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The Indirect Pro-Trade Effects of Indian Ethnic Networks

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DEMO-India – Developing Evidence based Management and Operations in India-EU Migration and Partnership (DEMO: India-EU MaP)

The Demo: India-EU MaP project, co-funded by the European Commission, is a continuation of the Carim India project (www.india-eu-migration.eu) and it examines the multiple facets of Indian migration to the EU. Its overall aim is to improve migration management between India and the EU, strengthen EU-India relations, and produce in-depth empirical knowledge about the different migration streams and pathways of Indian nationals in the EU. Its specific goals include providing:

1. Evidence based research for more informed policy making and state intervention.
2. Improved source country capacity in managing migration.
3. Raising awareness among potential migrants of the risks of irregular migration.
4. Collaboration with civil society groups.
5. Empirical research and analysis of Indian communities across the EU, and their impact.

The project is led by the Indian Centre for Migration in Delhi with the partnership of the Migration Policy Centre, RSCAS, EUI.

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Abstract

In the literature there's an established consensus on the strong and significant correlation between the stock of immigrants in the receiving country and the amount of trade with their country of origin. Surprisingly, only a few studies emphasize the role of ethnic minorities in triggering trade between various regions in the world. Rauch and Trindade (2002) was the first contribution to study those indirect links between Chinese in different host countries finding a large effect of those networks on trade. Following a similar approach, this paper studies the pro-trade effect of Indian ethnic minorities in 19 OECD countries. In particular, we investigate how the pro-trade effect of these networks varies with the quality of traded products over the period 1995-2005. Our findings show that the effect of Indian Networks is much larger than the correspondent impact of Chinese minorities. Furthermore, both these indirect effects seem to dominate the direct impact of the ethnic links between source and host countries: this result suggests that the pro-trade role of migrants in the OECD context is largely determined by the major ethnic minorities. Lastly, the indirect pro-trade effect of Indian networks is particularly strong for products of low and low-medium quality. We conjecture that this result is likely to be driven by specific information advantages of Indian Ethnic Networks over low-price commodities which follow the specialization on the low quality segment of their country of origin.

Key words: migration, product quality, gravity model

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1. Introduction

Most international migrants, around 70 per cent of the over 230 million foreign born in 2013 are born in the South (UN 2013). The majority are from Asia, which – according to UN – recently became the largest diaspora group. In 1990, international migrants born in Asia were around 21 million. By 2010, they almost doubled (+76.2%) reaching 37 million. Furthermore, Asian countries have been sending a large number of highly-skilled professionals and tertiary level students, predominantly to OECD countries. In this regard, UN-OECD (2013) report that more than 2 million tertiary educated migrants originating from this region arrived in the OECD countries in the period between 2008 and 2013. In particular, India has been recently characterized by sending high skilled, educated international migrants: according to UN-OECD (2013) around 2 million of Indian-born tertiary educated immigrants were living in OECD countries in 2010/11.

Migration, especially of skilled, has triggered controversial views. Some highlight the "brain drain" risk, other see it as an opportunity to enhance links, trade, FDI while at the same time increasing domestic skills and education levels. More precisely, a number of concerns point to the loss for sending countries of the positive externalities of high skilled workers. As first noted by Ratha *et al.* (2011) highly educated workers generate positive externalities that are crucial to economic growth and development. These externalities – such as (i) productivity spillovers to both high and low-skilled workers, (ii) public services such as healthcare and education that have both immediate and future social spillovers, (iii) innovative and creative activities that are at the core of long-term growth, and (iv) contributions to the health of social, political, and economic institutions – are lost for high skilled migrants' home countries upon their departure (the "*brain drain*").

Against this background, the *diaspora* – if properly managed – can contribute to the social and economic development of the sending countries. Ratha *et al.* (2011) argue that migration – especially of the highly skilled – generates numerous and important benefits for the home countries as well. Migrants send remittances to their families and enforce economic and social linkages between their native lands and the rest of the world. Furthermore, among other positive diaspora externalities are the return of professionals with enhanced skills, a positive impact on the demand for education in the sending country and the facilitation of Cross-Border Trade, Technology Transfer and Foreign Direct Investment (FDI) (see Ratha *et al.* 2011). Among these positive externalities, the link between ethnic networks and bilateral trade/FDI has been the object of many recent studies. A strand of trade literature (see for instance Gould 1994 and Javorcik *et al.* 2011) has documented a positive association between the presence of ethnic networks and international trade & FDI, normally estimated through a gravity equation. The underlying idea is that international transactions are negatively affected by *informal* trade barriers, other than *formal* hurdles such as transportation costs and tariffs. Among the main *informal* barriers to international transactions are the information costs, such as the difficulties associated with provision of information on many aspects, including sales channels, product characteristics, potential market opportunities, and with enforcing contracts across national boundaries. As pointed out by Javorcik *et al.* (2011: 231) "the presence of people with the same ethnic or national background on both sides of a border may alleviate these problems".

The relationship between trade and migration flows is likely to be biunivocal: in a perfectly competitive world, trade and migration are substitutes, while they are complement in an imperfect setting and the direction of causation is far from clear. More specifically, international migrants could enhance bilateral trade by lowering information costs and increasing demand for goods from their source countries. The existing literature assumes that both imports and exports are symmetrically affected by improved information while only import from source countries depend on migrants' preferences. Empirically this bi-univocal relationship and the uncertainty of the expected sign due to the complementary/substitutes relationship triggered contrasting results and lack of consensus. However, high skilled migrants tend to impact more on trade because of lower liquidity constraints and advantages in their human capital that imply lower costs. Hence, there seems to be some agreement on the fact that high-skilled migrants have a high pro-trade effect (see Herander and Saavedra 2005; Felbermayr and Jung 2009; Felbermayr and Toubal 2012).

In this context, while most of the literature focuses on the trade-enhancing role of direct ethnic links between source and host countries, only a few contributions study the *indirect links* of ethnic minorities that are seen “as middlemen who are active as cosmopolitan catalysts for economic transactions between global cities such as New York, London, or Singapore that form the backbone of the world economy” (Felbermayr, Jung, and Toubal 2010: 41). The seminal contribution which studies those indirect links between agents of the same ethnicity in different host countries is Rauch and Trindade (2002) who focus on Chinese minorities. They found a large indirect pro-trade effect of Chinese Ethnic Networks in comparison with other trade determinants, an impact which becomes stronger for differentiated goods. We decided to focus on India, whose recent emigration flows to OECD consist predominantly of skilled migrants and university students and – according to UN data – has recently become the top origin countries for the number of international migrants with 14.2 million.

We test empirically for the period 1995-2005 whether migration triggers trade and if/to what extent the relationship between migrants and trade varies with product quality and migrants skills. More precisely, we investigate how the pro-trade effect of ethnic networks varies with the quality of traded products. By building on Fontagné, Gaulier and Zignago (2008), we exploit the characteristics of BACI/CEPII dataset and divide the spectrum of traded goods into vertically differentiated varieties based on Export Unit Values (EUV) rather than sectors. To our knowledge the link between product quality and the pro-trade elasticity of ethnic networks has not yet been explored in the literature. Existing studies mainly focused on the variation of the pro-trade effect of ethnic networks due to different levels of goods’ heterogeneity, following the methodology adopted by Rauch and Trindade (2002). We extend their work by classifying traded goods according to their quality level and we separately estimate pro-trade elasticity of high-skilled networks for each subgroup.

Our empirical analysis first compare the indirect pro-trade effect of Indian networks with the correspondent effect for Chinese minorities. We find that in a selected sample of 19 OECD receiving economies Indian networks exert a pro-trade effect which is twice as big: this finding is in line with the conclusions of Felbermayr *et al.* (2010) whose results reveal that the trade creating potential of Chinese network is dwarfed by other networks. Furthermore, our statistics indicate that the *indirect* pro-trade effect of the networks formed by Indian and Chinese ethnic minorities dominates the correspondent *direct* effect between source and host OECD countries. We believe this result is striking: the pro-trade role of migrants in the OECD context seems to be driven mostly by the major ethnic minorities. As it emerges from the evidence, this effect is particularly strong for products of low and low-medium quality. We conjecture that this result may reflect the comparative advantage of their country of origin: since India is specialized in the production of varieties of low-medium quality, Indian networks – through their role in the matching of trading opportunities and provision of market and product information – tend to mostly facilitate trade of those varieties. Lastly, the high-skill Indian networks have a much greater impact on trade than low skilled migrants. This is consistent across quality levels and the same trend over quality applies: as for the total stock, the largest impact of the high skill is still on medium-low quality commodities. These findings have a number of policy implications that can be usefully used in the hot debate on migration.

The paper is structured as follows. Section 2 introduces the “*Indian Diaspora*” and presents some descriptive statistics on the size of Indian Minorities by destination country and skill level along with its evolution over time, while Section 3 provides some evidence on India’s trade specialization on the low market segment along with a larger import demand for low quality varieties. Section 4 reviews the literature on the pro-trade effect of migrants and summarizes the main stylized facts. Section 5 describes the data used in the analysis, the empirical methodology implemented and the econometric specification. Section 6 outlines the results and Section 7 summarizes the main findings and suggests some policy conclusions.

2. A Short Description of the Indian "*New Diaspora*"

The Indian Diaspora is estimated to be the second largest in the world and has a diversified global presence. The Diaspora estimated at over 25-30 million, represents around 1% of Indian population and it is spread across more than 200 countries. The history of migration from India dates back at least two thousand years. However, the destinations of Indian Diaspora have been varying over time: in the "*Old Diaspora*" – which is a pre-WW2 phenomenon and constitutes nowadays around 60% of the whole population of Indian Origin residing abroad – the most attractive destinations were Malaysia, Sri Lanka, Burma, Mauritius, Trinidad and Tobago, Fiji, Guyana, and Suriname.[1]

The "*New Diaspora*", on the other hand, consists of migrants who left India in large numbers from the mid-1960s onwards primarily to OECD countries like United Kingdom, United States, Canada, Australia, and Western Europe. The "*New Diaspora*" became particularly prominent in the 1960s when some developed countries introduced new immigration legislations. In United States, for instance the Hart-Celler Act abolished national-origins quotas, and made it possible for high-skilled immigrants, including Indians, to gain legal, permanent residence in the United States. Similar initiatives occurred in Canada (1968) and UK (in the period 1947-1962 and from mid 80s) where Indian immigration picked up considerably.[2] Lastly, other than OECD destinations, the 1970s oil boom in the Middle East triggered significant migration – predominantly middle and low skilled – from India towards the Gulf area. Table 1 illustrates the wave of both the "*New*" and "*Gulf*" Indian Diasporas over the years since 1970: it reports the total number of Indian emigrants along with the top 9 destinations for Indian emigrants in 2000 (Özden *et al.* 2011). The total number of Indian emigrants refer to the global stock of international migrants born in India and residing in 232 countries in the world.[3]

Table 1. The size of Indians' *Diaspora* (in millions), top Destination Countries[a]

Destination Country	**year 1970**	**year 1980**	**year 1990**	**year 2000**
Pakistan	4.86	3.90	3.13	2.51
Nepal	0.32	0.23	0.41	0.56
United States	0.07	0.23	0.49	1.04
United Kingdom	0.34	0.40	0.43	0.52
Saudi Arabia	0.07	0.36	0.93	1.01
Canada	0.04	0.08	0.15	0.31
Bangladesh	0.70	0.78	0.85	0.94
Sri Lanka	1.08	0.64	0.45	0.38
United Arab Emirates	0.02	0.23	0.44	0.75
TOTAL	8.26	7.58	8.18	9.52

[a] The figures refer to the total stock of migrants (in millions) born in India and resident in the reported countries.
Source: Özden *et al*. (2011).

Some of the top-destinations – Sri Lanka, Nepal, Bangladesh and Pakistan – are neighboring countries; the others – Canada, United States, United Kingdom, Saudi Arabia and United Arab

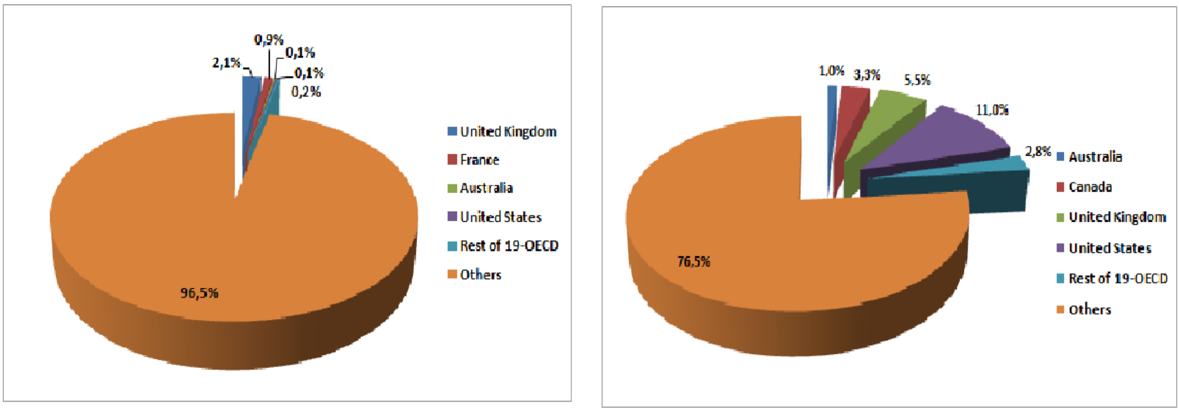
[1] Sources: The Fair Observer, February, *"The Indian Diaspora: Past, Present and Future"* and The Ministry of Overseas Indian Affairs.

[2] Source: The Fair Observer, February 2013, *"The Indian Diaspora: Past, Present and Future"*.

[3] Table 10 in Appendix shows in detail the evolution of the stocks of Indian emigrants in each of these countries.

Emirates – are OECD and Gulf economies that are among the most attractive destinations for international migrants according to UN (2013). Many of them figure among the top destinations in 1970 as well, but their shares over total numbers of Indian emigrants increased dramatically over the years meaning that Indian migration flows have become more and more concentrated into a restricted number of countries.

Figure 1. Share of Total Indian Emigrants in the 19-OECD Destination Countries: 1960 vs 2000[a]



[a] The graphs refer to the comparison of the share of the total Indian emigrants in our sample of 19 OECD countries between 1960 and 2000. The percentages are rounded to the first decimal. The graph in the left hand side refers to 1960 whereas the right hand side is for 2000.

Source: our elaboration from Özden *et al.* (2011) data.

Figure 1 illustrates the change in the share of total Indian emigrants resident in our selected 19-countries OECD sample between 1960 and 2000. United Kingdom and United States went from hosting 2.1% and 0.1% of the total number of Indians resident in countries other than India in 1960, to 6% and 11% in 2000, respectively. Interestingly, the largest share of the composition of the "*New Diaspora*" towards OECD economies has been of Indians High Skilled as documented in the literature. Docquier and Rapoport (2012) argue that the presence of highly educated Indians among the business, scientific, and academic elites of the United Kingdom, the United States, and other Western countries is impressive. Indeed, Indians represent the bulk of H1-B visas holders in the United States, a visa category aimed at skilled professionals in sectors with occupational shortages. In this regard, Kirkegaard (2015) investigates US-India labor migration and finds that Indian nationals account for about half of all US employment-based permanent migration (e.g. green cards) in recent years and they also make up half or more of the entrants on the two main high-skilled temporary US visa categories. Further evidence indicates that Indian Emigrants are concentrated predominantly in large cities that are the backbone of the world economy. Rienzo and Silva (2014) show that India is the most common country of birth among the foreign-born in the United Kingdom in 2013: more importantly, Indian Migrants stand for the biggest group among the foreign-born population in London (8.6%), the region where the share of foreign-born people relative to total population was greatest. In addition to the above, India has also been sending the largest number of internationally mobile students after China. As documented in Mukherjee and Chanda (2012) student flows from India have increased substantially since 2000 and grew by over 256 percent (from 53,266 to 190,781) between 2000 and 2009. In 2009, Indian students constituted 6.2 percent of all international students whose top destinations are United States, United Kingdom, Australia, New Zealand and Russia.

Table 2 provides some evidence in support of the predominance of the high skill emigrants in the "*New Diaspora*" composition. The table reports the evolution in the number of Indian Emigrants and the correspondent share on total population over time in our sample of 19 OECD countries. Data are from Brucker, Capuano, and Marfouk (2013). We separate the total stock from the high-skilled for the years 1995, 2000, 2005 and 2010. The statistics indicate that since 1995 more than 50% of Indian emigrants in our sample are high skilled; this share has also progressively increased over time, going from just above 50% in 1995 to almost 70% in 2010. Lastly, by looking at the cross-country differences in the more recent period 2005-2010, the largest Indian communities are in US, Canada, Great Britain, New Zealand and UK where more than half of those Indian residents are high skilled, with the only exception of Great Britain.

Table 2. Indian Emigrants in Selected OECD Economies[ab]

Iso3-Code	year	total	high	share total	share high	year	total	high	share total	share high
AUS	1995	62475	43241	0.35%	0.24%	2000	77428	55514	0.40%	0.29%
AUT	1995	4952	747	0.06%	0.01%	2000	6418	879	0.08%	0.01%
CAN	1995	206635	95185	0.70%	0.32%	2000	276835	134755	0.90%	0.44%
CHE	1995	5286	2226	0.08%	0.03%	2000	5680	2901	0.08%	0.04%
CHL	1995	2102	410	0.01%	0.00%	2000	2718	555	0.02%	0.00%
DEU	1995	26502	3377	0.03%	0.00%	2000	27345	4543	0.03%	0.01%
DNK	1995	1793	468	0.03%	0.01%	2000	2259	644	0.04%	0.01%
ESP	1995	4077	867	0.01%	0.00%	2000	6418	962	0.02%	0.00%
FIN	1995	513	90	0.01%	0.00%	2000	852	124	0.02%	0.00%
FRA	1995	11005	2347	0.02%	0.00%	2000	14327	3406	0.02%	0.01%
GBR	1995	403148	104618	0.69%	0.18%	2000	395955	125736	0.66%	0.21%
GRC	1995	2135	406	0.02%	0.00%	2000	4220	240	0.04%	0.00%
IRL	1995	1268	838	0.04%	0.02%	2000	2005	1383	0.05%	0.04%
NDL	1995	5644	974	0.04%	0.01%	2000	7047	1715	0.04%	0.01%
NOR	1995	3272	879	0.08%	0.02%	2000	3776	1396	0.08%	0.03%
NZL	1995	10518	4191	0.29%	0.11%	2000	16011	6951	0.42%	0.18%
PRT	1995	6651	1306	0.07%	0.01%	2000	6210	1280	0.06%	0.01%
SWE	1995	3908	1361	0.04%	0.02%	2000	5560	2053	0.06%	0.02%
USA	1995	475933	364484	0.18%	0.14%	2000	689703	537870	0.24%	0.19%
$\sum_{n=1}^{N} \text{mig}_{ni}$		**1237924[c]**	**628035 (50.7%)**				**1550995[c]**	**882987 (56.9%)**		
AUS	2005	88195	65901	0.43%	0.32%	2010	99488	77458	0.48%	0.38%
AUT	2005	7212	1427	0.09%	0.02%	2010	7704	1437	0.09%	0.02%
CAN	2005	390080	220180	1.21%	0.68%	2010	465098	303416	1.43%	0.93%
CHE	2005	5941	2957	0.08%	0.04%	2010	6307	3163	0.08%	0.04%
CHL	2005	3565	787	0.02%	0.00%	2010	4944	1210	0.03%	0.01%
DEU	2005	31682	7389	0.04%	0.01%	2010	37062	11666	0.04%	0.01%
DNK	2005	3123	891	0.06%	0.02%	2010	5347	1217	0.10%	0.02%
ESP	2005	18133	4405	0.04%	0.01%	2010	28976	7335	0.07%	0.02%
FIN	2005	1679	212	0.03%	0.00%	2010	3234	606	0.06%	0.01%
FRA	2005	14227	4091	0.02%	0.01%	2010	25988	7116	0.04%	0.01%
GBR	2005	445405	169173	0.74%	0.28%	2010	547395	249502	0.91%	0.41%
GRC	2005	5272	483	0.05%	0.00%	2010	5705	579	0.05%	0.01%
IRL	2005	4829	3761	0.12%	0.09%	2010	7657	6352	0.18%	0.15%
NDL	2005	8837	2109	0.05%	0.01%	2010	13940	3558	0.09%	0.02%
NOR	2005	4564	1494	0.10%	0.03%	2010	6911	2532	0.15%	0.05%
NZL	2005	32010	19410	0.78%	0.47%	2010	33360	18334	0.81%	0.44%
PRT	2005	7624	1724	0.07%	0.02%	2010	9212	2062	0.09%	0.02%
SWE	2005	8807	3707	0.10%	0.04%	2010	13551	6430	0.15%	0.07%
USA	2005	1224806	996308	0.41%	0.34%	2010	1457640	1195820	0.49%	0.40%
$\sum_{n=1}^{N} \text{mig}_{ni}$		**2306234[c]**	**1506498 (65.3%)**				**2779780[c]**	**1899893 (68.3%)**		

[a] Data are from IAB brain drain database by Brucker *et al.* (2013).
[b] *total* and *high* are the total and high skilled stocks of Indian Emigrants resident in each of the country of the selected OECD sample, respectively. *share total* and *share high* are the shares of total and high skilled stocks over populations of countries of destination.
[c] It is the sum of emigrants from India (i) resident in all countries (n) of our OECD sample. In brackets is the share of high skill over the total population of Indian Emigrants.
Source: data on populations are from CEPII. The calculations of these shares are our own.

3. India's Foreign Trade and Comparative Advantage

Back in the 1950s, India, like many other developing countries, including China, chose to follow an import substitution strategy, which involved insulation from the world. Later, during the 1980s, India's liberalization initiatives focused more on internal deregulation than on trade liberalization. Only in the 1990s, in response to a severe balance of payment crisis, things started to change in favor of a reduction in trade barriers. However, despite this substantial episode of unilateral trade liberalization, while China's share in the world exports steadily increased from less than 1% (in 1980) to more than 6% (2004) and over 10% (since 2009), India's exports have been increasing less since the early-1990s – both as a share of GDP and as a share of world exports. More precisely, Indian exports as a share of world goods exports almost tripled to 1.7 percent during 1995-2013, while India's services export more than tripled to over 3 percent of world service exports in a much shorter period, 2000-2013 (see Anand, Kalpana, and Mishra 2015). In this regard, as noted by Anand *et al.* (2015), the peculiarity of Indian foreign trade compared to other emerging economies is the large and growing share of services exports, especially modern services. More precisely, Indian services exports, as a share of total exports and in terms of sophistication, are comparable to high income countries.

As for the manufacturing sector, the evolution of Indian exports indicate an increasing share of manufacturing exports still dominated by relatively low-technology content.[4] Indeed, the quality, sophistication and complexity of Indian exported manufacturing products remain below the level of other emerging economies, which seems to denote a comparative advantage in unskilled labor-intensive goods. In support of this statement, the next two sections provide some evidence on the sector composition of India's exports as well as the specialization of Indians' exports on the low segment of the quality spectrum.

3.1 Sector Analysis

Table 3 reports the ten leading HS-2 sectors for India's exports in 1995, 2000 and 2005. The data are from BACI/CEPII dataset and each leading sector is reported along with its share on total exports and the correspondent HS product category. Exports are driven predominantly by labor and resource intensive manufactures. In 1995 and 2000 *Cotton* and *Articles of Apparel* are the leading exporting sectors: the two industries combined stand for 18.1% and 16.1% of total Indian exports, respectively. Furthermore, only five sectors figure regularly each year in the top-ten ranking, indicating an important change in the composition of Indian Exports over time. Indeed, in 2005 the textile sectors drop their share in total exports in favor of mineral-and-natural resource intensive manufacturing sectors such as *Pearls, precious stones, metals, coins, etc.* and *Mineral fuels, oils, distillation products, etc*.

Although the ranking reported in Table 3 is indicative of the sector composition of India's exports, it doesn't say much regarding India's specialization relative to other economies nor about the market positioning of Indian exports in international trade. In order to assess the comparative advantages of India we first report the indexes of Balassa Revealed Comparative Advantage (RCA) at HS-2 sector. Despite this Index suffers from several potential drawbacks (see Leromain and Orefice 2013, and De Benedictis and Tamberi 2004 for a discussion), it gives a rough approximation of international

[4] The evolution of Indian exports has not followed a "textbook" pattern. The pattern of evolution points to a dichotomy in the Indian economy – a well integrated, technologically advanced services sector, exporting high technology and high-value added services, and a relatively lagging manufacturing sector, exporting relatively low-tech and low-value products (see Anand *et al.* 2015).

$$\mathrm{RCA} = \frac{\frac{\mathrm{Exp}_{n,g}}{\mathrm{Exp}_{n,G}}}{\frac{\mathrm{Exp}_{w,g}}{\mathrm{Exp}_{w,G}}}$$

specialisation in industry/product categories by measuring the industry's share in the country's exports relative to its share in world trade. Formally the RCA index reduces to:

where *n* and *w* are the country and world indexes, respectively; while *g* and *G* are the commodity and the whole set of commodities indexes, respectively. The RCA index has a very simple and intuitive interpretation:

- The RCA index lower than 1 suggests that the country is not specialized in exporting the product i.e. the share of that product in the country's exports is less than the corresponding world share

- On the contrary, The RCA index which exceeds 1 implies that the country is specialized in exporting the product.

Table 4 reports the rank of HS-2 sectors based on the RCA index for the year 2005. The index of RCA is greater than one for 44 sectors out of 96 HS-2 industries where India has recorded exports, suggesting that India holds comparative advantage in these sectors in the world market. As expected, India holds comparative advantage in labour intensive manufacturing sectors – especially textiles – since wages are relatively low in comparison with the main OECD exporters. However, other than *cotton*, no other sector that ranks among the top ten according to the value of the RCA is able to retain the same ranking of comparative advantage at the constituent six-digit commodity level. The lower part of Table 4 shows that the commodities with RCA>1 are dispersed among various sectors: the maximum numbers of commodities with comparative advantage in the world market are concentrated in sectors like *Organic Chemicals* and *Nuclear reactors, boilers, machinery, etc.*, which include 156 and 91 HS-6 commodities with RCA>1, respectively. There are also some sectors where India is comparatively disadvantageously positioned at the aggregate level but reveal significant comparative advantage at the constituent commodity (HS-six digit) level. This indicates that the pattern of comparative advantage varies at different levels of disaggregation. These findings are in line with the recent strand of trade literature which sees international specialization – and therefore comparative advantage in the spirit of the Ricardian model of trade – occurring mostly within products across varieties, rather than across products or industries.[5] Indeed, considering differentiated varieties of commodities rather than sectors sheds new light on the perceived similarity in specialization across countries, especially between high income countries and emerging economies like India. As pointed out by Fontagné *et al.* (2008), we face a situation where countries are completely specialized within products, on varieties with different market positioning along the quality ladder. In particular, the literature has showed a positive relationship between the quality of exported varieties and the level of development of the exporter. This stylized fact – first identified by Schott (2004) and Fontagné *et al.* (2008) – supports the theoretical framework proposed by Falvey and Kierzkowski (1987) where advantage and North/South specialization on the supply side are based on a combination of differences in factor endowments and technological advance. Since products of different quality have different factor intensities, North countries well-endowed with skilled labour and capital will specialise in the more skill-intensive parts of the quality spectrum. On the contrary, South countries like India –

[5] Given the arbitrariness in the definition of *variety*, as in Fontagné *et al.* (2008) we rely on the distinction proposed by Schott (2004) between product and variety of a product. "Two different headings of the most detailed level of the international trade classification represent two different products (HS6). Two different market segments represent two different varieties of a product having different unit values. This departs from the vocabulary of the literature on intra-industry trade, which would use varieties to refer to products shipped under the same heading but having similar unit values (horizontal differentiation), as opposed to qualities having different unit values (vertical differentiation)".

characterized by lower levels of human capital and technology – will have a comparative advantage in the production of low-quality commodities. The next section further explores these conjectures.

Table 3. Indian Exports by HS-2 Digit Sectors

Rank	HS-2 Digit Sector	HS-2 Digit	% Total Exports	HS Group
Year 2005				
1	Pearls, precious stones, metals, coins, etc.	71	9.6	stone/glass
2	Mineral fuels, oils, distillation products, etc.	27	7.9	mineral products
3	Ores, slag and ash	26	6.4	mineral products
4	Articles of apparel, accessories, not knit or crochet	62	6.3	textiles
5	Iron and steel	72	5.7	metals
6	Organic chemicals	29	5.2	chemicals
7	Nuclear reactors, boilers, machinery, etc.	84	4.5	machinery/electrical
8	Articles of apparel, accessories, knit or crochet	61	4.2	textiles
9	Vehicles other than railway, tramway	87	3.5	transportation
10	Electrical Machinery, Parts, Sound & Television Recorders	85	3.2	machinery/electrical
Year 2000				
1	Articles of apparel, accessories, not knit or crochet	62	9.6	textiles
2	Cotton, Inc. Yarns and Woven Fabrics Thereof	52	6.5	textiles
3	Pearls, precious stones, metals, coins, etc.	71	5.9	stone/glass
4	Organic chemicals	29	5.1	chemicals
5	Articles of apparel, accessories, knit or crochet	61	4.9	textiles
6	Iron and steel	72	4.5	metals
7	Fish & Crustaceans	3	3.8	animal/animal prod.
8	Mineral Fuels, Oils, Waxes, Bituminous Sub	27	3.6	mineral products
9	Nuclear reactors, boilers, machinery, etc.	84	3.5	machinery/electrical
10	Electrical Machinery, Parts, Sound & Television Recorders	85	2.7	machinery/electrical
Year 1995				
1	Articles of apparel, accessories, not knit or crochet	62	11.0	textiles
2	Cotton, Inc. Yarns and Woven Fabrics Thereof	52	7.1	textiles
3	Organic chemicals	29	4.3	chemicals
4	Fish & Crustaceans	3	4.2	animal/animal prod.
5	Iron and steel	72	4.2	metals
6	Articles of apparel, accessories, knit or crochet	61	4.0	textiles
7	Nuclear reactors, boilers, machinery, etc.	84	3.8	machinery/electrical
8	Cereals	10	3.7	vegetable products
9	Articles of Leather, Saddlery, Harness etc.	42	3.6	raw hides/skins/leather
10	Coffee Tea, Mate and Spices	9	3.4	vegetable products

Source: Authors'own calculations using BACI/CEPII dataset.

Table 4. RCA Index by HS-6 Sectors VS
Sector-Wise distribution of HS-6 Digit products with RCA≥1

Ranking of RCA Index by HS-6 Sectors (2005)

Description	HS-2 Code	HS Group	Rank
Made-up Textile Articles Nesoi, Needlecraft Sets etc.	63	textiles	1
Carpets and Other Textile Floor Coverings	57	textiles	2
Lac, Gums, Resins etc.	13	vegetable products	3
Ores Slag and Ash	26	mineral products	4
Cotton, Inc. Yarns and Woven Fabrics Thereof	52	textiles	5
Coffee, Tea, Mate and Spices	9	vegetable products	6
Pearls, precious stones, metals, coins, etc.	71	stone/glass	7
Veg. Textile Fibers Nesoi, Yarns/Woven etc.	53	textiles	8
Cereals	10	vegetable products	9
Articles of Leather, Saddlery, Harness etc.	42	raw hides/skins/leather	10

Distribution of HS-6 Digit products with RCA≥1 (2005)

Description	HS-2 Code	HS Group	No. of HS-6 with RCA≥1	Rank
Organic chemicals	29	chemicals	156	1
Nuclear reactors, boilers, machinery, etc.	84	machinery/electrical	91	2
Articles of apparel, accessories, not knit or crochet	62	textiles	70	3
Articles of apparel, accessories, knit or crochet	61	textiles	69	4
Iron and steel	72	metals	69	5
Inorganic Chem., Compounds of Precious Metals etc.	28	chemicals	64	6
Articles of Iron or Steel	73	metals	63	7
Cotton, Inc. Yarns and Woven Fabrics thereof	52	textiles	58	8
Electrical Machinery, Parts, Sound & Television Recorders	85	machinery/electrical	58	9
Man-Made Stapale Fibers, Inc. Yarns etc.	55	textiles	50	10

Source: Authors'own calculations using BACI/CEPII dataset.

3.2 Market Positioning of India's Exported Varieties and Specialization along the Quality Ladder

One of the main perceived threats of globalization is the supposed increasing range of sectors facing direct competition from emerging economies. Indeed, by analyzing exports at the most detailed level of product classification (HS-6), India – along with other developing countries – seem to be in direct competition with the main OECD exporters on a wide spectrum of commodities. Almost the whole range of HS-6 digit product classification are covered by Indian exports. Out of 4996 products traded internationally in 2005, 4787 were exported by India, compared with 4902 for China and 4913 for United States.[6] However, as first noted by Schott (2004), although India may actually export as many products as United States, varieties exported by United States and India appear too different to be in direct competition. Table 5 reports the similarity indexes computed by Fontagné *et al.* (2008) for the year 2004 (i) at sectoral level (HS-2), (ii) at the most detailed level of commodity classification (HS-6), and ultimately (iii) considering varieties of products. By looking at the similarity indexes calculated at sectoral level (HS2) there seems to be strong competition between India and the other reported countries, regardless their level of income. Indeed, the similarity between India and China is comparable to the similarity between India and US or Germany. However, by repeating the same analysis at a more disaggregated level, the same indexes drop considerably: at the *variety level* the magnitude of all similarity indexes are less than half of the correspondent HS-2 coefficients, suggesting that India and China are hardly competing with advanced economies on the same varieties because of an evident specialization within products and across varieties. This specialization at the most detailed level occurs on different position along the quality ladder for North and South: the South specializes in the low quality segment whereas the North has comparative advantages mainly in up-market varieties.

Table 5. Similarity of export structures at various levels of detail of the classification (2004)[a]

		China	Germany	Japan	**India**	USA
Sector Level (ISIC Headings)	Germany	0.47	-			
	Japan	0.56	0.82	-		
	India	**0.56**	**0.47**	**0.38**	-	
	USA	0.55	0.81	0.77	**0.48**	-
Product Level (HS 6 Headings)	Germany	0.30	-			
	Japan	0.34	0.56	-		
	India	**0.30**	**0.27**	**0.23**	-	
	USA	0.34	0.59	0.53	**0.27**	-
Variety Level (Market Segment)	Germany	0.17	-			
	Japan	0.18	0.43	-		
	India	**0.23**	**0.20**	**0.16**	-	
	USA	0.24	0.46	0.40	**0.21**	-

[a] Similarity Index is a measure of the extent to which two countries export the same products. Similarity between country A (column) and B (row) is one minus half the sum of the absolute value of differences between the (e.g.) sectoral shares in manufacturing exports of country A and those of country B. It ranges between 0 (perfect dissimilarity) and 1 (perfect similarity). The table reports the indexes using a different degrees of products classification: from the more aggregated classification *Sector level*, to the more disaggregated *Variety level*.

Source: Fontagné *et al.* (2008) (Table 1) based on BACI-CEPII data.

[6] Authors own calculations. Data are from BACI/CEPII dataset classified as HS92-6 digit products.

Table 6. World Market Shares by transformation level and market segment (intra-EU exports excluded, 2004%)

Market Segment	Exporter	Intermediate goods	Consumer goods	Investment goods	All
Lower	EU-25	14.7	13.6	18.4	15.3
	USA	14.4	7.4	11.5	11.9
	Japan	8.1	4.6	9.4	7.5
	China	14.9	25.0	25.7	20.1
	India	**2.7**	**3.0**	**0.3**	**2.2**
	All	100	100	100	100
Upper	EU-25	28.7	38.8	26.1	30.6
	USA	14.6	9.9	18.5	14.4
	Japan	15.8	9.9	16.8	14.6
	China	2.6	5.8	5.6	4.1
	India	**0.8**	**1.1**	**0.6**	**0.8**
	All	100	100	100	100

Source: Fontagné *et al.* (2008) (Table 3) based on BACI-CEPII data.

The market positioning of exporters and the market shares by market segment confirm the specialization of India in the low-quality varieties. By splitting the world distribution of export unit values (EUV) into three equal market segments (low, medium, high), Fontagné *et al.* (2008) computes the world market shares by transformation level and market segment for a few selected countries including India. What emerges from Table 6 (above) is a larger share of Indian Exports in the lower quality segment:[7] more generally, the statistics show a positive correlation between country's level of development and the quality segment in which the country is specialized. Indeed, as opposed to India and China which show a similar pattern in terms of world market shares by quality segment, the shares of USA, Japan and EU suggest a specialization on high quality varieties.

Other than Ricardian supply-side factors determining country's specialization – such as differences in technology (i.e. productivity) and factor endowments – there are also demand-side explanations of the regularities observed in India's foreign trade. More specifically, Fontagné *et al.* (2008) show that developing countries like India spend smaller shares of their income on the low market segment and import products of lower quality. Table 7 reports the share of up-market products in manufactured exports by destination market. On the demand side, the data suggests a clear difference in the market positioning of the various exporters on their different destination markets, suggesting that importers at different levels of development do consume a different bundle of varieties. In 2004, 72.9% of European exports to Japan were up-market varieties, compared with 49.1 to India.

It turns out that showing the dynamics of North/South competition in terms of different specialization of countries within products and across varieties rather than sectors is instrumental for addressing our research question: indeed, India's advantage in exporting low-market products – along with the larger share of Indian imports on the same quality segment – are the crucial stylized facts for interpreting the role of Indian migrants on bilateral trade. Our contention is that the magnitude of pro-trade effect of Indian emigrants will be dependent on the supply and demand characteristics of their country of origin.

[7] With the exception of Investment goods which show a larger share in the upper market segment.

Table 7. Share of up-market products in manufactured exports, by destination market (2004,%)[a]

Importer / **Exporter**	EU-25	Brazil	Japan	China	**India**	Total
EU-25	41.3	34.0	72.9	46.5	**49.1**	43.2
Brazil	22.8	-	37.8	9.1	**14.2**	15.9
Japan	54.5	33.4	-	42.1	**48.6**	43.0
China	16.6	24.4	20.7	-	**20.9**	11.6
India	**22.0**	**17.6**	**19.3**	**15.6**	-	**17.8**
Total	40.5	30.0	43.9	34.4	**36.2**	35.1

[a] The sample covers manufacturing HS-6 goods including the food industry.

Source: Fontagné *et al.* (2008) (Table 12) based on BACI-CEPII data.

4. Literature Review

There is a large literature on the pro-trade effect of migrants (see for a survey Genc *et al.* 2012 and Parsons and Winters 2014). This literature focuses on the *direct ethnic links* between source and host countries: since the seminal contribution of Gould (1994), several papers using different samples, time coverage and econometric techniques have investigated the relationships between bilateral trade and migration flows to find a strong and significant empirical correlation between the stock of immigrants in the destination country and the volume of trade with their country of origin (see Parsons and Winters (2014) for a detailed discussion). As mentioned above the underlying idea is that migrants have a comparative advantage in conveying reliable information on markets which are very different from the host country. These could be the origin countries but also countries which are similar to the origin in terms of religion, culture, structure of the society. The majority of the contributions study the pro-trade effect of immigrants into a single country, while relatively few papers focus on a multicountry analysis. With the recent availability of more and better data on migrant stocks, some studies also exploit the regional distribution of immigrants and look at the bilateral trade relationship between regions (or provinces) and foreign countries.[8]

Three main stylized facts emerge from the literature: (1) the trade-migration link appears stronger for differentiated goods than for homogeneous commodities (2) the effect of immigrants on imports is typically estimated to be larger than the one on exports and (3) there is ample evidence of a stronger pro-trade effect for high skilled migrants.

1. The first stylized fact implies greater importance of ethnic networks in reducing information costs for more differentiated goods. This rather intuitive statement has been tested empirically mostly by dividing the spectrum of traded goods into three broad subclasses that differ with respect

[8] Genc *et al.* (2012) analyze the distribution of immigration elasticities of imports and exports across 48 studies that yielded 300 observations: they report the meta-modal elasticities of immigrants which are, respectively, 0.12 for exports and 0.15 for imports. Among the main contributions on a single country analysis of the pro-trade effect of immigrants we cite Dunlevy and Hutchinson (1999) for US, Head and Ries (1998) for Canada, Tai (2009) for Switzerland and Girma and Yu (2002) for UK. The most important articles on a multicountry analysis are Felbermayr and Jung (2009), Aleksynska and Peri (2014), Ehrhart *et al.* (2014), Egger, Ehrlich, and Nelson (2012) and Felbermayr and Toubal (2012). Lastly, the most influential papers that study the bilateral trade relationship between regions (or provinces) and foreign countries are: Herander and Saavedra (2005) for US; Wagner, Head, and Ries (2002) for Canada; Bratti *et al.* (2014) for Italy; Peri and Requena-Silvente (2010) for Spain; Combes, Lafourcade, and Mayer (2005) and Briant, Combes, and Lafourcade (2014) for France.

to the degree of differentiation according to the classification proposed by Rauch (1999).[9] By running a gravity model separately for each aggregated group, Rauch and Trindade (2002) estimate separate elasticities of trade with respect to immigrant stocks for differentiated goods, goods traded on organized exchanges, and goods that display some reference price. Following Rauch (1999) and Rauch and Trindade (2002) products that possess references prices are deemed sufficiently homogeneous so that the price differential between two countries' markets convey enough information – given customs and transport costs – on the profitability of shipping the product as opposed to buying the same commodity locally. On the contrary, commodities that do not possess reference prices are considered to be sufficiently differentiated so that prices cannot provide all the required information relevant for international trade: therefore for those commodities the role of transnational networks in overcoming informal barriers and attenuating frictions due to asymmetric information is likely to be much more prominent. Rauch and Trindade' (2002) statistics show that the pro-trade effect of ethnic networks on differentiated products is at least 24% larger in magnitude compared to the correspondent impact on goods that exhibit some reference price and 60% greater with respect to goods traded on organize exchanges.[10] The same classification and a similar methodology have been used – among others – by Felbermayr and Toubal (2012) and Ehrhart *et al.* (2014).

2. As for the second stylized fact, the explanation of the gap between the immigrants elasticity of imports and exports is rooted in the *preference channel* of migration. Bratti, De Benedictis, and Santoni (2014) summarize the results of a sample of some of the most influential contributions to the trade-migration literature and find a significant difference in magnitude. Furthermore, the meta-analysis proposed by Genc *et al.* (2012) – which is based on 48 studies and it contains about 300 estimates – indicates a discrepancy in the meta-modal elasticity between imports and exports of approximately 0.03. Given the lack of theoretical models which enable to separately identify the two channels, the gap in favor of the pro-import elasticity has commonly been the workaround strategy to determine the presence of the *preference channel* of migration.[11] As Bratti *et al.* (2014) argue, this gap is commonly attributed '*by deductive reasoning*' to a persistent difference in tastes between immigrants and natives.

3. Lastly, the third stylized fact indicates that the better the ability of the ethnic networks to receive and process information on trading opportunities, the higher the pro-trade effect. By focusing on a balanced panel of low-income Southern sending countries and high-income Northern receiving countries, Felbermayr and Jung (2009) find that the pro-trade elasticity of high-skilled workers is almost four times bigger than that of low-skilled workers when migration of all skill groups is accounted for. Other studies such as Ehrhart *et al.* (2014), Herander and Saavedra (2005) and Felbermayr and Toubal (2012) show higher pro-trade effects of high-skilled ethnic networks compared to the correspondent impact of the total stock of immigrants.

[9] Peri and Requena-Silvente (2010) and Aleksynska and Peri (2014) use Broda and Weinstein (2006) classification to characterize the degree of differentiability of traded products according to their elasticity of substitution across varieties. Although Peri and Requena-Silvente (2010) and Aleksynska and Peri (2014) use a different classification of goods to characterize the degree of differentiability of products, they follow the same procedure of grouping these products into three broad categories: highly differentiated, moderately differentiated and less differentiated.

[10] This result refers to the effect of the variable "CHINSHARE" in Rauch and Trindade (2002) – which proxies for the size of Chinese ethnic networks – on goods with reference price, goods traded in organized exchanges and differentiated products according to Rauch (1999) conservative classification estimated for the years 1980 and 1990. Similar results emerge for using the liberal classification.

[11] As Felbermayr, Grossmann, and Kohler (2012) point out, a few papers – such as Felbermayr and Toubal (2012) – attempt to disentangle the transaction cost from the *preference channel* of migration. However, so far, according to Felbermayr *et al.* (2012) no conclusive answer to this identification problem is provided and therefore they suggest to leave this important question open.

Against this background, *indirect links* of ethnic minorities may play an even bigger role in promoting bilateral trade. Not only because the larger size – the bilateral stock of migrants between source and host countries which is normally related to bilateral trade is often far smaller than local Indian and Chinese communities – but also because their qualitative effect on bilateral trade: as argued by Curtin (1984) trade diasporas – defined as "the interrelated net of commercial communities forming a trade network" dominated cross-cultural trade in most parts of the world until the nineteenth century.

However, the literature on the indirect pro-trade effect of ethnic networks is much more limited. Rauch and Trindade (2002) has been the first contribution that focus on the pro-trade effects of indirect links. They examine the trade-creating effects of one of the largest transnational network in the world: the overseas Chinese. Rauch and Trindade (2002) inserted the indirect links of Chinese descent into a "naive" gravity equation: they have data on ethnic Chinese population shares for a reasonably large sample of countries in 1980 and 1990, and estimate cross-section gravity models for the log of bilateral trade (sum of exports and imports) for each year separately.[12] They find that the network formed by the overseas Chinese population (of Chinese descent) has an important trade creating effect: this applies not only with mainland China but, most importantly, also between country-pairs which don't have China as trading partner but do host these Chinese ethnic minorities. They find a trade creating effect of Chinese ethnic networks which is relatively large if compared with other trade determinants.[13] Felbermayr *et al.* (2010) revisit the Rauch and Trindade (2002) intuition and argue that shared ethnic ties increase trade as a result of common tastes rather than reducing transaction costs; in addition they find that Rauch and Trindade (2002) results suffer from missing variable bias: they estimate a smaller 15 percent increase in trade from shared ethnic networks. Using an alternative econometric technique (namely PPML) Felbermayr *et al.* (2010) extended the cross-section analysis of Rauch and Trindade (2002) to 63 ethnic networks other than the Chinese for the year 2000 using aggregate trade. In order to examine the pro-trade role of other networks they use data from World Bank which refer to the bilateral stock of migrants, rather than the population of ethnic descent as in Rauch and Trindade (2002). Mexico, India, China, Turkey and Morocco figure as the top sending countries worldwide. They find that the trade creating potential of the Chinese network is dwarfed by other ethnic networks, e.g., the Polish, the Turkish, the Mexican, or the Pakistani networks; in their analysis the second largest sending country, India, is associated with a weak network, whose effect is indistinguishable from zero.[14]

5. Data, Methodology & Econometric Specification

5.1 Data

Trade data: Trade data are from BACI database of CEPII. This database is particularly suitable for a quality analysis since it provides information about the value of trade – in thousands of US dollars and the quantity – in tons – for products classified at 6-digit level using Harmonized System (HS) for the period 1995-2005 (year by year).[15] It allows to calculate unit values which is the core of our quality classification in line with Fontagné *et al.* (2008), Hallak (2006), Schott (2004) and others.

[12] The sample consists of 59 countries for 1980 and 59 for 1990.

[13] They estimate a trade-creating effect for relatively large Chinese ethnic networks on differentiated products nearly of 60%.

[14] Using a larger sample with the same Migration and Trade datasets in Appendix we estimate a very similar model for Indirect Links for Indian Ethnic Networks by pooling 4 years in a OLS model with country*year FE and we obtain a positive and significant effect.

[15] We use the HS 1992 version; other versions – namely 1996 and 2002 – are available.

Migration data: Data on Indian Emigrants are from the recent IAB brain drain database by Brucker *et al.* (2013). Brucker *et al.* (2013) provide a comprehensive database on bilateral migrants resident in a selected group of 19 OECD economies and born in almost 200 different countries of origin for the period 1980-2010 (five years in five years). Rather than including all persons with any Indian ancestry as in Rauch and Trindade (2002), we use the total number of Indians-born aged 25 years and older: in any case, the focus of the migrant network is on people who have moved during their lifetime. Given the structure of IAB brain drain database we consider a reduced OECD sample since – in order to create the proxy for the size of Indian ethnic networks in line with Rauch and Trindade (2002) and Felbermayr *et al.* (2010) – both the number of Indians resident in importer and exporter countries are needed.[16] Despite the relatively limited country coverage we prefer the IAB brain drain dataset over the World Bank since it divides migrants by skill level: this suites very well to the purpose of this paper. Indeed, in our analysis we divide Indian emigrants in high-skilled, low skilled and total number of migrants. Brucker *et al.* (2013) label as *high skilled* those immigrants with tertiary education (higher than high-school leaving certificate or equivalent); *low skilled* are the ones who attain lower secondary, primary or no schooling. As it emerges from Table 2 the largest Indian communities as a share of hosting country's total population are Canada, Great Britain, New Zealand and UK.

Gravity Variables: All the proxies for trade costs along with the data on country's GDP and population are from CEPII. Geographic distance proxies both for transport costs and for the lack of information on products. CEPII includes *Weighted Distance* which calculates the distance between two countries based on bilateral distances between the biggest cities of those two countries. Those inter-city distances are weighted by the share of the city in the overall country's population. More formally, *Weighted Distance* between *n* and *i* reduces to:

$$\mathrm{Dist}_{ni} = \left(\sum k \epsilon n \frac{pop_k}{pop_n}\right)\left(\sum l \epsilon i \frac{pop_l}{pop_i}\right) \mathrm{dist}_{kl}$$

where pop_k stands for the population of agglomeration *k* belonging to country *n* while pop_l is the population of agglomeration *l* belonging to country *i* (see Head and Mayer 2010). The set of gravity variables we use also include a dummy for common language, common border and the joint belonging to a regional trade agreement. The CEPII gravity database has yearly data until 2006. By merging trade data with data on migration and gravity variables we end up with a pooled cross section structure with 3 years: 1995, 2000 and 2005.

Replication of Rauch and Trindade (2002): We also perform the replication of the results of Rauch and Trindade (2002) and Felbermayr *et al.* (2010) for the correspondent indirect pro-trade effect of Indian Networks by using data from different sources: migration data are from World Bank, Trade Data are from Feenstra and the gravity dataset are again from CEPII. More details on the methodology and the data employed for the replication are outlined in Appendix. This exercise allows us to compare our results with those agreed upon in the recent literature.

5.2 Methodology & Econometric Specification

In what follows we classify traded goods according to their quality level *k* and we separately estimate pro-trade elasticity of ethnic networks for all subgroups. We utilize one of the two classifications of quality based on the differences of traded goods in terms of unit values proposed by Fontagné *et al.* (2008). As in Hallak (2006) we assume that all cross-country variation in unit values can be attributed to differences in quality. Since unit value is the ratio between the value and the quantity of exports, observations with zero trade flows and zero or no quantities are automatically dropped.

[16] We don't include Luxembourg as destination country.

Despite this loss of information, we're able to estimate consistently the pro-trade effect of immigrants using a very large number of observations. Furthermore, the lack of zero trade flows in our dependent variable allows to avoid the issue of treatment of zeroes in gravity log-log specifications as warned by Santos Silva and Tenreyro (2006) and Head and Mayer (2014). Following the methodology proposed by Fontagné *et al.* (2008), market segments are simply defined by percentiles in each year. We define the relative unit value ratio for any trade flow s: $r = (UV_s/UV_{world})$, where the reference group is the trade weighted (geometric) average of UV over all flows in the world of a given HS-6digit category. We use data at 6-digit level which encompass different traded commodities under the same HS6 category, reported by firms in a given country at time t. Given the possibility of some selection bias due to the relatively small size of the samples – i.e. some country pairs may appear solely in some specific deciles and not in others – we first divide the spectrum of traded goods based on relative unit values into quartiles ($K = 4$): the down market segment lies under the 25^{th} percentile, whereas the up-market segment above the 75th percentile, in between the other two intermediate classes. The samples are therefore divided into classes of approximately equal size of around 1/4 of the total observations.

The empirical strategy is very similar to Fontagné *et al.* (2008) who estimate a single gravity equation where the proxies for trade costs are interacted with binary variables which indicate the quality level g. They consider three quality segments k while they estimate only the effects for the up-market and down-market. We depart from their approach, in that we set $K = 4$ and we interact gravity variables with each quality segment.

We estimate the following specification:

$$\ln X_{ni,k,g} = \alpha + \theta \ln(\mathrm{GDP}_i * \mathrm{GDP}_n) + \mathrm{S}_i + \mathrm{S}_n + \mathrm{S}_g + \mathrm{S}_k + \sum_{k=1}^{4} \mathrm{S}_k \ln \mathrm{Dist}_{ni}^k + \sum_{k=1}^{4} \mathrm{S}_k \mathrm{Lang}_{ni}^k + \sum_{k=1}^{4} \mathrm{S}_k \mathrm{Contig}_{ni}^k + \sum_{k=1}^{4} \mathrm{S}_k \mathrm{RTA}_{ni}^k + \sum_{k=1}^{4} \mathrm{S}_k \mathrm{IndShare}_{ni}^k + \delta_{ni,g} \quad (1)$$

where:

– $\mathbf{X}_{ni,k,g}$: is imports from i to n of quality k and sector g.

– $\mathbf{GDP}_i * \mathbf{GDP}_n$: is the product of importer's n and exporter's i GDP.

– $\mathbf{S}_t$: stand for year Fixed Effects.

– $\mathbf{S}_i$: stand for Exporter Fixed Effects.

– $\mathbf{S}_n$: stand for Importer Fixed Effects.

– $\mathbf{S}_g$: stand for HS-6digit sector Fixed Effects.

– $\mathbf{S}_k$: stand for Quality Fixed Effects. k goes from 1 to 4 according to the Quality segment considered.

– $\mathbf{RTA}_{ni}$: is a dummy which equals 1 if trading partners both belong to a RTA, 0 otherwise.

– $\mathbf{Dist}_{ni}$: is the weighted distance between i and n.

– $\mathbf{Lang}_{ni}$: is a dummy which equals 1 if importer and exporter speak the same language, 0 otherwise.

– $\mathbf{Contig}_{ni}$: is a dummy which equals 1 if trading partners share a border, 0 otherwise.

– $\mathbf{IndShare}_{ni}$: equals the product of the ethnic Indian population shares for countries i and n.

$$\ln\mathrm{IndShare}_{ni} = ln\left[\frac{\mathrm{Ind}_n * \mathrm{Ind}_i}{Pop_i * Pop_n}\right]$$

– $\delta_{ni,k}$: stand for the error term.

Unlike Rauch and Trindade (2002) who use the log of the sum of imports and exports as dependent variable, we select imports from i to n in line with the EK empirical analysis. All independent variables are in logarithm including $\mathbf{IndShare}_{ni}$ since we prefer an elasticity interpretation also for the size of Indian Networks.[17] As in Rauch and Trindade (2002) the strength of ethnic Indian networks is measured by the probability that, if we select an individual at random from each country, both will be ethnic Indian. Equation 1 is estimated with OLS using a set of high dimensional HS-6digit sector fixed effects. The structure of the model and the econometric technique are identical to Fontagné *et al.* (2008). However, unlike Fontagné *et al.* (2008) – who use the ISIC classification, in which there are 25 manufacturing sectors which are introduced as fixed effects – we are able to include a very large number of Fixed Effects, one for each HS-6 digit category.[18] Unfortunately, given memory limitation in our model we cannot include country*time fixed effects or performing robustness checks with PPML and GPML as suggested by Head and Mayer (2014) with the same set of high dimensional (HD) fixed effects.

6. Results

Before turning to quality analysis we report the estimates of the gravity equation with no interactions with quality segments k in Table 8. The goal is to measure the importance of the *indirect* pro-trade effect of Indian ethnic networks and compare it to (a) the correspondent effect of Chinese Networks which has been object of some influential studies on the trade-migration literature such as Rauch and Trindade (2002) and Felbermayr *et al.* (2010) and to (b) the *direct* pro-trade effect of the bilateral stock of migrants from OECD economies. All the gravity coefficients have the expected sign and are statistically significant, with the exception of GDP. A possible explanation for the insignificance of GDP (i.e. of the high standard error for the $\ln GDP_i * GDP_n$ coefficient) is the likelihood of high collinearity between the number of Indian immigrants and GDP of the destination countries since high income countries tend to be those that attract the largest flows of immigrants. We test this conjecture by running the same gravity model without $\ln IndShare_{ni}$ and we obtain a positive GDP coefficient of 0.131 (0.038) statistically significant at 1%.[19] Therefore in this case a more parsimonious gravity specification – as the one utilized by Eaton and Kortum (2002) and Harrigan (1996) – which includes only exporter and importer fixed effects as proxy for country size may be preferable.

Columns (1) and (2) of Table 8 compare the indirect pro-trade effect of the Indian networks with the Chinese one: in our 19 countries OECD sample the effect of the Indian networks are almost twice as big. This confirms the general conclusions of Felbermayr *et al.* (2010), who found that the trade creating potential of the Chinese network is dwarfed by other ethnic networks.

In columns (3) and (4) we run the same regressions by controlling for the *direct* pro-trade effect of the bilateral stock of migrants between the source and the host countries. More precisely, we include $\ln MigShare_{ni}$ as additional independent variable which proxies for the size of the bilateral ethnic networks between i and n:

[17] This is in contrast with the literature on indirect ethnic networks effect on trade, see for instance Rauch and Trindade (2002) and Felbermayr *et al.* (2010) who estimate the same impact on trade by using simply the product of the shares.

[18] The estimates are obtained with the STATA command *areg:depvar indepvar, absorb(hs96) cluster(countrypair).*

[19] As additonal test we use the *vif* command in STATA (where VIF stands for variance inflation factor) to check for multicollinearity. As a rule of thumb, a variable whose VIF values are greater than 10 may merit further investigation. Tolerance, defined as 1/VIF, is used by many researchers to check on the degree of collinearity. As a rule of thumb a tolerance value lower than 0.1 may merit further investigation. We obtain a 1/VIF value of 152.29.

$$\text{lnMigShare}_{ni} = \ln\left[\frac{\text{Mig}_{ni} * \text{Mig}_{in}}{Pop_i * Pop_n}\right]$$

where Mig_{ni} stands for the stock of immigrants from country *i* and resident in country *n*. As the variable lnMigShare_{ni} is introduced, both the *indirect* network effects slightly decrease in magnitude, meaning that some of the Chinese and Indian network effects previously estimated in column (1) and (2) were capturing some of the impact of bilateral OECD ethnic networks. More importantly, both the Chinese and Indian Networks coefficients are larger than the Mig_{ni}. We believe this result is striking: in the OECD context the *indirect* pro-trade role of the major ethnic networks dominates the correspondent *direct* effect of the bilateral stocks of migrants from OECD.

As a robustness check the lower part of Table 8 reports the correspondent 2SLS estimates. Indeed, a major econometric issue likely to arise when estimating this gravity equation is an endogeneity bias that may be derived from measurement errors, omitted variables and/or potential reverse causality between trade flows and the size of Indian networks. To our knowledge this is the first contribution which uses an IV approach to study the indirect pro-trade effect of ethnic networks. We utilize the STATA command *ivreg2hdfe* recently written by Bahar (2014) which allows to estimate 2SLS with 2 sets of High Dimensional fixed effects. Similarly to Briant, Combes, and Lafourcade (2014) and Combes, Lafourcade, and Mayer (2005) we instrument the size of ethnic networks with the correspondent 15-years lags.[20] As an additional instrument we utilize the past total number of immigrants over hosting country population for each country pair:

$$\left[\frac{\sum_{i=1}^{N} \text{Mig}_{ni} * \sum_{n=1}^{N} \text{Mig}_{in}}{Pop_i * Pop_n}\right]$$

We select the 15 years lags since these are the earliest stocks of bilateral immigrants available from Brucker *et al.* (2013). The 2SLS estimates essentially confirm our main findings: the effect of Indian ethnic networks remain larger compared to the Chinese. In line with Combes *et al.* (2005) endogeneity appears to introduce a downward bias: we find that the coefficients for migrant network variables are way larger, when instrumented.

Table 9 reports the results of the OLS estimation of Equation 1.[21] The effects of the proxies for trade costs vary substantially according to the quality segment. As noted by Fontagné *et al.* (2008) bilateral distance may proxy for two different effects: (a) firstly, as a proxy for transport costs, distance increases the relative price of the lower-market segment for the consumer, making the upper market commodities relatively more convenient (Alchian Allen conjecture); (b) secondly, distance is a proxy for the lack of information on products and may therefore reduce the consumption of expensive varieties. Our results suggest that the information effect is likely to dominate since the parameters on distance interacted with the medium-high and high market segments are larger in absolute value than the low quality market.

Furthermore, the upper segment of the market is more sensitive to cultural proximity proxied by the common language dummy Lang_{ni}. On the contrary, the effect of Contig_{ni} is larger for cheap commodities: country-pairs that share a border tend to trade more with each other especially in commodities of lower quality. Lastly, country-pairs that both belong to a Regional Trade Agreement has much weaker effects: only for low quality segments Rta_{ni} exhibit a positive impact on trade statistically significant at 10%.

[20] We refer to the size of Indian and Chinese networks for 1980 to construct the instrumental variable for the Indian and Chinese shares in year 1995.

[21] The 2SLS estimates are not reported since the number of instruments is not sufficient to match the number of endogenous variables in our regression.

The indirect pro-trade effect of Indian networks in OECD countries is positive and statistically significant across all quality levels. Our results suggest that ethnic Indian networks have a quantitatively important impact on bilateral trade. More specifically, as it emerges from the evidence, this effect is particularly strong for products of low and low-medium quality. Our hypothesis is that the magnitude of the pro-trade effect of Indian networks is associated with the comparative advantage of their country of origin. Given that India is specialized in the production of varieties of low-medium quality, Indian networks – through their role in matching trading opportunities and provision of market and product information – tend to mostly facilitate trade of those varieties.

In general the pro-trade coefficients of Indian ethnic networks increases with the skill level of migrants. This confirms the hypothesis of the high skilled having a more prominent role in reducing information cost in bilateral trade given higher human capital and lower liquidity constraints. However, skill level doesn't affect the trend of the pro-trade effect over quality: as for the total stock, the largest effects for both the low and the high-skilled are on products of low-medium quality.

Table 8. Ethnic Networks Indirect effect on trade – India vs China[abc]

Dependent Variable	$\ln X_{ni,g}$	$\ln X_{ni,g}$	$\ln X_{ni,g}$	$\ln X_{ni,g}$
Estimator	**OLS (1)**	**OLS (2)**	**OLS (3)**	**OLS (4)**
$\ln GDP_i * GDP_n$	0.068*	0.064	0.054	0.061
	(0.038)	(0.041)	(0.040)	(0.043)
$\ln Dist_{ni}$	−0.721***	−0.721***	−0.642**	−0.642**
	(0.072)	(0.072)	(0.068)	(0.068)
Rta_{ni}	0.200	0.202	0.295**	0.296**
	(0.150)	(0.149)	(0.148)	(0.148)
$Contig_{ni}$	0.636***	0.635***	0.580***	0.579***
	(0.074)	(0.107)	(0.104)	(0.104)
$Lang_{ni}$	0.275***	0.275***	0.181**	0.182**
	(0.071)	(0.084)	(0.090)	(0.090)
$\ln MigShare_{ni}$			0.041***	0.041***
			(0.012)	(0.012)
$\ln IndShare_{ni}$	0.119***		0.113***	
	(0.026)		(0.026)	
$\ln ChiShare_{ni}$		0.060***		0.047**
		(0.018)		(0.019)
Year FE	X	X	X	X
Imp/Exp FE	X	X	X	X
HS-6digit FE	X	X	X	X
R^2	0.40	0.40	0.40	0.40
RMSE	1.92	1.94	1.92	1.94
Estimator	**2SLS (5)**	**2SLS (6)**	**2SLS (7)**	**2SLS (8)**
$\ln GDP_i * GDP_n$	−0.017	−0.131*	−0.029	−0.159**
	(0.048)	(0.062)	(0.050)	(0.064)
$\ln Dist_{ni}$	−0.720***	−0.720***	−0.642***	−0.647***
	(0.072)	(0.072)	(0.068)	(0.067)
Rta_{ni}	0.201	0.208	0.296*	0.296*
	(0.150)	(0.149)	(0.149)	(0.147)
$Contig_{ni}$	0.637***	0.633***	0.582***	0.582**
	(0.107)	(0.107)	(0.104)	(0.105)
$Lang_{ni}$	0.277***	0.277***	0.183*	0.191*
	(0.084)	(0.084)	(0.359)	(0.091)
$\ln MigShare_{ni}$			0.041**	0.037**
			(0.012)	(0.013)
$\ln IndShare_{ni}$	0.285***		0.289***	
	(0.067)		(0.068)	
$\ln ChiShare_{ni}$		0.238***		0.252***
		(0.046)		(0.048)
Year FE	X	X	X	X
Imp/Exp FE	X	X	X	X
HS-6digit FE	X	X	X	X
Hansen J P-val	0.607	0.780	0.599	0.442
R^2				
RMSE	1.94	1.94	1.94	1.94
Obs.	1736235	1736235	1736235	1736235

[a] The estimated equation for column (2) is:

$\ln X_{ni,g} = \theta_1 \ln(GDP_i * GDP_n) + \theta_2 \ln Dist_{ni} + \theta_3 Lang_{ni} + \theta_4 Contig_{ni} + \theta_5 RTA_{ni} + S_i + S_n + S_g + \theta_6 \ln MigShare_{ni} + \theta_7 \ln IndShare_{ni} + \theta_8 \delta_{ni,g}$

[b] *, **, *** indicate significance at 10%, 5% and 1%, respectively.

[c] Estimates are obtained with clustered by country-pair standard errors. The model includes the intercept.

Table 9. Indirect Pro-Trade Effects of Indian ethnic networks by skill and quality of traded products[ab]

Dependent Variable	$\ln X^k_{ni,g}$	$\ln X^k_{ni,g}$	$\ln X^k_{ni,g}$
Estimator	OLS	OLS	OLS
Skill Level	Total	Low	High
$\ln\mathrm{GDP}_i * \mathrm{GDP}_n$	**0.084****	**0.118****	0.059
	(0.042)	(0.038)	(0.044)
$\ln\mathrm{Dist}^L_{ni}$	**−0.603*****	**−0.616*****	**−0.581***
	(0.070)	(0.070)	(0.069)
$\ln\mathrm{Dist}^{ML}_{ni}$	**−0.597*****	**−0.612*****	**−0.576***
	(0.070)	(0.071)	(0.069)
$\ln\mathrm{Dist}^{MH}_{ni}$	**−0.674*****	**−0.691*****	**−0.653*****
	(0.068)	(0.068)	(0.066)
$\ln\mathrm{Dist}^H_{ni}$	**−0.630*****	**−0.646*****	**−0.606*****
	(0.069)	(0.068)	(0.068)
Rta^L_{ni}	**0.353****	**0.352****	**0.366****
	(0.157)	(0.153)	(0.157)
Rta^{ML}_{ni}	**0.379****	**0.362****	**0.398*****
	(0.148)	(0.149)	(0.147)
Rta^{MH}_{ni}	0.134	0.126	0.157
	(0.144)	(0.144)	(0.141)
Rta^H_{ni}	0.217	0.224	0.260
	(0.156)	(0.153)	(0.155)
Lang^L_{ni}	0.108	0.142	0.093
	(0.105)	(0.099)	(0.107)
Lang^{ML}_{ni}	0.160	**0.212****	0.136
	(0.107)	(0.104)	(0.110)
Lang^{MH}_{ni}	**0.198****	**0.236*****	0.165
	(0.100)	(0.098)	(0.103)
Lang^H_{ni}	**0.265*****	**0.286*****	**0.204****
	(0.087)	(0.089)	(0.087)
Contig^L_{ni}	**0.717*****	**0.728*****	**0.707*****
	(0.117)	(0.116)	(0.117)
$\mathrm{Contig}_{ni^{ML}}$	**0.632*****	**0.631*****	**0.626*****
	(0.111)	(0.113)	(0.108)
$\mathrm{Contig}^{MH}_{ni}$	**0.468*****	**0.467*****	**0.470*****
	(0.103)	(0.104)	(0.101)
Contig^H_{ni}	**0.288*****	**0.295*****	**0.315*****
	(0.103)	(0.106)	(0.100)
$\ln\mathrm{MigShare}_{ni}$	**0.040*****	**0.028*****	**0.056*****
	(0.012)	(0.010)	(0.114)
$\ln\mathrm{IndShare}^L_{ni}$	**0.109*****	**0.091*****	**0.131*****
	(0.028)	(0.024)	(0.025)
$\ln\mathrm{IndShare}^{ML}_{ni}$	**0.115*****	**0.088*****	**0.139*****
	(0.026)	(0.022)	(0.024)
$\ln\mathrm{IndShare}^{MH}_{ni}$	**0.100*****	**0.075*****	**0.131*****
	(0.026)	(0.022)	(0.024)
$\ln\mathrm{IndShare}^H_{ni}$	**0.090*****	**0.072*****	**0.132*****
	(0.028)	(0.022)	(0.025)
Year FE	X	X	X
Imp/Exp FE	X	X	X
HS-6digit FE	X	X	X
Obs.	1736235	1736235	1736235
R^2	0.40	0.40	0.40
RMSE	1.93	1.93	1.93

[a] *,**, *** indicate significance at 10%, 5% and 1%, respectively.

[b] Estimates are obtained with clustered by country-pair standard errors. The model includes the intercept. The subscripts L, ML, MH and H stand for Low, Medium Low, Medium High and High quality segment, respectively.

7. Summary and Policy Implications

International migrants trigger bilateral trade as their presence reduces information costs or boost additional demand for goods from their source countries. This paper contributes to the strand of literature on the indirect role of ethnic minorities in promoting trade, following a similar approach as Rauch and Trindade (2002). We focus on the pro-trade effect of Indian Networks, which has recently become the largest network worldwide. As opposed to Rauch and Trindade (2002) who divide traded commodities according to their level of product differentiation based on the classification proposed by Rauch (1999), we focus on quality. More precisely, we test how the indirect pro-trade effect of Indian Networks vary with quality of traded commodities.

Our empirical framework follows the analysis of Fontagné *et al.* (2008) both for the quality classification of traded goods as well as for the gravity specification. Unlike Fontagné *et al.* (2008), however, we use a reduced sample of 19 OECD countries: the number of countries has been limited by the availability of data on ethnic minorities divided by skill level from the recent IAB brain drain database by Brucker *et al.* (2013). Four main results stand out:

- Indian co-ethnic networks exert a pro-trade effect which is twice as big as the correspondent impact of Chinese minorities. This result is in line with Felbermayr *et al.* (2010) who find that the pro-trade role of Chinese Networks is substantially smaller with respect to other networks.

- The *indirect* pro-trade effect of both Indian and Chinese networks dominates the correspondent *direct* effect between source and host country. This result suggests that in the OECD context the pro-trade role of migrants is largely determined by the major ethnic minorities.

- The impact of Indian co-ethnic networks on trade is particularly strong for products of low and low-medium quality. Our hypothesis is that the resulting trend over quality is likely to be driven by specific information advantages of Indian Ethnic Networks over low-price commodities, which in turn depend on India's specialization across varieties. Since India is specialized in the production of varieties of low-medium quality, Indian networks – through their role in the matching of trading opportunities and provision of market and product information – are more likely to facilitate trade in the low quality segment. Another plausible explanation may be that, regardless their skill level, Indian emigrants tend to prefer consuming low price varieties because of (on average) stricter budget constraints with respect to OECD natives.

- The high-skill Indian networks have a much greater impact on trade and this is consistent across quality segments. Our results suggest that skill level doesn't seem to play any role in determining the trend over quality: as for the total stock, the largest impacts of both the high- and-low-skilled are still on medium-low quality commodities.

In general the results highlight the importance of the trade promoting role of the networks created by the largest ethnic minorities in OECD countries. This argument is often overlooked or underestimated in the political debate on migration issues, as the potential benefits of a growing diasporas for OECD economies are often confined and associated only to highly qualified workforce at lower costs. From an OECD perspective, the results indicate the inflow of Indian and Chinese migrants as desirable at least for boosting bilateral trade relationships across countries. An interesting topic for further research would be to study whether the same networks have similar indirect effects for Foreign Direct Investments.

As for India, the statistics clearly suggest that the trade enhancing role of Indian Networks can provide a valuable contribution to their homeland's economic growth and development. Given the large trade-promoting effect in OECD economies, there's no reason to believe that a similar impact can't be found on bilateral trade relationships with India as well, considering for instance the larger utility that can be derived by Indian emigrants for goods produced in their native country. Furthermore, one could also speculate on the likelihood that Indian migrants could substitute for the still relatively weak institutional framework of the country. When contract enforcement is problematic and issues of trust become key, skilled migrant have an even more important role to play.

In connection to the above, Indian Foreign Trade seems to be well positioned to benefit from the increasing size of *Indian Diaspora* (especially high skilled): since India has great potential in (i) expanding exports to new areas, (ii) increasing the share of high-quality manufacturing exports and (iii) enhancing the sophistication of traded goods and services, Indian Emigrants may play an important and decisive role in promoting and facilitating international transactions of those goods and services in the new export destinations.

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Appendix. Replication of Rauch and Trindade (2002) results for Indian Ethnic Networks

The seminal contribution of Rauch and Trindade (2002) was the first empirical paper that studies the indirect links between agents of the same ethnicity in different host countries. They use a gravity framework estimated with a threshold Tobit model to show that the network formed by the overseas Chinese population CHINSHARE has a major trade creating effect not only with mainland China but also between countries that host these Chinese ethnic minorities. Quantitatively, they find that the pro-trade effect of Chinese co-ethnic networks is large compared to other determinants of bilateral trade.

In particular, Rauch and Trindade (2002) estimate a larger effects for ethnic Chinese networks on bilateral trade in differentiated commodities compared to products that exhibit “reference prices” or that are traded in organized exchanges. In the following econometric exercise we replicate the Rauch and Trindade (2002) result for Indian Ethnic Networks. Similarly as in Rauch and Trindade (2002) we focus on the effect of **IndShare**, which is the product of the ethnic Indian population shares for importers and exporters. However, instead of 63 countries we extend the sample to 154 destination& origin countries. As Felbermayr *et al.* (2010) we use trade data from NBER-UN World Trade Data, a comprehensive dataset which covers world bilateral trade for the period 1962-2000. Trade data are available at industry level according to SITC-4 digit classification: we aggregate trade data for each country-pair. Unlike Rauch and Trindade (2002) who as emigrants consider all persons with any Chinese ancestry, our only available source for migrants with such an extensive country coverage is the World Bank dataset of Özden *et al.* (2011) which comprises only the stocks of bilateral migrants i.e. Indians born in India and resident in a foreign country for the years 1970, 1980, 1990 and 2000.

Table 10 illustrates the Indian Diaspora over the years since 1970: the total number of Indians resident in foreign countries increased drastically from 1990 to 2000. The countries in bold are the top 9 destinations for Indian emigrants in 2000: some of them – Sri Lanka, Nepal, Bangladesh and Pakistan – are neighboring countries; the others – Canada, United States, United Kingdom, Saudi Arabia and United Arab Emirates – are OECD and Gulf economies which are common destinations for all emigrants regardless the ethnic origins. We merge the Özden *et al.* (2011) migration dataset with NBER-UN World Trade Data and we combine it with the gravity proxies for trade costs from CEPII in order to obtain a pooled structure with 4 years and 154 importers and exporters. The gravity equation we estimate is:

$$\ln X_{ni} = S_t + \theta \ln \mathrm{Remote} + \theta \ln \mathrm{dist}_{ni} + \theta \ln \mathrm{GDP}_{ni} + \theta \mathrm{lang}_{ni} + \theta \mathrm{contig}_{ni} + \theta \mathrm{RTA}_{ni} + \theta \mathrm{IndShare} + \theta\delta_{ni} \qquad (2)$$

where:

– $\mathbf{X}_{ni}$: is imports from *i* to *n*.

– $\mathbf{GDP}_{ni}$: is the product of importer’s *n* and exporter’s *i* GDP at time *t* from CEPII.

– $\mathbf{RTA}_{ni}$: is a dummy from CEPII which equals 1 if trading partners both belong to a RTA at time *t*, 0 otherwise.

– $\mathbf{dist}_{ni}$: is the weighted distance between *i* and *n* at time *t* from CEPII.

– $\mathbf{lang}_{ni}$: is a dummy from CEPII which equals 1 if importer and exporter speak the same language at time *t*, 0 otherwise.

– $\mathbf{contig}_{ni}$: is a dummy from CEPII which equals 1 if trading partners share a border, 0 otherwise.

– $\mathbf{S}_t$: stand for year Fixed Effects.

– δ_{ni}: stand for the error term.

– $\mathbf{Remote}_{ni}$: equals the product of the weighted sum of country *i*’s distances from all other countries in the sample and the same weighted sum for country *n*, where the weights are the GDPs of the other countries.

– IndShare: equals the product of the ethnic Indian population shares for countries *i* and *n*.

Contrary to the original cross section structure of the gravity equation of Rauch and Trindade (2002), our version includes 4 different years and therefore we include year Fixed Effects as in Girma and Yu (2002). Given the presence of only 4 zero trade flows out of more than 35 thousand observations, we deem a standard OLS model as preferable compared to the threshold Tobit model of Eaton and Tamura (1994) utilised in Rauch and Trindade (2002). In addition, Head and Mayer (2014) discourage the use of the threshold Tobit model because of two drawbacks: (a) the threshold parameter lacks a compelling structural interpretation and (b) it is not a "canned" program. We compare our "naive" version of Rauch and Trindade (2002) gravity specification with a standard OLS fixed effects model, as firstly introduced by Harrigan (1996).[22] In order to capture country-year heterogeneity we augment the gravity model by including country*year fixed effects. Our model specification and the data sources are very similar to Felbermayr *et al.* (2010), who revisited Rauch and Trindade (2002)'s findings and discover other ethnic communities which act as global trade facilitators. They find that the trade creating potential of the Chinese network is dwarfed by other ethnic networks, e.g., the Polish, the Turkish, the Mexican, or the Pakistani network. As for the Indian Networks, Felbermayr *et al.* (2010) find that India – their second largest sending country of the numerous networks analysed in their paper – "is associated with a weak network, whose effect is indistinguishable from zero". However, one limitation of their empirical exercise is the cross section structure of their model: due to the impossibility of merging data for many years they estimate a cross section model for the year 2000.[23]

The results are reported in Table 11. As in Rauch and Trindade (2002) we include a dummy **DUM** which equals 1 when the populations of both trading partners are at least 1% Ethnic Indians, 0 otherwise. The results indicate that Indian Ethnic Networks exert a positive effect on trade: the coefficient **IndShare** is way larger than the correspondent effect of the Chinese networks "CHINSHARE" from Rauch and Trindade (2002) and Felbermayr *et al.* (2010). The trade creating potential of the Indian Networks decreases in terms of magnitude when we remove the remoteness variable and we include importer*year and exporter*year fixed effects.

[22] Since most of the size effect of GDP is mostly captured by country*time year fixed effects, GDP is omitted from the regression. This structure is very similar to Harrigan (1996) and Eaton and Kortum (2002).

[23] Given the high number of Fixed Effects in our model PPML led to non-convergence and therefore we cannot compare OLS with PPML and GPML as suggested by Head and Mayer (2014) as robustness check.

Table 10. The size of Indians' *Diaspora* by Destination Country

Destination Country	year 1970	year 1980	year 1990	year 2000	Destination Country	year 1970	year 1980	year 1990	year 2000
Afghanistan	26242	5639	3352	6904	Ecuador	6	9	9	79
Albania	2	3	3	3	Egypt, Arab Rep.	519	689	45	826
Algeria	4	3	3	2	El Salvador	5	17	25	4
American Samoa	4	8	7	9	Equatorial Guinea	17	84	44	72
Andorra	28	9	17	22	Eritrea	429	473	124	113
Angola	288	115	126	198	Estonia	0	0	0	53
Anguilla	0	0	3	6	Ethiopia	1168	1228	1291	1357
Antigua and Barbuda	13	22	33	46	Faeroe Islands	5	6	7	14
Argentina	306	434	220	337	Falkland Islands (Malvinas)	0	0	0	3
Armenia	0	0	0	0	Fiji	7861	4802	3891	4531
Aruba	25	24	111	184	Finland	93	181	522	1136
Australia	18165	40170	59297	94110	France	8074	15718	23455	136233
Austria	764	2815	4718	6887	French Guiana	0	0	2	3
Azerbaijan	0	0	0	0	French Polynesia	5	9	21	27
Bahamas, The	74	130	168	187	Gabon	112	128	181	276
Bahrain	6668	15286	30533	39310	Gambia, The	58	431	614	887
Bangladesh	704574	779720	854364	936151	Georgia	0	0	0	0
Barbados	209	419	462	529	Germany	7573	29642	21616	35486
Belarus	0	0	0	0	Ghana	1941	628	2198	3767
Belgium	623	1598	2700	3533	Gibraltar	5	41	3	35
Belize	97	113	0	271	Greece	92	364	4250	6934
Benin	40	52	68	116	Greenland	6	7	7	6
Bermuda	11	55	1	91	Grenada	4	0	9	17
Bhutan	12370	16699	22544	30431	Guadeloupe	30	79	181	163
Bolivia	4	6	91	116	Guam	248	12	120	156
Bosnia and Herzegovina	13	23	110	86	Guatemala	5	9	4	16
Botswana	9	116	1903	3867	Guinea	87	129	52	76
Brazil	357	1014	693	759	Guinea-Bissau	4	4	8	8
Brunei Darussalam	1071	1341	2619	3725	Guyana	303	366	95	0
Bulgaria	111	113	112	522	Haiti	11	13	18	24
Burkina Faso	2	3	144	56	Honduras	28	36	78	14
Burundi	142	114	48	38	Hong Kong SAR, China	6439	1304	3096	58685
Cambodia	433	6	52	319	Hungary	532	463	395	373
Cameroon	335	267	1	1	Iceland	1	36	92	149
Canada	45737	84397	149951	313999	India	0	0	0	0
Cape Verde	7	8	0	0	Indonesia	48166	24793	7190	6424
Cayman Islands	1	5	61	40	Iran, Islamic Rep.	218	826	1979	1669
Central African Republic	7	15	13	4	Iraq	865	587	484	61
Chad	1045	1155	1276	1446	Ireland	1623	2885	3522	3355
Chile	69	176	273	540	Israel	18458	20680	16249	15159
China	826	127	349	5767	Italy	1206	1370	8198	43249
Colombia	48	59	73	116	Jamaica	602	746	661	1123
Comoros	6	23	90	88	Japan	768	1698	3220	7518
Congo, Dem. Rep.	67967	42758	29548	24192	Jordan	61	194	593	3475
Congo, Rep.	213	543	902	166	Kazakhstan	0	0	0	0
Cook Islands	0	3	8	12	Kenya	14401	11500	8133	551
Costa Rica	9	12	22	41	Kiribati	0	9	0	14
Cote d'Ivoire	209	268	424	39	Korea, Dem. Rep.	86	34	63	512
Croatia	0	2	30	5	Korea, Rep.	12	2	3	1443
Cuba	927	439	190	39	Kuwait	21896	59060	106856	100904
Cyprus	27	46	66	1249	Kyrgyz Republic	0	0	0	210
Czech Republic	6	7	50	244	Lao PDR	33	34	36	34
Denmark	569	1940	2841	4400	Latvia	0	0	0	55
Djibouti	62	125	197	253	Lebanon	317	1127	20213	35326
Dominica	4	1	10	15	Lesotho	46	36	382	132
Dominican Republic	282	291	316	351	Liberia	518	1360	1360	1294

Source: Özden *et al.* ***(cont.)***

Table 10. The size of Indians' *Diaspora* by Destination Country (cont.)

Destination Country	year 1970	year 1980	year 1990	year 2000	Destination Country	year 1970	year 1980	year 1990	year 2000
Libya	57	145	213	256	Samoa	3	4	3	7
Liechtenstein	0	0	1	9	San Marino	0	0	0	0
Lithuania	0	0	0	19	Sao Tome and Principe	5	4	5	5
Luxembourg	56	192	1142	390	**Saudi Arabia**	70109	357516	931457	1007649
Macao SAR, China	94	342	375	406	Senegal	129	136	254	250
Macedonia, FYR	22	39	1129	1312	Serbia				
Madagascar	10371	4059	6502	5878	Serbia and Montenegro	121	217	68	251
Malawi	3982	129	127	125	Seychelles	343	638	587	1650
Malaysia	150723	98724	32931	67701	Sierra Leone	317	391	385	356
Maldives	945	212	154	275	Singapore	50875	42266	43696	105187
Mali	55	54	53	4	Slovak Republic	3	3	9	19
Malta	0	4	8	23	Slovenia	0	0	0	5
Marshall Islands	5	6	7	7	Solomon Islands	2	0	58	11
Martinique	8	21	42	50	Somalia	629	808	191	217
Mauritania	0	2	11	12	South Africa	21765	16833	8897	17047
Mauritius	908	1200	1240	8185	Spain	0	0	3888	7353
Mayotte	7	15	38	76	**Sri Lanka**	1080645	644956	447083	384789
Mexico	357	101	112	401	St. Kitts and Nevis	1	1	10	35
Micronesia, Fed. Sts.	3	8	13	12	St. Lucia	4	1	14	72
Moldova	0	0	0	0	St. Vincent and the Grenadines	3	3	6	10
Monaco	21	267	333	392	Sudan	1762	2261	4465	5386
Mongolia	19	23	28	34	Suriname	296	145	113	4
Montserrat	0	0	20	2	Swaziland	262	37	203	273
Morocco	5	3	2	2	Sweden	890	4438	8171	10988
Mozambique	539	691	2353	6312	Switzerland	671	396	1462	6419
Myanmar	100011	67188	44087	35178	Syrian Arab Republic	7714	5612	7938	10438
Namibia	142	228	365	349	Taiwan, China	0	0	32	181
Naura	45	72	59	26	Tajikistan	0	0	0	0
Nepal	322152	229585	407123	563571	Tanzania	21055	3942	3796	7151
Netherlands	1009	2783	8010	10834	Thailand	939	2557	4434	14419
Netherlands Antilles	143	125	429	52	Timor-Leste	69	64	75	77
New Caledonia	76	85	68	62	Togo	752	791	826	851
New Zealand	5629	6279	7131	20667	Tokelau	1	0	0	0
Nicaragua	8	9	10	12	Tonga	6	61	132	77
Niger	500	675	508	163	Trinidad and Tobago	460	954	766	631
Nigeria	1112	6258	1753	2939	Tunisia	35	15	30	28
Niue	0	0	0	0	Turkey	579	691	1251	567
Norfolk Island	0	0	2	2	Turkmenistan	0	0	0	0
Northern Mariana Islands	2	2	145	175	Turks and Caicos Islands	0	0	6	6
Norway	354	1874	4485	5241	Tuvalu	0	0	0	0
Oman	31427	73080	211955	312053	Uganda	21435	10918	1192	5390
Pakistan	4858023	3899706	3130431	2512906	Ukraine	0	0	0	13
Palau	1	2	35	41	**United Arab Emirates**	21584	235611	437179	751142
Panama	531	896	1509	2159	**United Kingdom**	336567	401255	429885	524796
Papua New Guinea	377	458	355	267	**United States**	69997	227684	494290	1041320
Paraguay	0	18	23	123	Uruguay	15	11	11	2
Peru	44	54	177	145	Uzbekistan	0	0	0	0
Philippines	3647	2096	4400	12439	Vanuatu	69	38	29	8
Poland	6	101	195	330	Venezuela	17	376	379	221
Portugal	1558	4070	6450	6466	Vietnam	490	602	374	2319
Puerto Rico	60	86	798	801	Virgin Islands	128	16	350	325
Qatar	1696	16667	33750	52788	Virgin Islands, British	4	5	17	19
Reunion	83	203	271	401	Wallis and Futuna	0	0	1	4
Romania	1	0	0	2	West Bank and Gaza	181	214	282	436
Russian Federation	0	0	0	26	Yemen, Rep.	6190	7664	9488	11092
Rwanda	607	769	562	2014	Zambia	7081	6845	5320	4814
Saint Helena	4	4	3	3	Zimbabwe	3117	2940	2773	2550
Saint Pierre and Miquelon	0	0	0	0	**TOTAL**	**8260687**	**7582096**	**8176592**	**9516831**

Source: Özden *et al.*

Table 11. Replicating Rauch and Trindade (2002) results for Indian Emigrants[ab]

Dependent Variable	$\ln X_{ni}$	$\ln X_{ni}$	$\ln X_{ni}$	$\ln X_{ni}$
Estimator	OLS	OLS	OLS-FE	OLS-FE
lndist_{ni}	$\mathbf{-0.952}^{***}$	$\mathbf{-0.951}^{***}$	$\mathbf{-1.215}^{*}$	$\mathbf{-1.216}^{***}$
	(0.025)	(0.025)	(0.023)	(0.023)
lngdp_{ni}	$\mathbf{0.907}^{***}$	$\mathbf{0.907}^{***}$		
	(0.005)	(0.005)		
rta_{ni}	$\mathbf{0.684}^{***}$	$\mathbf{0.687}^{***}$	0.011	0.010
	(0.049)	(0.049)	(0.059)	(0.059)
lang_{ni}	$\mathbf{0.510}^{***}$	$\mathbf{0.511}^{***}$	$\mathbf{0.449}^{*}$	$\mathbf{0.451}^{***}$
	(0.045)	(0.045)	(0.043)	(0.043)
contig_{ni}	$\mathbf{0.306}^{***}$	$\mathbf{0.312}^{***}$	$\mathbf{0.461}^{*}$	$\mathbf{0.462}^{*}$
	(0.092)	(0.092)	(0.096)	(0.096)
colony_{ni}	$\mathbf{1.364}^{***}$	$\mathbf{1.350}^{***}$	$\mathbf{1.242}^{*}$	$\mathbf{1.231}^{*}$
	(0.082)	(0.082)	(0.077)	(0.077)
lnremoteness_{ni}	$\mathbf{0.320}^{***}$	$\mathbf{0.315}^{***}$		
	(0.053)	(0.052)		
IndShare	$\mathbf{101.66}^{***}$		$\mathbf{48.35}^{**}$	
	(24.94)		(19.73)	
IndShare*DUM		$\mathbf{95.58}^{***}$		$\mathbf{49.99}^{**}$
		(23.90)		(19.53)
IndShare*(1-DUM)		$\mathbf{1005.1}^{***}$		$\mathbf{868.97}^{***}$
		(292.32)		(252.86)
Year FE	X	X	X	X
Imp/Exp FE			X	X
R^2	0.64	0.65	0.71	0.76
RMSE	2.01	2.01	1.76	1.70

[a] *, **, *** indicate significance at 10%, 5% and 1%, respectively.
[b] Obs. = 35012. Estimates are obtained with clustered by country-pair standard errors.