Online Appendices

A Data information

Table A.1: GIs project motives description

Classification	Project Motive	Description	Nb.	%
Asset-seeking	Government Support	The company has cited non-financial support from the local IPA or government body as a reason for locating there.	166	3.09%
Asset-seeking	Technology & Innovation	A company has identified a location as being an area of high innovation, development and technology advances.	198	3.69%
Asset-seeking	Industry Cluster	The company identifies the location as having multiple similar companies or companies working on similar projects in the area.	153	2.85%
Asset-seeking	Universities or Researchers	a company has decided to locate in a city or country to be close to institutions of research and learning.	128	2.38%
Efficiency-seeking	Market Access	The company has identified a location as beneficial due to its location being close to existing customers and potential clients.	1183	22.02%
Efficiency-seeking	Transport & Utility Infrastructure	The company has identified the location as being easily accessible by any method of transport and also having good physical utilities infrastructure, including electricity grids, water works etc.	169	3.15%
Efficiency-seeking	Location Attractiveness	The company has identified the country or city's general attractiveness as a place to be located.	125	2.33%
Efficiency-seeking	Real Estate Availability	The company has identified a building, business park etc. as the reason for locating itself in the area.	28	0.52%
Efficiency-seeking	Supply Chain	The company cites a location as being desirable because its suppliers are close by.	162	3.02%
Efficiency-seeking	Language Availability	The company has stated that a multilingual workforce in the area was one of the reasons to establish itself there.	13	0.24%
Efficiency-seeking	ICT Infrastructure	The company has identified the location's internet or telecoms infrastructure as the reason for locating itself there.	35	0.65%
Market-seeking	Domestic Market Potential	The company has identified that demand in this market/country/city is growing or is on the cusp of growth.	1950	36.29%
Resource-seeking	Skilled Workforce Availability	The company has stated that a qualified, skilled or appropriately educated workforce in the area was one of the reasons it chose to establish itself there.	579	10.78%
Resource-seeking	Lower Costs	The company identifies lower cost labor or other resources when compared to competing locations.	58	1.08%
Resource-seeking	Natural Resources	The company has cited the natural resources the locality has to offer as a factor in its decision to locate itself there.	32	0.60%
NA	Business Environment	The company has identified the wider economic and political climate in the country as a reason to locate there.	388	7.22%
NA	Taxation	A company highlights the attractiveness of the local taxation structure in relation to corporate tax planning	2	0.04%
NA	Access to Finance	A company has identified the ability to raise significant money by being listed in the location as a key reason for choosing to invest there.	4	0.07%

The classification is based upon Dunning (1994).

Table A.2: Share of managers by position

Position	%
Administration Department	1.92
Advisory Board	0.83
Audit Committee	1.06
Board Of Directors	**20.33**
Branch Office	0.29
Corporate Social Responsibility Committee	0.02
Chairman's Committee	0.00
Corporate Governance Committee	**0.21**
Customer Service	1.73
Environment Committee	0.04
Ethics Committee	0.02
Executive Board	**1.74**
Executive Committee	**0.61**
Finance & Accounting	4.93
Government & Public Affairs	0.04
Human Resources (HR)	2.64
Health & Safety	0.52
Legal Department	1.47
Marketing & Advertising	2.67
Nomination Committee	0.68
Operations & Production & Manufacturing	4.22
Other Board Or Committee	1.19
Other Or Unspecified Department	17.29
Product/Project/Market Management	2.42
Purchasing & Procurement	1.10
Proxyholders	3.38
Quality Assurance	0.64
Remuneration Committee	0.77
Risk Committee	0.18
Safety Committee	0.06
Sales & Retail	6.71
Senior Management	**25.69**
Other Specific Positions	1.51
Supervisory Board	**1.50**
Information Technology (IT) & Information Systems (IS)	5.91
Research & Development / Engineering	8.10

In bold, apical managers' positions that we retain for the empirical analysis. Also note that managers can occupy several positions within the same company.

Table A.3: Average number of apical managers per firm, by investor country

Country	Nb.
Austria	5.0
Australia	7.3
Belgium	8.9
Canada	10.5
Switzerland	14.3
Chile	8.1
China	2.8
Czechia	3.5
Germany	5.1
Denmark	6.3
Estonia	4.4
Spain	5.1
Finland	6.5
France	6.6
U.K.	8.4
Greece	3.0
Hungary	5.6
Ireland	6.8
Israel	6.5
Iceland	4.5
Italy	11.9
Japan	3.7
South Korea	14.0
Luxembourg	6.4
Mexico	5.9
Netherlands	4.6
Norway	6.9
New Zealand	5.8
Poland	3.7
Portugal	7.1
Russia	5.0
Sweden	6.7
Slovenia	6.3
Slovakia	2.7
Turkey	5.0
U.S.A.	35.7

Table A.4: Summary statistics, M&As

	Mean	SD	Min	Max	N
Dependent variable					
Focal investment	0.40	0.49	0	1	887
Independent variables					
Managers from target	0.18	0.39	0	1	887
Subsidiary in target	0.29	0.45	0	1	887
Moderating variable					
TMT diversity	0.84	0.13	0	0.94	887

Table A.5: Summary statistics, GIs[a]

	Mean	SD	Min	Max	N
Dependent variable					
Focal investment	0.34	0.48	0	1	3454
Independent variables					
Managers from target	0.19	0.39	0	1	3454
Subsidiary in target	0.44	0.50	0	1	3454
Moderating variable					
TMT diversity	0.84	0.12	0	0.94	3454

[a] Sample obtained using the basic matching scheme (see section 4).

Table A.6: Summary statistics, GIs[b]

	Mean	SD	Min	Max	N
Dependent variable					
Focal investment	0.43	0.50	0	1	719
Independent variables					
Managers from target	0.22	0.41	0	1	719
Subsidiary in target	0.38	0.48	0	1	719
Moderating variable					
TMT diversity	0.85	0.13	0	0.93	719

[b] Sample obtained using the alternative matching scheme (see section 4).

B Name analysis

B.1 Managers-from-target identification: methodology

Our key resource for name analysis is the IBM-GNR data library, which associates names and surnames to vectors of countries in which their use is attested, plus information on their frequency inside each country and across countries. The raw information exploited by IBM-GNR comes from the US Immigration Authorities archives, which recorded names and nationality of all entrants in the country throughout the 1990s. Such records allow establishing the diffusion of both names and surnames both within each country (except the United States) and across all countries worldwide (except, once again, the United States).

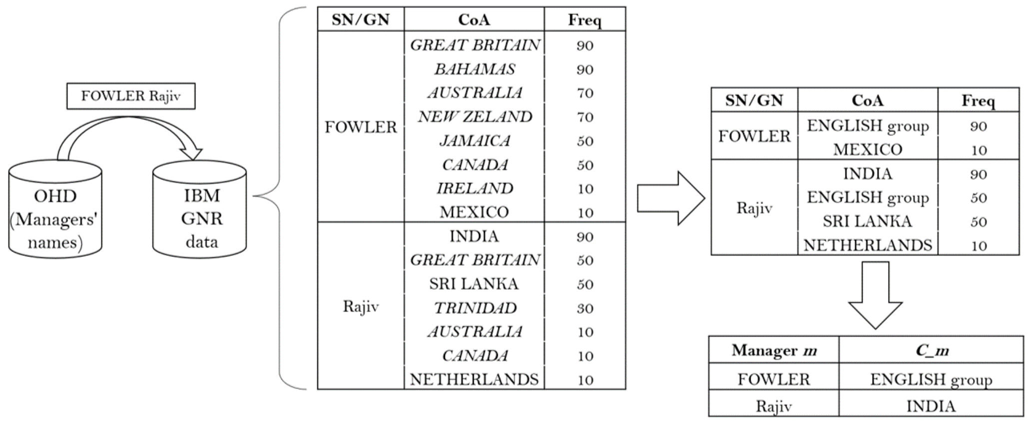
IBM-GNR data library associates each item (a name or a surname) to all countries in which it appears, along with information - among others - on its frequency within each country, expressed in percentiles (with 90 being the highest frequency and 10 the lowest).[1]

Consider for example the case of a manager called Raijv Fowler, in figure B.1. IBM-GNR associates the name Rajiv to India, Great Britain, Sri Lanka, the Netherlands and a few other countries. While very frequent within India (90th percentile), however, this name is not that frequent in Great Britain nor in Sri Lanka (where it belongs to the 50th percentile), and not frequent at all in the Netherlands (10th percentile). As for the surname Fowler, this is present in seven English-speaking countries plus Mexico, but it is very frequent (90th percentile) only in Great Britain and the Bahamas.

We first deal with these countries of association as follows. We regroup all same-language speaking countries in groups and assign to each of these linguistic group the maximum frequency in the group. In the example of figure B.1 the four English-speaking countries associated to the name Raijv (Great Britain, Trinidad, Australia and Canada) will be reduced to one generic "English-speaking group" with frequency in the 50th percentile (that of Great Britain, which is the highest among the four). In turn, this will reduce the countries or linguistic groups associated to Rajiv to just four (India, the English-speaking group—in italics, Sri Lanka and the Netherlands). Similarly,

[1] For each item, IBM-GNR also provides information on the cross-country frequency (or "significance", according to IBM-GNR definition), with values from 1 to 100; as well as an accuracy index, which is based on the absolute frequency of the item in the data library (the higher the frequency, the higher the score). Details on these other pieces of information, which we do not use in this paper, can be found in Breschi et al. (2014) and Breschi et al. (2017). IBM-GNR also provides information on names' gender, as described in Toole et al. (2019).

Figure B.1: Example of name analysis conducted trough GNR's results



the countries or linguistic groups associated to the surname Fowler will reduce to two (the English-speaking group and Mexico). Table B.1 lists all the linguistic groups we created, plus information on their numerosity (more on this below).[2]

Based on such transformation, we create, for each manager in our sample a C list of his/her most likely countries of origin (where for country of origin we also refer to all members of a linguistic groups). This will include the all countries in which his/her name and surname are associated to a frequency equal 90; or, in the absence of such countries for either the name or the surname, those with the highest frequency. In figure B.1 the C list for Rajiv Fowler includes all the highlighted countries, namely India and the English-speaking group.

For each investment i at time t, undertaken by company j from country w and with target country z, we retrieve the C_m list we have created for each of m=1...M working for j at time $t-1$ (where C_m indicates the C list for manager m). Based on this, we produce the variable $Managers\ from\ target$ as described in figure B.2).

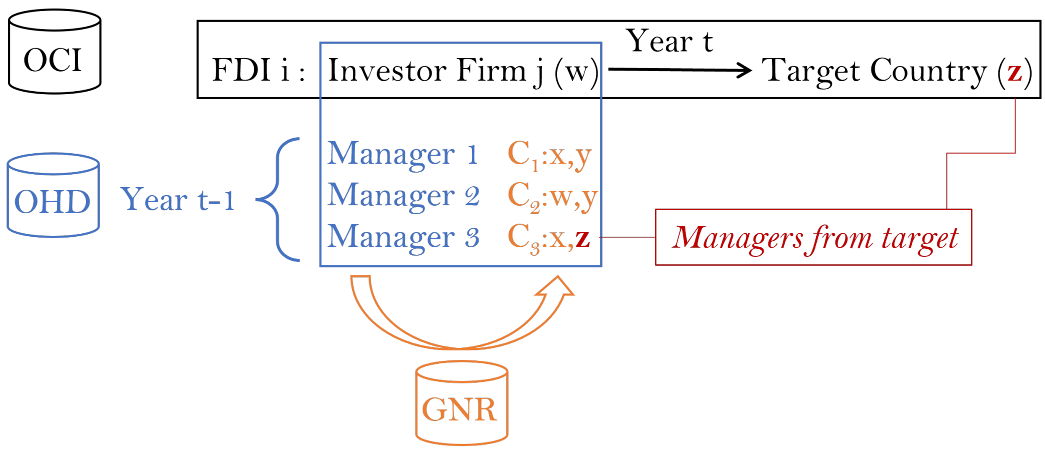
We first create a flag variable for each manager m working for j at $t-1$, which takes value 1 if the manager for whom z is a likely country of origin (and 0 otherwise). This is the case for all managers whose C_m list includes z, but not w. Following with the previous example, we flag as of Indian-origin any manager named Rajiv Fowler working at time $t-1$ for a Swiss company investing in India at time t (India appears in the manager's C_m list via the manager's name, while

[2]For sake of precision, we must specify that Canada belongs to two linguistic groups, the English and the French. So, in the example of B.1, what really happens is that Canada both gets absorbed in the English-speaking group and originates a new group, the French-speaking one, with the same frequency as Canada. So, to be more precise, the countries or linguistic groups associated to the name Rajiv are in reality five: India, the English-speaking group, Sri Lanka, the Netherlands and the French-speaking group.

Table B.1: List of countries by linguistic group

Linguistic Group	Country
Arabic	Algeria, Bahrain, Egypt, Iraq, Jordan, Kuwait, Lebanon, Libya, Mauritania, Morocco, Palestine, Qatar, Saudi Arabia, Syria, Tunisia, United Arab Emirates, Western Sahara, Yemen.
Baltic	Latvia, Lithuania.
Chinese	China, Hong Kong, Macao, Singapore, Taiwan.
Dutch	Belgium, Netherlands, Suriname.
English	Anguilla, Antigua and Barbuda, Australia, Bahamas, Barbados, Belize, Bermuda, Canada, Cayman Islands, Cook Islands, Dominica, Falkland Islands, Australia, Fiji, Grenada, Guernsey, Guyana, Ireland, Isle of Man, Bahamas, Jamaica, Jersey, Micronesia, New Zealand, Norfolk Island, Pitcairn, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Sint Maarten, Trinidad and Tobago, Turks and Caicos Islands, United Kingdom, United States of America, Virgin Islands (British), Virgin Islands (U.S.).
Finnic	Estonia, Finland.
French	Belgium, Canada, France, French Guiana, French Polynesia, Haiti, Luxembourg, Monaco, New Caledonia, Réunion, Saint Martin, Saint Pierre and Miquelon, Switzerland.
German	Austria, Belgium, Germany, Liechtenstein, Luxembourg, Switzerland.
Greek	Cyprus, Greece.
Italian	Holy See, Italy, San Marino, Switzerland.
Korean	North Korea, South Korea.
Malay	Brunei Darussalam, Indonesia.
West Scandinavian	Faroe Islands, Iceland, Norway, Svalbard and Jan Mayen.
East Scandinavian	Denmark, Sweden.
East Slavic	Bulgaria, Macedonia.
Persian	Afghanistan, Iran.
Portuguese	Brazil, Portugal.
Russian	Belarus, Russia, Ukraine.
Serbo-Croatian	Bosnia and Herzegovina, Croatia, Montenegro, Serbia, Slovenia.
Slavic	Czechia, Poland, Slovakia.
Spanish	Andorra, Argentina, Bolivia, Chile, Colombia, Costa Rica, Cuba, Dominican Republic, Ecuador, El Salvador, Gibraltar, Guatemala, Honduras, Mexico, Nicaragua, Panama, Paraguay, Peru, Puerto Rico, Spain, Uruguay, Venezuela.
Turkic	Azerbaijan, Kazakhstan, Kyrgyzstan, Turkey, Turkmenistan, Uzbekistan.

Figure B.2: Name analysis and identification of managers from target countries



Notes: The figure summarizes how we combine our three major data sources, namely OCI, OHD, and IBM-GNR. We extract from OCI each investment i at time t, undertaken by company j from country w and with target country z. We then search, in OHD, for the names and surnames of all M members of j's TMT at time $t-1$, which we feed into IBM-GNR in order to get, for each manager m (m=1...M), a list C_m of his/her most likely countries of origin (in the figure we limit the list to two countries, such as x, y, w, y or x, z, but they could be more; we also set M=3, just for sake of simplicity). Based on such list, we produce for each investor-investment combination (j,i) the $Managers\ from\ target$ variable, which takes value 1 if at least one member m of j's TMT at time t bears a name or surname extremely common in country z but not in w (as it is the case for manager 3 in the figure), which is suggestive of z being possibly the manager's country of origin; and zero otherwise. Where necessary, we apply the same procedure to members of j's TMT at time $t-2$ or $t-3$.

Switzerland does not appear at all). However, we would flag the same migrant as a British one, too, had his company invested, at time $t-1$, not in India but in Great Britain (indeed, we would have flagged him as a likely migrant from any English speaking target country).

Instead, any manager named Rajiv Fowler employed by a Swiss company investing in any country different from India or any members of the English-speaking group, will never be flagged as coming from the target country. Notice that this excludes also Sri Lanka and the Netherlands, which IBM-GNR associates to the name Rajiv, but we do not retain in the manager's C list. Notice also that we remain indifferent to the possibility that he may have a country of origin different than the target country and that he has no foreign origin at all (that is, he is Swiss). Table B.2 sums up all these cases concerning our Rajiv Fowler example.

After flagging in this way all managers working for company j one year before its investment i at time t, we produce the variable $Managers\ from\ target$, which takes value 1 if at least one

Table B.2: Example of foreign manager identification

Investor's manager	Investor's country	Target country	Manager from target country
FOWLER Rajiv	CH	IN	Yes
FOWLER Rajiv	CH	GB	Yes
FOWLER Rajiv	CH	NL	No
FOWLER Rajiv	GB	IN	No

manager is flagged as migrant from the target country z, and 0 otherwise.

This variable-creation strategy is meant to be conservative, that is to minimize false positives (mistaking for migrants those who are not), at the price of creating an unknown quantity of false negatives (missing real migrants). Our main preoccupation in this respect is that we could mistake some members of ethnic minorities or second-generation migrants in the investor's country as first-generation migrants from the target country.

Following this logic requires however to impose one important restriction to our sample, which consists in dropping from it all investments in which the investor and target countries w and z belong to the same linguistic group. In this case, by construction, no manager could appear as a migrant from the target country (w and z always coincide). Table B.3 lists the most common FDI corridors in our original sample and highlights in italics those we drop. Table B.4 reports the top countries and corridors we retain for our analysis.

One could consider further, similarly-motivated exclusions. For example, the very large size of the English-speaking group includes many disparate countries, some of which receive a substantial amount of FDIs. This implies that any manager originally from an English-speaking country (say, Great Britain) and working for a company investing to another country of the same group (say Australia) would be considered a migrant from the target country, despite the two countries not being the same and even in the case in which the investor's country w is not an English-speaking one. Other large linguistic groups may indeed create the same problem as the English-speaking one (for example, the Spanish-speaking group comprises all Latin America except Brasil, plus Spain). For this reason, we check the robustness of our empirical results to dropping from our sample the investments directed to countries in such important linguistic groups (see below).

Notice that these same linguistic groups do not pose problem when they coincide with the

Table B.3: Selected FDI corridors by number of operations

Investor	Target	Nb.	Percent
United Kingdom	*U.S.A.*	*528*	*2.75*
Canada	*U.S.A.*	*509*	*2.65*
U.S.A.	*United Kingdom*	*446*	*2.32*
U.S.A.	China	326	1.70
U.S.A.	*Canada*	*326*	*1.70*
U.S.A.	India	298	1.55
U.S.A.	Germany	289	1.51
Germany	U.S.A.	224	1.17
U.S.A.	Mexico	172	0.90
United Kingdom	Germany	169	0.88
Germany	China	166	0.87
France	U.S.A.	150	0.78
U.S.A.	*Australia*	*144*	*0.75*
U.S.A.	France	141	0.73
Australia	*U.S.A.*	*140*	*0.73*
United Kingdom	Spain	130	0.68

In *italics* country pairs within the same linguistic group, excluded from the analysis.

investor's country w. On the contrary, in this case, the high probability of the managers' C_m list to include the linguistic group reduces the probability of considering him/her a migrant from the target country z, which goes in the direction of reducing the false positives, as we wish.

B.2 TMT diversity

To compute $\textit{TMT diversity}_{(j,t-1)}$, we follow these steps:

- For each manager m in investor j's TMT, we identify their list of countries of origin, denoted as C_m. If a manager m has multiple countries of origin, we assign an equal weight to each of them. For instance, the manager Rajiv Fowler, in the example reported in section B.1, has two countries of origin, thus each country will be assigned a weight of 0.5.

- We compile the weighted country lists from all managers m in firm j's TMT to identify all the countries of origin represented in the TMT.

- We then measure TMT diversity using a fractionalization index, calculated as follows:

$$[1 - \sum_{c=1}^{C} S_c^2]_{(j,t-1)}$$

Table B.4: Top 10 FDIs corridors and countries (retained for analysis)

Top corridors				Top countries					
Investor	Target	Nb.	%	Investor	Nb.	%	Target	Nb.	%
U.S.A.	India	93	5,99	U.S.A.	641	41,30	China	158	10,18
U.S.A.	China	83	5,35	Germany	197	12,69	India	132	8,51
U.S.A.	Germany	67	4,32	U.K.	192	12,37	Germany	100	6,44
Germany	China	33	2,13	France	162	10,44	Mexico	64	4,12
U.S.A.	France	31	2,00	South Korea	65	4,19	U.S.A.	60	3,87
U.S.A.	Singapore	27	1,74	Australia	57	3,67	Spain	58	3,74
U.S.A.	Mexico	27	1,74	Canada	50	3,22	Singapore	54	3,48
U.S.A.	Japan	25	1,61	Spain	35	2,26	France	52	3,35
U.S.A.	Spain	24	1,55	Sweden	34	2,19	Brazil	48	3,09
U.S.A.	Israel	23	1,48	Netherlands	31	2,00	Poland	42	2,71

where, S_c represents the share of investor j's TMT members from country c, and C is the total number of countries of origin represented in the TMT.

This index captures the diversity of the TMT by considering the distribution of countries of origin among its members, though it does so in a somewhat approximate manner. It tends to overestimate diversity due to the small size of TMTs. In fact, in small TMTs, a few managers with dual countries of origin (such as Rajiv Fowler in our example) can significantly boost the index.

Take as an example a TMT with four members, where one member has a different country of origin. In this case the diversity index would be 0.37. If this member had dual origins, like Rajiv Fowler, the index would increase to 0.41. Similarly, if all four members were from different countries of origin, the index would reach 0.75, and it would rise to 0.87 if each member had dual and distinct countries of origin. In fact, the average value the indicator is around 0.84 and the median is around 0.88, which are very close to theoretical maximum value of 1 (the maximum value observed in the sample is 0.94). This is a drawback of our indicator which we need to take into account when interpreting our regression results.

B.3 Managers-from-target identification: Robustness checks

We subject our empirical analysis to two sets of robustness checks aimed specifically at verifying the soundness of our name analysis methodology.

First, we manually searched online all the 1,963 managers we identified as ”from target” (country z), looking for information on either their birthplace, legal status or country of education. We both looked for their curricula on their employer's websites or social networks such as LinkedIn and queried various search engines in search of news concerning them. This returned at least one piece of information, most often concerning education, for 1,452 managers.

Based on this information, we considered as nationals from target country z all managers with at least one piece of nationality information connecting them to it (either having z citizenship or being born in z or having been educated there). We then compared nationality so defined to the country of origin obtained via name analysis. For around 53.8% of managers the two coincide. For 36.6% the nationality does not correspond to z, but to w, that is the investor's country. This may suggest a mistake in our name analysis, but also that the manager is either a first-generation migrant who has acquired the host country's nationality, a second-generation migrant with parents from z, or a member of a longstanding diaspora from z in w.

As for the remaining 9.6%, nationality information points at neither z nor w. Clearly, the level of noise for this group is the highest. While it is still possible that we are having to do with managers from country of origin z working in w while having a third-country nationality, it is more likely that in this case our name-country match is wrong.

We then exploit the information so obtained to check the robustness of our results. We do so by referring to our three groups of managers as "z-nationals", "w-national" and "neither from z nor from w". We then test whether our results hold when restricting our analysis to one or more groups. Tables B.5 and B.6 report our results.

We find that, in the case of M&As, the manager-from-target effect remains basically unchanged when we remove the group of managers with "neither z nor w" nationality (see column 2 in table B.5); and that it diminishes in magnitude and significance (p-value is just above 0.12) when also removing the w-nationals (see column 2 in table B.6). Notice that this result goes against the intuition by which first generation migrants should produce a stronger manager-from-target effect than their offspring or descendants, in line with our theoretical argument for considering all foreign-origin managers, and not just first-generation migrants. As for GIs, the subtraction of observations with manager "neither z nor w" determines the loss of significance (even though the p-value is just above 0.10), which persists when also removing the w-nationals (see column 3 in table B.5 and B.6, respectively).

As a second set of robustness checks, we investigate whether our results may depend on some specific investment corridors, in particular those in which the target country z belongs to a large lin-

Table B.5: Baseline results, including only managers from target with either z or w nationality

	(1) All	(2) M&As	(3) GIs[b]
Managers from target	0.080	0.428	0.171
	(0.042)	(0.142)	(0.120)
	[0.057]	[0.003]	[0.157]
Observations	3944	838	627
R^2	0.119	0.144	0.100

The sample is obtained after excluding all case and related control observations in which for cases the managers are identified as from z based on name analysis, but have neither w nor z nationality.
[b] Sample obtained using the alternative matching scheme (see section 4).
Subsidiary in target and fixed effects for investor, year, target sector and corridor included in all models. Deal clustered SE in parentheses; p-value in square brackets.

Table B.6: Baseline model, including only managers from target with z nationality

	(1) All	(2) M&As	(3) GIs[b]
Managers from target	0.028	0.274	0.121
	(0.047)	(0.164)	(0.166)
	[0.542]	[0.097]	[0.468]
Observations	3632	773	484
R^2	0.128	0.142	0.086

The sample is obtained after excluding all case and related control observations in which for cases the managers are identified as from z based on name analysis, but have no z nationality (i.e. exclusion of all those with w nationality or neither z nor w).
[b] Sample obtained using the alternative matching scheme (see section 4).
Subsidiary in target and fixed effects for investor, year, target sector and corridor included in all models. Deal clustered SE in parentheses; p-value in square brackets.

guistic group, for which our name-based strategy for identifying migrant managers may be weaker. The check consists in re-running our baseline regression after dropping from the sample all the investments directed to countries belonging to large, cross-border linguistic groups. The results are reported in tables B.7 and B.8, respectively for M&As and GIs. For M&As, the only meaningful change in the coefficient for *Managers from target* occurs in column 1, when we drop the investments in English-speaking countries. Still, the order of magnitude and significance level do not change considerably. On the other hand, in the case of GIs, the results are robust to dropping English-speaking target countries, but the coefficient of *Managers from target* is not significant in the other cases, even if the magnitude is similar to what we get in the baseline model.

Table B.7: Baseline results for M&As; robustness check for target countries in selected linguistic groups

	(1) w/o English	(2) w/o Spanish	(3) w/o French	(4) w/o German	(5) w/o All
Managers from target	0.307	0.364	0.443	0.504	0.335
	(0.132)	(0.140)	(0.145)	(0.137)	(0.176)
	[0.021]	[0.010]	[0.002]	[0.000]	[0.058]
Observations	792	679	756	740	435
R^2	0.155	0.188	0.187	0.183	0.306

Subsidiary in target and fixed effects for investor, year, target sector and corridor included in all models. Deal clustered SE in parentheses; p-value in square brackets.

Table B.8: Baseline results for GIs[b]; robustness check for target countries in selected linguistic groups

	(1) w/o English	(2) w/o Spanish	(3) w/o French	(4) w/o German	(5)) w/o All
Managers from target	0.208	0.224	0.165	0.135	0.075
	(0.116)	(0.140)	(0.122)	(0.138)	(0.178)
	[0.073]	[0.111]	[0.178]	[0.330]	[0.671]
Observations	703	643	689	618	522
R^2	0.099	0.137	0.115	0.174	0.242

[b] Sample obtained using the alternative matching scheme (see section 4).
Subsidiary in target and fixed effects for investor, year, target sector and corridor included in all models. Deal clustered SE in parentheses; p-value in square brackets.

C Further results and robustness checks

In this section we report a series of robustness checks for our baseline results reported in table 1 of section 5.

First, we perform some tests on non-name related aspects of our operationalization of the *Managers from target* variable. Tables C.1 and C.2 reproduce our baseline analysis, but building our focal variable *Managers from target* within the investor company's at time $t-2$ (table C.1) and $t-3$ (table C.2), so to further reduce our concerns of reverse causality. All the results remain substantially unaltered for M&As and they loose significance for GIs (p-value is 0.148) when considering *Managers from target* in $t-3$.

Second, in table C.3 we re-estimate once more our baseline model after removing investor firms based in the USA. In this way, we aim to take into account a possible source of bias due to US firms having on average a much higher number of managers in the TMT than all other countries (see table A.3), even if this should bias our baseline results negatively, and not positively. In any case, the table shows that our results for *Managers from target* are robust both in the case of M&As and GIs.

Finally, the last robustness checks concern our definition of TMT membership, based on the managers' job description. First, we consider the possibility of having wrongly considered too many managers as being influential with respect to FDI location decisions. Hence we re-estimate our baseline model after considering only managers in the Board of Directors. The results of the regression analysis show that the manager-from-target effect becomes stronger and more significant, especially for GIs (table C.4). Second, we perform a *placebo* test by considering the possibility that our baseline results would hold also when considering managers in non-apical positions. Were this the case, suspects of our main results to be spurious would certainly increase. We check for this possibility after replacing our variable of interest *Managers from target* with *MFT* (*non-apical*), the latter being identical to the former except that we produced it by considering only managers outside the TMT. Table C.5 reports our results. We find that the coefficient of *MFT* (*non-apical*) is not significant in all columns.

Table C.1: Baseline results, *Managers from target* measured at $t-2$

	(1) All	(2) M&As	(3) GIs[a]	(4) GIs[b]
MFT (t-2)	0.044	0.313	0.007	0.368
	(0.042)	(0.157)	(0.045)	(0.187)
	[0.292]	[0.046]	[0.872]	[0.050]
Observations	3366	708	2658	473
R^2	0.112	0.111	0.119	0.127

[a] Sample obtained using the basic matching scheme (see section 4).
[b] Sample obtained using the alternative matching scheme (see section 4).
Subsidiary in target and fixed effects for investor, year, target sector, and investment corridor included in all models. Deal clustered SE in parentheses; p-value in square brackets.

Table C.2: Baseline results, *Managers from target* measured at $t-3$

	(1) All	(2) M&As	(3) GIs[a]	(4) GIs[b]
MFT (t-3)	0.033	0.362	-0.018	0.309
	(0.056)	(0.198)	(0.061)	(0.212)
	[0.564]	[0.068]	[0.768]	[0.148]
Observations	2235	500	1735	438
R^2	0.122	0.138	0.127	0.129

[a] Sample obtained using the basic matching scheme (see section 4).
[b] Sample obtained using the alternative matching scheme (see section 4).
Subsidiary in target and fixed effects for investor, year, target sector, and investment corridor included in all models. Deal clustered SE in parentheses; p-value in square brackets.

Table C.3: Baseline results, robusteness check without US-based investor firms

	(1) M&As	(2) GIs[b]
Managers from target	0.458	0.747
	(0.235)	(0.377)
	[0.052]	[0.050]
Observations	642	233
R^2	0.141	0.161

[b] Sample obtained using the alternative matching scheme (see section 4).
Subsidiary in target and fixed effects for investor, year, target sector, and investment corridor included in all models. Deal clustered SE in parentheses; p-value in square brackets.

Table C.4: Baseline results, robusteness check for managers in Board of Directors

	(1) All	(2) M&As	(3) GIs[a]	(4) GIs[b]
MFT (BoD only)	0.089	0.481	0.005	0.551
	(0.051)	(0.163)	(0.054)	(0.185)
	[0.080]	[0.003]	[0.932]	[0.003]
Observations	3346	793	2553	533
R^2	0.118	0.137	0.122	0.136

[a] Sample obtained using the basic matching scheme (see section 4).
[b] Sample obtained using the alternative matching scheme (see section 4).
Subsidiary in target and fixed effects for investor, year, target sector, and investment corridor included in all models. Deal clustered SE in parentheses; p-value in square brackets.

Table C.5: Baseline results, robusteness check for managers in non-apical positions

	(1) All	(2) M&As	(3) GIs[a]	(4) GIs[b]
MFT (non-apical)	0.023	-0.179	0.071	-0.263
	(0.080)	(0.330)	(0.082)	(0.211)
	[0.771]	[0.589]	[0.392]	[0.215]
Observations	2940	528	2412	482
R^2	0.110	0.122	0.113	0.125

[a] Sample obtained using the basic matching scheme (see section 4).
[b] Sample obtained using the alternative matching scheme (see section 4).
Subsidiary in target and fixed effects for investor, year, target sector, and investment corridor included in all models. Deal clustered SE in parentheses; p-value in square brackets.

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