economics*, 77(1), pp. 207-228
- Giudici P. and Figini S. (2009) *Applied Data Mining for Business and Industry*, Second edition. Wiley.
- Helpman E. Melitz M. and Yeaple, S.R. (2004) Export versus FDI with Heterogeneous Firms, *American Economic Review*, 94, pp. 300-316.

- Kalasin K., Dussage P. and Rivera-Santos M. (2014) The expansion of emerging economy firms into advanced markets: the influence of intentional path-breaking change, *Global Strategy Journal*, 4, pp. 75-103.
- Kolstad I. and Wiig A. (2012) What determines Chinese outward FDI?, *Journal of World Business*, 47, pp. 26-34.
- Kottaridi C. (2007) The ‘core–periphery’ pattern of FDI-led growth and production structure in the EU, *Applied Economics*, 37, pp. 99-113.
- Lu J., Liu X. and Wang H. (2011) Motives for outward FDI of Chinese private firms: Firm resources, industry dynamics, and government policies, *Management and Organization Review*, 7, pp. 223–248.
- Luo Y. and Tung R.L. (2007) International expansion of emerging market enterprises: A springboard perspective, *Journal of International Business Studies*, 38(4), pp. 481–498.
- Makino S., Lau C.M. and Yeh R.S. (2002) Asset-exploitation versus asset seeking: Implication for location choice of foreign direct investment from newly industrialized economies, *Journal of International Business Studies*, 33 (3), pp.403-421.
- Mathews, J.A. (2002) *Dragon Multinational – A New Model for Global Growth*, Oxford and New York: Oxford University Press.
- Meyer E. K. , Estrin S. and Bhaumik S.K. (2009a) Institutions, resources and entry strategies in emerging economies, *Strategic Management Journal*, 30, pp. 61-80.
- Meyer E. K. and Sinani E. (2009b) When and where does foreign direct investment generate positive spillovers? A meta-analysis, *Journal of International Business Studies*, 40, pp. 1075-1094.
- Minier, J. (1998) Democracy and growth: alternative approaches, *Journal of Economic Growth*, 3, pp. 241-266.
- Montesor, S., Perani, G. and Vezzani, A. (2014) How do companies ‘perceive’ their intangibles? New statistical evidence from the INNOBAROMETER 2013, *European commission, JRC report 26561*.
- Narula R. (2006) Globalization, new ecologies, new zoologies, and the purported death of the eclectic paradigm, *Asia Pacific Journal of Management*, 23(2), pp. 143–151.
- Piscitello L., Rabellotti, R. and Scalera V. 2014, “Chinese and Indian acquisitions in Europe: The relationship between motivation and entry mode choice”, in Risberg, A., King, D. and Meglio,

- O. (Eds), *The Routledge Companion to Merger and Acquisition*. London: Routledge (forthcoming)
- Pradhan J.P. (2008) The evolution of Indian outward foreign direct investment: Changing trends and patterns, *International Journal of Technology and Globalization*, 4, pp. 70–86.
- Pradhan J. P. (2011), Emerging Multinationals: A Comparison of Chinese and Indian Outward Foreign Direct Investment, *International Journal of Institutions and Economies*, 3 (1), pp. 113-148.
- Ramamurti, R. and Singh, J. V. (2009), *Emerging multinationals in emerging markets*, Cambridge: Cambridge University Press.
- Ramamurti, R. (2012) What is really different about emerging market multinationals? , *Global Strategy Journal*, 2, pp. 41-47.
- Sheridan, B. J. (2014), Manufacturing exports and growth: when is a developing country ready to transition from primary exports to manufacturing exports ?, *Journal of Macroeconomics*, 42, pp. 1-13.
- Sutherland, D. and Anderson, J. (2014) The Pitfalls of Using Foreign Direct Investment Data to Measure Chinese Multinational Enterprise Activity, *The China Quarterly*, pp. 1-28.
- UNCTAD (2013) The rise of BRICS FDI and Africa, *Global Investments Trend Monitor*, 12, Geneva, UNCTAD.
- UNCTAD (2014) *World Investment Report. Investing in the SDGs: An Action Plan*, Geneva, UNCTAD.
- Venables W. N. and Ripley B. (2002) *Modern Applied Statistics with S*, Springer Verlag.
- Vermeulen F. and Barkema H.G. (2001) Learning through acquisitions, *Academy of Management Journal*, 44(3), pp. 457-476.
- Zhang,Y. and Filippov S. (2009) Internationalization of Chinese firms in Europe, *UNU-Merit Working Paper Series*, N. 2009-041.
- ZhangJ. , Di Minin A. and Quan X. (2011) A Comparison of International R&D Strategies of Chinese Companies in Europe and the U.S., *Technology Management Conference (ITMC)*, 2011.
- Zhang, X. and Daly, K. (2011) The determinants of China’s outward foreign direct investment. *Emerging Markets Review*, 12, pp. 389-398.

Zhou C., van Witteloostuijna A. and Zhangb J. (2014) The internationalization of Chinese industries: Overseas acquisition activity in Chinese mining and manufacturing industries, *Asian Business & Management*, 13, pp. 89–116.

Tables

Tab.1 - Investments by destination country (# of deals and %) (2003-2011)

	China			India		
	Greenfield	M&A	Total*	Greenfield	M&A	Total*
Germany	268 (40)	32 (24)	304 (36)	96 (18)	63 (17)	163 (17)
UK	108 (16)	28 (21)	144 (17)	225 (43)	146 (38)	391 (41)
France	50 (7)	20 (15)	74 (9)	30 (6)	30 (8)	65 (7)
Netherlands	32 (5)	17 (14)	53 (6)	30 (6)	21 (5)	51 (5)
Italy	33 (5)	11 (8)	47 (6)	14 (3)	29 (7)	47 (5)
EU-15	592 (88)	126 (96)	718 (89)	461 (89)	353 (92)	814 (90)
EU-12	81 (2)	5 (4)	86 (11)	59 (11)	32 (8)	91 (10)
EU27	673 (100)	131 (100)	804(100)	520 (100)	385 (100)	905(100)
World	2092	623	2715	2559	290	2849

In parentheses % of the total

*Total values include minority acquisitions

Source EMENDATA

Tab.2 - Investments by sector (# of deals and %) (2003-2011)

CHINA	<i>Greenfield</i>	<i>M&A</i>	<i>Total*</i>
Electronics	114	9	128 (25)
Industrial Machinery & Engines	79	30	114 (14)
Communications	97	0	97 (12)
Automotive	49	13	62 (7)
All other sectors	334	79	440 (52)
Total	673	131	841 (100)
INDIA			
Software & IT services	134	58	197 (22)
Business Services	79	36	118 (12)
Biotech & Pharmaceuticals	41	48	95 (10)
Financial Services	73	5	79 (8)
All other sectors	193	238	460 (48)
Total	520	385	949 (100)

In parentheses % of the total

* Total values include minority acquisitions

Source EMENDATA

Tab.3 –Indian and Chinese MNEs: number of investments (2003-2011)

	<i>China</i>	<i>India</i>
1 greenfield	336 (68)	144 (33)
1 M&A	58 (12)	139 (32)
> than 1 greenfield	60 (12)	40 (9)
> than 1 M&A	11 (2)	37 (9)
Greenfield and M&A	30 (6)	72 (17)
Investments in more than 1 country	68 (14)	108 (25)
Total	495 (100)	432 (100)

In parentheses % of the total

Source EMENDATA

Tab.4 - Top Chinese and Indian investors in the EU27 (# of deals) (2003-2011)

	Country	Greenfield	M&A	Total
Tata Group	India	62	9	71
Huawei Technologies	China	52	0	52
ZTE	China	24	0	24
Mahindra Group	India	11	11	22
China National Chemical	China	13	9	22
Wipro	India	15	5	20
Reliance	India	10	6	16
Industrial and Commercial Bank of China (ICBC)	China	15	0	15
State Bank of India (SBI)	India	13	0	13
Suzlon Energy	India	8	4	12
ICICI Bank	India	11	0	11
Infosys Technologies	India	11	0	11
Punjab National Bank (PNB)	India	11	0	11
Shanghai Automotive Industry Corporation (SAIC)	China	8	3	11
Ranbaxy Laboratories	India	5	5	10
Suntech Power Holdings	China	9	1	10

Source: EMENDATA

Tab. 5. Structural characteristics of the investing firms

Variable	Mean	Median	S.D.	10 th percentile	90 th percentile
Y (US\$ million)					
Full sample	2400	238	6450	15.4	7390
China	2840	234	7180	14.5	9030
India	1590	240	4810	22.9	2460
KL (US\$ million)					
Full sample	2.496	0.102	14.4	0.024	1.611
China	2.834	0.102	15.9	0.028	1.425
India	1.018	0.135	3.1	0.017	2.053
INN					
Full sample	0.038	0.012	0.067	0.0	0.113
China	0.033	0.017	0.044	0.0	0.087
India	0.046	0.002	0.090	0.0	0.190
SOLV (%)					
Full sample	37.610	37.142	25.621	5.994	73.243
China	36.962	36.982	25.713	6.4	68.611
India	38.778	38.394	25.588	5.668	75.858
ROA (%)					
Full sample	6.576	5.077	8.593	-0.168	17.429
China	5.856	4.279	8.264	-1.541	16.438
India	7.739	6.903	9.035	0.479	18.679

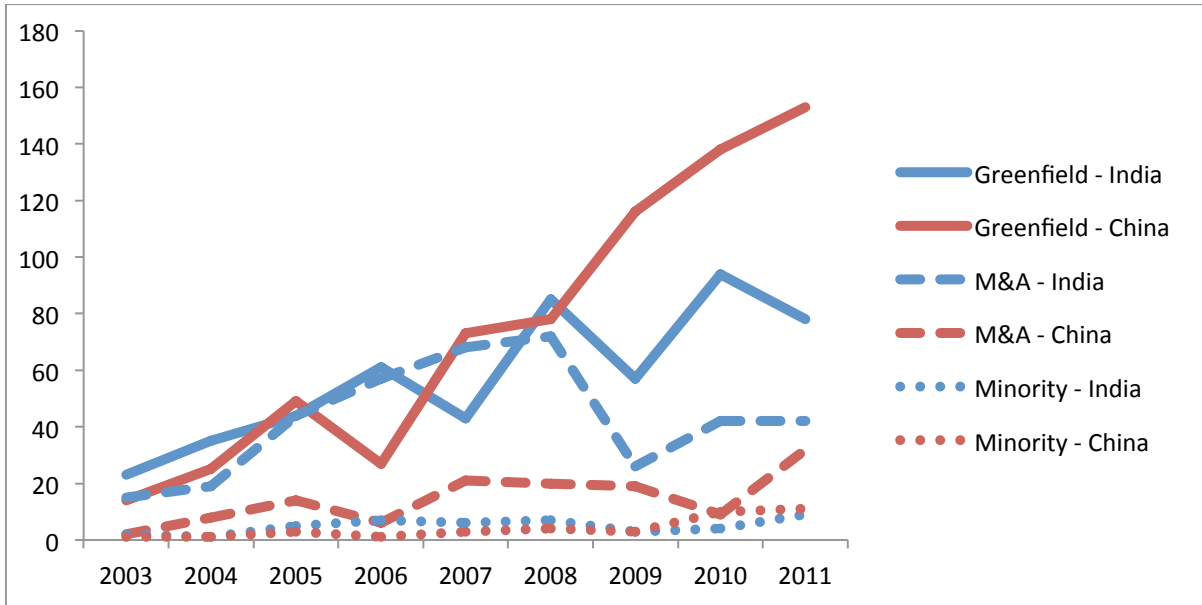
Source: EMENDATA

Table 6.Chinese and Indian FDIs: a comparative perspective

	Chinese FDIs	Indian FDIs
Mode of entry	Mainly greenfield	Greenfield and M&A
Top Destination	Germany	UK
Top 4 Sectors	Manufacturing, Electronics, Industrial Machinery, Communication, Automotive	Software and IT Services, Business Services, Biotech and Pharmaceuticals, Financial Services
Top Investor	Huawei	Tata

Figures

Fig. 1 - Chinese and Indian FDI to Europe (2003-2011)



Source: EMENDATA

Figure 2: Mode of entry: Greenfield vs. M&A

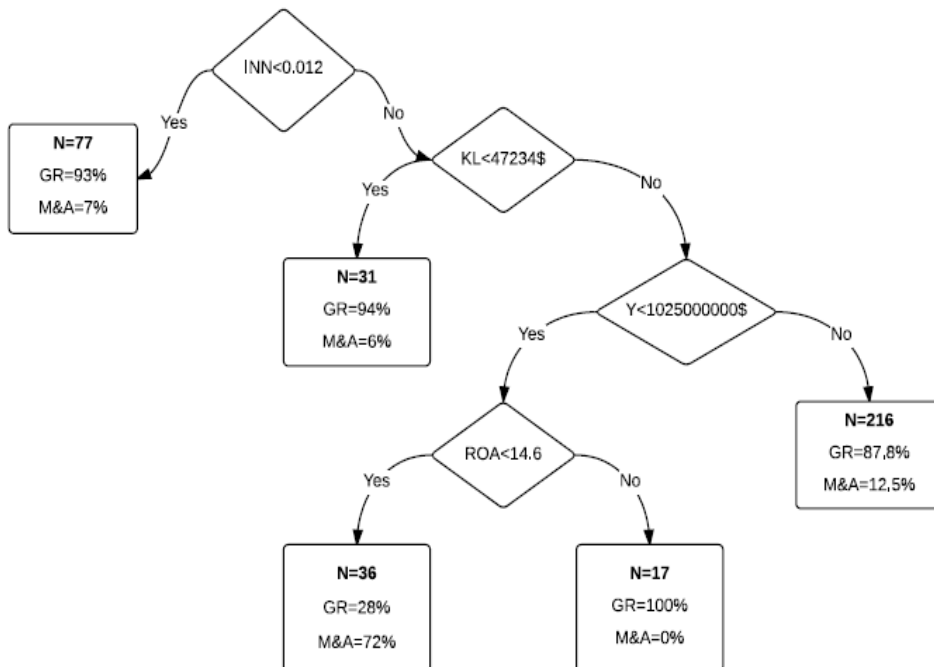


Figure 3: Location: EU-core vs. EU-periphery

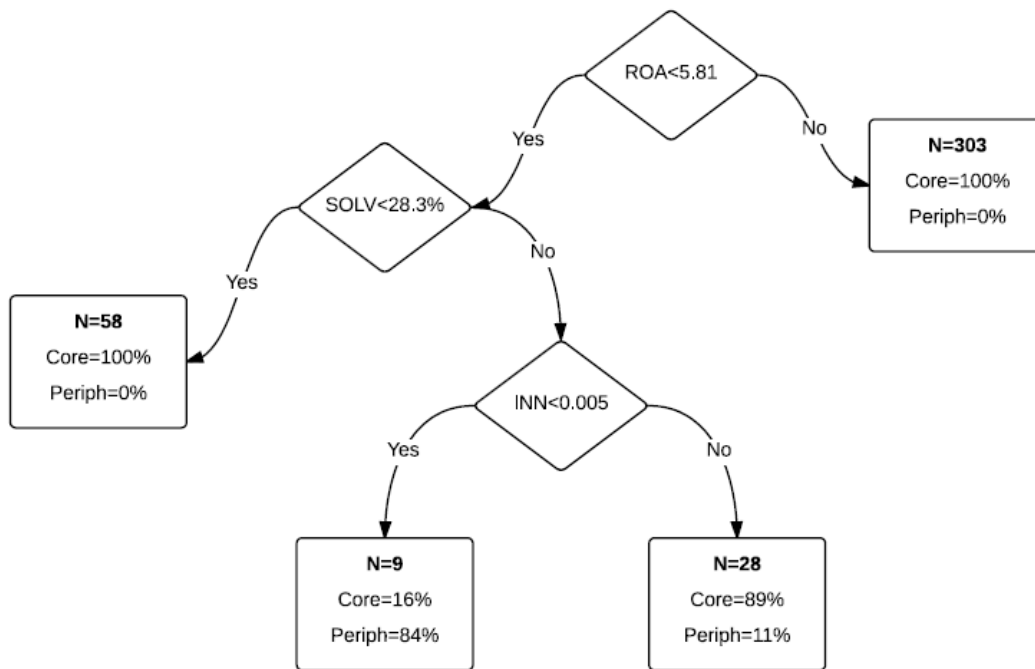


Figure 4: Motivation: TFDI vs. other FDI

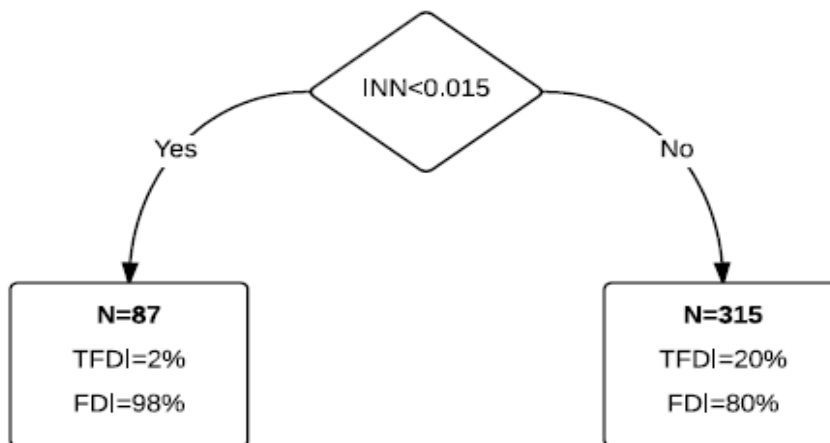
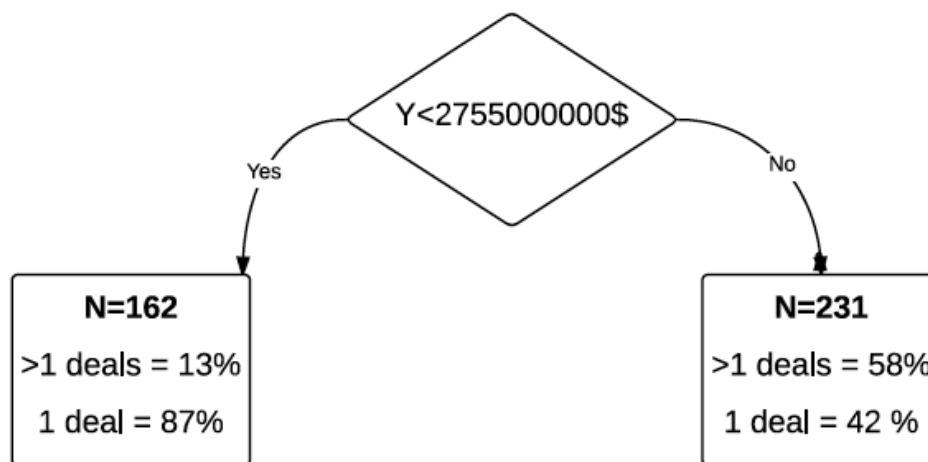


Figure 5: Number of deals: One deal vs. more than one deal in more than one country



Appendix

Classification trees

In classification trees, the units in the sample are divided into groups through a division rule that maximizes the homogeneity (“purity”) of a discrete or a categorical output variable within each group. The first stage of the statistical analysis is partitioning which involves sub-dividing the space into smaller regions. Partitioning goes on until the sum of the squared errors for each tree is larger than a certain threshold (recursive partitioning):

$$S = \sum_{c \in \text{leaves}(T)} \sum_{i \in c} (y_i - m_c)^2,$$

where y_i is the value of the output variable for unit i , while $m_c = \frac{1}{n_c} \sum_{i \in c} y_i$ is the prediction of the output variable for all the units belonging to leaf c .

The second stage is estimating. The model in each leaf is a constant estimation of the output variable, which is given simply by the sample mean of the response variable in that leaf. Thus, if as in our cases, the output variable is a binary dummy (0-1), then the fitted values represent the proportion of 1-output units within each group (i.e. leaf) and can be read as fitted probabilities.

The ideal final tree configuration is both parsimonious and accurate. The first property implies that the tree has a limited number of leaves, and therefore its interpretation should be easy. The second property is that the tree is of a sufficient size to have leaves that are as “pure” as possible, within each of which the variance across the sample units’ outputs is minimized (the smaller the leaf size, the smaller the expected variance).

In practice, optimal pruning can minimize the loss function which takes account of both the complexity and total impurity of the tree: the larger the size of the tree, the lower the total impurity and the greater the complexity (which is penalized) (see Venables and Ripley, 2002, and Giudici and Figini, 2009 for further details on this econometric approach).

Empirically, the size of the tree is found by a cross-validation procedure. The data are split into a training set and a testing set. A classification tree is built first on the training data, with no penalization for complexity, which results in the largest possible tree. Then, for each pair of leaves with a common parent node, the error (“impurity”) is evaluated on the testing data. If removal of the two leaves causes the error to collapse, then the parent node becomes a leaf, otherwise the two leaves remain. In more detail, a 10-fold cross-validation is implemented: the training set is divided into 10 parts of (approximately) the same size. Thus, nine parts are used to grow the tree and one

part is a testing sample. This exercise is repeated ten times to allow each part to assume the role of testing sample in one of the ten periods. Finally, the results are averaged.

Tab. A1- Correlation matrix

	Y	KL	INN	SOLV	ROA
Y	1.0				
KL	0.115	1.0			
INN	-0.088	-0.126	1.0		
SOLV	-0.299	-0.213	0.261	1.0	
ROA	-0.079	-0.142	0.081	0.594	1.0