Understanding Technology Diffusion: The Role of Trade, FDI, and Migration*

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Abstract

Many of the world's innovations are generated in a few developed countries and then adopted globally. I examine to what degree different channels spread technologies across borders in a cointegrated panel framework. This study adds to the literature on technology diffusion by expanding the traditional set of diffusers by migration, and allowing for idiosyncratic effects between developed and developing countries. Results show that technology diffuses indeed differently to developed and developing countries. First, FDI significantly increases relative technology usage in developing countries, while there is no significant effect in developed countries. Second, trade increases technology usage in developed countries, while it reduces technology usage in developing countries. Last but not least, migration raises technology usage in both developed and developing countries. However, the higher a developed country's educational level, the lower the positive effect of migration. For developed countries with an educational threshold above the 99th percentile, the overall effect of migration becomes even negative. Finally, extreme bounds analysis suggests that these findings are robust to different combinations of alternative model specifications.

Keywords: Technology Diffusion, Migration

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1 Introduction

Endogenous growth theory casts technological progress in a critical role for explaining sustainable growth and productivity differences across countries. However, with increasing globalization, a country's own R&D effort becomes relatively less important compared to R&D activity abroad. According to Keller (2004), foreign sources of technology account for about 90 percent of domestic productivity growth in most countries. In other words, many of the world's innovations are generated in a few countries and then adopted globally, making the developing world dependent on the developed. On the opposite, developed countries also rely on developing countries in form of human capital. For example, the World Economic Prospect from 2008 reports that developing countries account for three-quarters of the 3.3 million immigrant scientists and engineers living in the United States in 2003. For some developing countries, this migration of high skilled individuals represents a significant problem limiting the home country's capability to invent and adopt new technology. Yet, migration has the potential to enhance technology diffusion through re-migration, remittances or knowledge sharing.

I use a cointegrated panel framework to analyze the long-run effects of migration, and other factors, on technology diffusion. Further, I investigate differences in technology diffusion between developed and developing countries. Throughout the paper, technology diffusion refers to the distance of a country's technology usage from the technology frontier. The implicit assumption underlying this interpretation is that most countries are not innovating themselves. Thus, if a country catches up to the technology frontier it is due to technology diffusion.

The paper's contribution is threefold: First, I allow for idiosyncratic channels of technology diffusion between developed and developing countries.[1] Traditionally, most of the cross-country technology diffusion literature focuses on OECD countries with little understanding of how technology diffuses to developing countries. However, access to new technology is imperfect, and depends on a country's economic integration (see e.g. Coe and Helpman (1995), Keller and Yeaple

[1]Countries are categorized into 25 developed and 46 developing countries according to the definition of the IMF's World Economic Outlook 2012. The IMF's classification takes into account per capita income, export diversification, and the degree of integration into the global financial system.

(2009), and Van Pottelsberghe De La Potterie and Lichtenberg (2001)). Since developing countries are less integrated relative to developed countries, they face higher barriers of information flow. At the same time, most developing countries invest less in R&D and infrastructure, and have worse institutions, making them more dependent on technology adoption and imitation relative to industrialized countries. This paper finds that technology diffuses indeed differently to developed and developing countries. A one percent increase in FDI increases relative technology usage by 0.4% in developing countries, while there is no significant effect in developed countries. Further, trade affects diffusion idiosyncratically. A one percent increase in the trade volume increases technology usage in developed countries by 1.3%, while it reduces technology usage in developing countries by 4%.

The second contribution of the paper contemplates the role of migration as a potential channel of technology diffusion. Previously, literature has established a long run relationship between FDI, trade and technology diffusion, however the role of migration is less examined. According to census data collected by Artuc et al. (2014) migration stocks have increased by 30% between 1990 and 2000. This movement of human capital across borders bears a huge potential for knowledge transfers. On the one hand, migration accelerates technology diffusion through remittance flows, investment in the home-country, and knowledge gains that can be transferred to the home-country. On the other hand, migration might lower the diffusion of new technology by limiting its ability to process and apply new information and innovation. A priori, which effect dominates is unclear. The introduction of migration puts this paper at the crossroads of two strands of literature, as it combines the literature on growth impact of migration with the literature on technology diffusion.[2] Results indicate that migration has positive effects on diffusion in both developed and developing countries. A one percent increase in migration raises technology usage by 3.5% in developed and 1.65% in developing countries. In developed countries education mitigates the positive effect of migration. The higher a developed country's educational level, the lower the positive effect of migration. For developed countries with an educational threshold above the 99th percentile, the

[2] see Docquier and Rapoport (2012) for an overview

overall effect of migration becomes even negative. In contrast, education does not influence the overall effect of migration in developing countries.

Finally, I contribute to the diffusion literature by improving on the quality of technology diffusion data. I use the Cross-country Historical Adoption of Technology (CHAT) data set by Comin, Hobijn, and Rovito (2006), which measures usage intensities for over 115 technologies in 150 countries over time. The CHAT data removes some of the traditional concerns regarding TFP growth as approximation for technology diffusion: TFP growth captures variation in capacity utilization, labor hoarding, inefficiencies of the economy, and ignores innovations that increase product variety. Further, the CHAT dataset improves over patent citation data which measure diffusion along the extensive margin, and can thus not be used to identify the usage intensity of a certain technology. Moreover, patent citation data does not capture potential patent infringement or the time gap between the implementation of a patent and the actual usage of the technology.

2 Channels of Technology Diffusion

The theoretical predictions about the determinants of technology diffusion build on models by Nelson and Phelps (1966), Benhabib and Spiegel (2005), Romer (1990) or Aghion and Howitt (1992). Grossman and Helpman (1993) provide an overview of the basic models on technology diffusion. Since these models are widely discussed in the literature I focus on their theoretical predictions relevant for this paper, instead of their technical derivations. Keller (2004) provides an overview of both theoretical and empirical work in the area of technology diffusion. Traditionally, this literature identifies five main channels through which technology spreads across countries: Trade, Foreign Direct Investment, Geographic Characteristics, Human Capital and R&D investment.

Among others, Grossman and Helpman (1993) identify international trade as the main channel of technology diffusion. First, trade increases the variety and quality of intermediate goods in an economy. Second, trade enhances the international discussion of production process and organizational behavior. Lastly, trade facilitates the imitation of foreign technologies, and increase a country's R&D performance, by enhancing capital inflow, and freeing up resources that would otherwise have been used to produce the traded good. In summary, all these channels accelerate technology diffusion either through providing a larger variety of products, or through providing new knowledge that would otherwise have been costly to acquire.[3]

Besides trade, FDI affects technology diffusion through investments and knowledge transfers to existing companies. Investments in a company can increase diffusion as new shareholders try to maximize profits and dividends through influencing production processes. Knowledge transfers affect productivity through either a larger variety of inputs or higher input quality. A company's internal knowledge can then spread to other companies through imitation, or a combination of employees gaining new knowledge and labor turnover.[4]

Geographic characteristics influence technology diffusion through transportation costs, and by influencing trade and FDI volume, similar to the gravity model framework. The bigger the geographical distance between technology leader and adopter, the lower the diffusion rate. Moreover, person to person communication and cultural proximity declines with distance, thus further reducing the diffusion of technology.[5]

Finally, Keller (2004) suggests human capital and R&D expenditure influence technology diffusion by increasing a countries absorptive capacity. Higher human capital facilitates the implementation and usage of new technologies. R&D investment accelerates technology diffusion because they facilitate acquiring outside technology by enabling the country to understand and evaluate new technological trends and innovations.[6]

In addition to these commonly identified channels, this paper considers migration as a channel of technology diffusion. When emigrants gain new knowledge abroad, it can be imported to the

[3]Studies relating imports to technology diffusion include Eaton and Kortum (2001), Coe and Helpman (1995) and Sjoholm (1996). Studies regarding exports include Clerides, Lach, and Tybout (1998) and Bernard and Jensen (1999)

[4]Studies relating FDI to technology diffusion include Griffith, Redding, and Simpson (2003), Harrison and Aitken (1999) , and Keller and Yeaple (2009)

[5]Studies showing the effect of geographical proximity include Sjoholm (1996), Bottazzi and Peri (2003) and Keller (2002)

[6]Studies linking human capital to technology diffusion include Eaton and Kortum (1996) and Xu (2000). Studies showing the importance of R&D investment include Griffith, Redding, and Reenen (2004) and Coe and Helpman (1995)

home-country either through re-migration (Luo and Wang (2002)) or information sharing within networks (Agrawal et al. (2011) and Kerr (2008)). According to the World Bank, especially in developing countries a majority of foreign students who earned their doctorate in the U.S. return home within 5 years after completing their degree, bringing along technological knowledge. Moreover, many migrants remit money back home to support their families and friends (Bollard et al. (2011), Niimi, Ozden, and Schiff (2010)), or invest in their home-economy. In both cases, the resource envelope in the home-country increases, raising the ability to purchase, invest and adopt new technology. Finally, migration prospects increase the expected returns to human capital, creating an incentive to invest in education, and thus increasing the ability to apply new technology (Batista, Lacuesta, and Vicente (2012) and Beine, Docquier, and Rapoport (2008)). Park (2004) supports these spillover effects of migration by analyzing the role of international student flows in OECD countries. In contrast, Engelbrecht (1997) extends the work by Coe and Helpman (1995) including human capital. He finds that human capital positively affects TFP growth, implying that migration can negatively affect technology diffusion through the brain drain channel. A country's human capital is important as it determines how fast new technology can be learned and applied. Work by Haque and Kim (1995), McCulloch and Yellen (1977) or Bhagwati and Hamada (1974) analyze the negative consequences from migration and show that high skilled emigration increases inequality. While more recent literature has moved away from this strictly negative view of a brain drain, the effects of migration on technology diffusion are, a priori, not clear.

3 Data

Based on these traditional channels, the benchmark model measures the relationship between technology diffusion and emigration, further controlling for additional factors:

$$Diff_{j,t} = \beta_1 Migration_{j,t-1} + \beta_2 \mathbf{X}_{j,t-1} + \alpha_j + \theta_t + \varepsilon_{j.t} \quad (1)$$

$Diff_{j,t}$ is the diffusion of technology at time t for country j, and $\mathbf{X}_{j,t-1}$ is a vector including FDI, trade, education and private investment. Both dependent and independent variables are expressed as logs. I use lagged values of the above controls to minimize concerns about simultaneity. Further, I include both country fixed effects, α_j, and time fixed effects, θ_t, to reduces potential endogeneity stemming from unobserved factors that do not change over time, such as geographical proximity, or that are common to all countries, such as the global economic climate.

3.1 Measuring Technology Diffusion

I compute technology diffusion from the Cross-country Historical Adoption of Technology (CHAT) data introduced by Comin, Hobijn, and Rovito (2006). The data contain information on usage intensities of over 115 technologies in 150 countries since 1800. Each technology represents a capital good that is used to produce a final good or service.[7] A potential producer decides whether to incur a fixed cost of adopting the new production method, which represents the extensive margin. Once the production method has been introduced, its productivity determines how many units of the capital good are used. This represents the intensive margin. To determine whether one of the above mentioned covariates contributes to technology diffusion, I compute the distance of each technology usage from its technology frontier. Since most countries don't innovate themselves, a reduction in the gap between a countries technology usage relative to the technology frontier is attributed to technology diffusion. Formally, the distance between a country j's usage intensity of technology i at time t and the technology frontier is

$$Diff_{i,j,t} = \frac{A_{i,j,t}}{max\{A_i\}} \tag{2}$$

where $A_{i,j,t}$ is the usage intensity of technology i at time t in country j, and $max\{A_i\}$ is the maximum usage intensity of technology i at any given time and country. To make relative usage intensities comparable across countries, I consider only technologies for which I have data on a wide range of countries. Therefore, I first exclude countries that have less than 50% of observations for

[7] This is similar to e.g. Romer (1990)

more than half of the technologies relative to the average. This leaves me with 91 countries. Next, I exclude technologies for which data are only available for a small share of countries. For example, usage intensities for health technologies, such as mammographs or MRI units are only available for OECD countries. These low observation technologies include all technologies which differ from the mean number of observation by more than 1.5 standard deviations. This leaves me with 23 technologies.[8] Finally, the selected 23 production technologies are scaled by either population or GDP, depending on their measurement unit. To control for the possibility that technologies might become obsolete over time, I compute technology diffusion relative to the year of maximum usage intensity, which is the year that precedes 3 consecutive years of increasing GDP with declining usage intensity. This ensures that changes in relative usage intensities are not due to an outdated technology.[9] In a last step, I average the relative usage intensities across technologies to obtain the measure in equation (1):

$$Diff_{j,t} = \frac{1}{I}\sum_{i=1}^{I} Diff_{i,j,t} \tag{3}$$

These intensities provide a direct measure of technology along the intensive margin. For instance, computers and cellphones are measured as the number used in a given year per capita, while other technologies, such as electricity, are measured as MW-hr of electricity produced per unit of real GDP. Measuring technology along this intensive margin is important because it is not only of interest whether computers are used, but also how intensively. Despite these advantages, the CHAT data are defined in broad categories. For example, the CHAT data do not distinguish between dial-up modems or high-speed internet, but combine them under the category internet usage. However, it is possible to infer that increasing usage intensities reflect increasing quality, without determining the exact quality of an innovation. For example, increased computational power, storage and software applications have increased the use of computers in production over the last years. While relatively few computers were used in production in 1980 due to their limited technology, today the

[8] For a complete list of included technologies refer to Table A.1

[9] The time when a certain technology becomes obsolete varies between countries. The number of observations of obsolete technology varies greatly between technologies ranging from 55% of observations for older agricultural technologies to 0 observation for state-of-the-art technologies such as cellphones and computers.

quality of computers is much higher. Thus, the intensive margin allows one to draw conclusions about the quality and efficiency of each technology.

Table 1 shows the average usage intensity relative to the frontier for several technology categories and separates between developed and developing countries. The average usage intensity is 18% relative to the technology frontier, with 26% in developed and 11% in developing countries. This means that, on average, developed countries are more than twice as close to the technology frontier as developing countries. Regarding agriculture, there is a 8 percentage point gap between developed and developing countries. With only 9% of the usage intensity relative to the frontier, developing countries are particularly far behind in the categories general purpose, telecommunication and transportation technologies, which explains the growing interest of researchers in the role of cell phones and internet in development. Last but not least, developed countries are relatively close to the technology frontier in transportation technologies, while the gap between developed and developing countries is 25 percentage points. There are a few potential reasons for this large gap such as inappropriate infrastructure to support transportation technologies in developing countries, inefficient public capital through which infrastructure is usually financed, and low transferability due to high installation costs.

Table 1: Technology Usage relative to Technology Frontier

	Total	Developed Countries	Developing Countries
Relative Technology Usage	0.18	0.26	0.11
	(0.11)	(0.10)	(0.06)
Agriculture	0.20	0.24	0.16
	(0.13)	(0.13)	(0.11)
General Purpose	0.15	0.22	0.09
	(0.13)	(0.14)	(0.07)
Telecommunication	0.16	0.23	0.10
	(0.14)	(0.15)	(0.09)
Transportation	0.21	0.34	0.09
	(0.17)	(0.14)	(0.08)
N	1314	630	684

Technology Usage as share of Technology Frontier. Table A.1 describes technology categories; Sample includes 25 developed and 46 developing countries with at least 5 observations between 1973 and 1999; Standard Deviations in parenthesis;

3.2 Independent Variables

Data on the covariates come from the World Bank and Penn World Tables.[10] I use private investment data to approximate for R&D expenditures due to the lack of such data in developing countries. Besides data availability, private investment has the advantage that it affects technology diffusion directly and indirectly. Firms invest in the development of new intermediate inputs or the imitation of existing technology. By increasing private investment, more resources are available for R&D and imitation, thereby directly increasing the diffusion of technology. Moreover, much of new technology is useless without appropriate infrastructure. High speed internet technology cannot be implemented without new fiber cables, and innovations in the transportation sector require road infrastructure. This indirect channel is not accounted for by R&D expenditure data.

Migration stock data are not available annually. Consequently, I compute annual stocks based on country j's migration stock in the year 1970, as provided by the World Bank's Global Bilateral Migration Database.[11] I add annual, net emigration flow data from the UN to the 1970 migration stock, and scale the computed migration stock data by population. Emigration flow is measured as the sum of country j's immigration to 43 reporting countries covered by the 2010 Revision of the UN Global Migration Database. These data provide the most comprehensive annual emigration stock data available. I focus on migration stocks rather than flows to capture diaspora effects that facilitate access to technology, capital and professional contacts in advanced economies, as highlighted by Saxenian (1999) or Plaza, Ratha, and Clemons (2011). Unfortunately, computing migration stocks as described has the disadvantage that it measures emigration to only 43 different countries, resulting in a true emigration stock that is most likely higher than the one used in this study. However, the Global Migration Database includes mostly middle to high income countries that adopt new technologies relatively fast, and that are ranked among the top migrant receiving countries. Consequently, it is unlikely that migrants learn about new technologies in countries that are not included in the Global Migration Database.

[10]see Table A.2 for details

[11]Migration stock is the aggregate of bilateral migration stocks from over one thousand census and population register records, and based on the foreign-born concept.

3.3 Descriptives

Data availability limits the observation period to 1971 - 2001. As I will explain in the next section, the inclusion of leads and lags in the regression requires at least 5 consecutive observations over the sample period. To account for gaps in the series, I use linear interpolation. This reduces the number of countries to 46 developing and 25 developed countries over 27 years.[12]

Comparing developing and developed countries shows that FDI flow and private investment relative to GDP are 50% and 15% smaller in developing economies. Moreover, both total trade relative to GDP and education are each 25% smaller in developing countries. Finally, the emigration stock of developed countries, i.e. the number of people from developed countries living abroad relative to their population, is almost three times as high as the emigration stock of developing countries. This can either be caused by an under-reported number of migrants from developing countries due to illegal migration status, or by a larger propensity to migrate in developing countries thanks to better financial and educational means.

Table 2: Summary Statistics

	Total	Developed Countries	Developing Countries
Relative Technology Usage	0.18	0.26	0.11
	(0.11)	(0.10)	(0.06)
FDI	2.65	3.45	1.74
	(5.14)	(6.55)	(3.08)
Trade	62.72	72.09	52.65
	(48.07)	(59.21)	(28.55)
Emigration	5.08	7.95	2.77
	(5.47)	(6.49)	(3.02)
Private Investment	22.84	24.66	21.24
	(8.09)	(6.54)	(8.88)
Education	2.35	2.73	2.02
	(0.55)	(0.39)	(0.45)
N	1314	630	684

Sample includes 25 developed and 46 developing countries with at least 5 observations between 1973 and 1999 (see Table A.3). Gaps in the sample are filled with linear interpolation; Table A.2 contains variable definitions; Standard Deviations in parenthesis;

[12]The inclusion of 2 leads and lags reduces the effective estimation period from 31 to 27 years

4 Estimation

Since Coe and Helpman (1995)'s attempt to determine the effects of foreign R&D effort and trade on a country's TFP growth, time series econometrics and panel data analysis have focused on unit root and cointegration properties of variables observed over a relatively long period across a large number of cross section units (Breitung and Pesaran, 2008). Coe and Helpman (1995) discover that all of their data exhibit a trend, and unit root tests on these data indicate that TFP, domestic, and foreign R&D capital stocks are non stationary. Moreover, they confirm cointegration of TFP and the R&D capital stocks. As Kao, Chiang, and Chen (1999) point out, the asymptotic distributions of estimators and standard errors in panel regression are affected by the presence of unit roots and cointegration. Accounting for unit roots and cointegration, their study shows that the estimated coefficients in Coe and Helpman's regressions are subject to estimation bias and that trade has no significant effect on R&D spillovers, thus underlining the importance of panel cointegration regression.

4.1 Panel Unit Root Tests

Non-stationarity in panel data requires unit root tests to deal with the cross-section dimension of the data in addition to the traditional time series dimension. New developments of such panel unit root tests include the Levin-Lin-Chu test, Breitung test, Im-Pesaran-Shin test, Choi test and the Maddala-Wu test.[13] Given the nature of the data, Table A.4 presents results from the Im-Pesaran-Shin (IPS) test and Fisher-type tests (Augmented Dickey-Fuller and Phillips-Perron) because they allow for unbalanced data. Further, both tests allow for heterogeneity in the autoregressive coefficient of the Dickey-Fuller regression. The large reported p-values in Panel A indicate presence of a unit root for most variables. In contrast, p-values in Panel B from testing first differences, rather than levels, indicate stationarity.

[13]See Breitung and Pesaran (2008) for a detailed overview over unit roots and cointegration in panels.

4.2 Panel Cointegration Tests

In the presence of unit roots, standard inference is invalid. This problem can be avoided by estimating the model in first differences. However, first-differencing raises the problem of spurious regression in the presence of a cointegrating vector between the variables. Two commonly used panel cointegration tests include Kao and Chiang (2001) and Pedroni (1999) tests. Both are Engle-Granger based tests, calculated by regressing I(1)-variables on each other and then testing the resulting residuals for stationarity.[14] Table A.5 reports test statistics and p-values for both Pedroni and Kao cointegration tests.

The results indicate that the null hypothesis of no cointegration between technology diffusion and its determinants can be rejected at any significant level. Therefore, I resort to dynamic OLS (DOLS) for panel cointegration, developed by Kao and Chiang (2001) to estimate the long-run relationship between technology diffusion and migration, trade, and FDI. This estimator is developed for non-stationary panels and corrects the standard OLS estimator for serial correlation and endogeneity that are usually present in long-run economic relationships.[15]

4.3 Cointegration Vector Estimation using DOLS

Kao and Chiang (2001) generalize the time series DOLS estimator derived by Stock and Watson (1993) for a panel data framework. The estimator corrects for endogeneity and serial correlation by including leads and lags of the differenced I(1) regressors.

$$Diff_{j,t} = \beta \mathbf{X}_{j,t-1} + \sum_{s=-q_1}^{q_2} c\Delta \mathbf{X}_{j,t-1+s} + \varepsilon_{j,t} \quad (4)$$

$$Diff_{j,t} = \beta \mathbf{X}_{j,t-1} + \delta_j \mathbf{Z}_{j,t-1} + \varepsilon_{j,t} \quad (5)$$

[14] The Pedroni tests allow for heterogeneous coefficients for explanatory variables across cross-sections. Further, Pedroni separates his statistics into 2 classes: the panel statistic pools residuals across the within dimension of panel, while the group statistic pools residuals across the between dimension.

[15] Other studies employing this estimator include Adedeji and Thornton (2008), Chintrakarn and Herzer (2012), Funk (2001) and Mark and Sul (2003). The advantage of estimating a panel data cointegration model, as opposed to a times series cointegration model separately for each country, is that i) a larger data base increases the power of testing and leads to more precise point estimates of the cointegration vector with reasonably accurate asymptotic approximation, and ii) heterogeneity in the short-run dynamics across individuals can generate disparities in single equation DOLS estimates of the homogenous cointegration vector.

where $\mathbf{X}_{j,t}$ is a vector including trade, FDI, migration, education and private investment, $[q_1,\ q_2]$ determine the range of lags and leads of the first differences, and Δ is the difference operator. The addition of leads and lags removes the detrimental effects that short-run dynamics of the equilibrium process have on the estimate of the cointegrating vector. The DOLS estimator is consistent, asymptotically normally distributed and efficient.

Mark and Sul (2003) extend the basic estimator derived by Kao and Chiang (2001) to allow for country and time fixed effects. The inclusion of both time and country fixed effects significantly reduces the concerns about endogeneity. Allowing for both fixed effects changes equation 5 to

$$Diff_{j,t} = \beta \mathbf{X}_{j,t-1} + \delta_j \mathbf{Z}_{j,t-1} + \alpha_j + \theta_t + \varepsilon_{j,t} \tag{6}$$

where α_j represent country fixed effects, and θ_t are the common time effects. Because I allow heterogeneity in the projection coefficients δ_j across j, the resulting cross-sectional averages will involve sums such as $\sum_{j=1}^{N} \delta_j Z_{jt-1}$ which complicates estimation of the coefficients. Therefore, Mark and Sul (2003) suggest to address the endogeneity correction separately from the cointegration vector estimation. They project each element of $\text{Diff}_{j,t}$ onto $n = (1, z_{j,t-1})$, and each element of $\mathbf{X}_{j,t-1}$ onto n to predict errors $\text{Diff}^*_{j,t}$ and $\mathbf{X}^*_{j,t-1}$ from each projection. Substituting the projection representation into equation 6 gives

$$Diff^*_{j,t} = \beta \mathbf{X}^*_{j,t-1} + \theta_t + \varepsilon_{j,t} \tag{7}$$

which is equivalent to equation 6 to estimate and draw inference. To eliminate the common time effects, take cross-sectional averages of equation 7 and subtract them from equation 7 to get

$$Diff^{\dagger}_{j,t} = \beta \mathbf{X}^{\dagger}_{j,t-1} + \varepsilon^{\dagger}_{j,t} \tag{8}$$

where $Diff^{\dagger}_{j,t} = Diff^*_{j,t} - \frac{1}{N}\sum Diff^*_{j,t}$, $\mathbf{X}^{\dagger}_{j,t-1} = \mathbf{X}^*_{j,t-1} - \frac{1}{N}\sum \mathbf{X}^*_{j,t-1}$ and $\varepsilon^{\dagger}_{j,t} = \varepsilon_{j,t} - \frac{1}{N}\sum \varepsilon_{j,t}$. The panel DOLS estimator of β is

$$\beta = \left[\sum^{T}\sum^{N}\mathbf{X}'^{\dagger}_{j,t-1}\mathbf{X}^{\dagger}_{j,t-1}\right]^{-1}\left[\sum^{T}\sum^{N}\mathbf{X}'^{\dagger}_{j,t-1}Diff^{\dagger}_{j,t}\right] \tag{9}$$

I estimate Equation (8) with Driscoll and Kraay (1998) standard errors to account for heteroskedasticity, autocorrelation, and cross-sectional and temporal dependence.[16] The optimal lag and lead length of the first differences, based on the first step of the Newey and West (1994) plug-in procedure, is two and purges serial correlation. Automatic lead and lag specification based on the Akaike Information Criterion confirms an optimal lead and lag length of two.

5 Results

In this section I will provide insight into the determinants of cross-country technology diffusion by estimating regression equation 8 for developed and developing countries separately. Moreover, I test the results for robustness along two dimensions. First, I use Instrumental Variables (IV) regression to address some of the remaining concerns about simultaneity. Second, I use Extreme Bounds Analysis (EBA) to test the robustness of the model to a combination of additional, potential explanatory variables. All variables are expressed in natural logarithms.

5.1 Benchmark Model

Columns 1) - 2) show the effect of FDI, trade, education, private investment and migration on technology diffusion. In developed countries, a one percent increase in FDI raises a country's usage intensity relative to the frontier by 0.018%. This effect seems negligible at first, however, FDI has almost increased 50-fold since 1970 according to the OECD Environmental outlook. Thus, FDI contributed to closing the technology gap between the leader and the average developed country by 90%. Education has the largest effect on technology. A one percent increase in education levels

[16] see Mark and Sul (2003) for a detailed derivation of the estimator and limiting distributions of the DOLS estimator in a fixed effects model with cross-sectionally correlated panels and heterogeneous trends

raises the technology usage by over 1%. Moreover, private investments contribute to technology diffusion: a one percent increase in private investment raises a developed country's usage intensity by 0.23% relative to the leader. Finally, a one percent increase in a country's diaspora increases its technology usage relative to the frontier by 0.18%.

Similarly, a one percent increase in migration from developing countries increases technology usage by 0.25%. In contrast to developed countries, private investment and education do not influence technology diffusion. This supports the results by Benhabib and Spiegel (2005) who find that technology diffusion requires a minimum education threshold that many developing countries have not yet reached.[17] Finally, FDI and Trade have opposite effects on diffusion. A one percent increase in FDI lowers a country's relative usage intensity by 0.04%, while the same increase in trade volume raises it by 0.3%.

In conclusion, the benchmark model suggests that, in developed countries, investment and human capital are the major determinants of diffusion, while developing countries mostly benefit from trade and migration.

5.2 Robustness

This section addresses two concerns regarding the results presented in Columns 1) and 2). First technology diffusion and the covariates could be determined simultaneously. Second, additional factors correlated to the covariates, could potentially influence technology diffusion. In both cases endogeneity would introduce a bias to the coefficient estimates in Columns 1) and 2).

5.2.1 Instrumental Variable Regression

I follow Tavares (2003) by using a combination of geographical and cultural ties between the technology leader and follower countries to instrument for FDI, trade, and migration. For each country in the sample, I compute 3 variables that indicate the geographic and cultural closeness between

[17] The educational level in developing countries in my sample is, on average, 25% lower relative to developed countries.

each country and the United States.[18] Then, I take the value of FDI, trade and migration for the United States and multiply them by these proximity variables. Additionally, I use an indicator for a country's freedom of domestic movement from Cingranelli and Richards (2010) and interact the indicator with FDI, trade and immigration. Thus, for FDI, each country in the sample will have four exogenous variables that will serve as instruments:

$$
\begin{aligned}
FDI-DI_i &= (Inverse\,of\,Bilateral\,Distance_{i,US}) * FDI_{US} \\
FDI-RE_i &= Religion_{iUS} * FDI_{US} \\
FDI-LA_i &= Language_{iUS} * FDI_{US} \\
FDI-MO_i &= (Domestic\,Movement_i) * FDI_{US}
\end{aligned}
$$

The instruments for trade and migration are built similarly. I construct the instrument this way because the use of fixed effects would not allow me to observe the effect of the time invariant proximity variables on FDI, trade, and migration. Intuitively, the instrument is justified because upon an increase in total FDI, trade and migration by the technology leader, countries that are culturally and geographically closer to the leader should experience a bigger increase in trade, FDI, and migration than countries that are further away. Additionally, a country's freedom of domestic movement is correlated with trade and FDI because restricting movement limits the efficient allocation of labor, resulting in lower productivity and FDI, as well as higher imports due to the lack of competitiveness of the domestic industry. Further, freedom of domestic movement can be seen as an indicator for international migration because countries that restrict domestic migration are likely to restrict international migration as well.

To instrument for education, I follow the approach by Barro and Lee (2013) and use parental education. Parental education was accumulated by their past investment in education, and is thus uncorrelated with the error term. Specifically, I use the 10 year lag average years of schooling

[18] I choose the United States as the reference point because it is among the world's most innovative countries. Further, the United States is the technology frontier for over half of the technologies in the sample. Consequently, the diffusion of new technology is most likely to originate from the US. The 3 proximity variables are Bilateral distance, same majority religion, and same official language.

of the population being 40 years and over to represent parent's education. In the first stage of the instrumental variable regression, I regress trade, FDI, education and migration separately on the exogenous instruments above. The predicted value of the dependent variable in that regression is then used in the second stage regression to examine its effect on technology diffusion. The instruments pass all relevant tests for validity, including the Anderson canonical correlations likelihood-ratio test for identification and relevance, the Kleibergen-Paap rk-test for weak identification and the Hansen J-statistic for over-identification.[19]

The second stage regression results are presented in Columns 3) - 4) of Table 3. In contrast to the benchmark model, FDI and trade switch roles regarding significance in developed countries. Trade is now a major determinant as a one percent increase in the trade volume raises technology usage by 1.3%. The Benchmark model measures the effect of trade on usage intensity, but ignores that higher technology usage, in turn, might increase the trade volume. In other words, trade and technology diffusion might be determined simultaneously. The ignorance of this feedback channel leads to the underestimation of trade in the benchmark model. Moreover, migration is no longer a significant channel of diffusion in developed countries. Similar to the benchmark model, education is still the major determinant of technology diffusion in developed countries. A one percent increase in education accelerates diffusion by 1.7%. As with trade, the ignorance of potential simultaneity can cause the benchmark estimate to be downward biased. Education increases technology diffusion as higher human capital facilitates the implementation and usage of new technologies. Increasing technology usage, can then enhance education through the availability of better learning technologies such as the computer and the internet, or through increasing demand for skilled labor as a result of high-tech production.

In developing countries, migration is still a major determinant of diffusion. A one percent increase in migration leads to a 1.4% acceleration in technology diffusion. This is a 5 fold increase relative to the benchmark model. The main discrepancy between the benchmark and IV model is the effect of trade in developing countries. In contrast to developed countries, as well as in contrast

[19]see Table A.6 for test results

to the benchmark model, trade significantly slows down technology diffusion to developing countries. This can be caused by two reinforcing effects. Many imported technologies are designed to increase production with the skills of developed countries' workforces. Differences in education create a mismatch between the requirements of these technologies and the skills of developing workers, resulting in low imports of innovative production technologies (Acemoglu and Zilibotti, 2001). Consequently, imports consist predominantly of final goods rather than intermediate production technologies. Further, the high share of final goods imports reduces the need for new technologies in the production sector and forces domestic firms out of the market, thus reducing domestic technology usage for production.[20]

Columns 5) - 6) include an interaction term between migration and education. Migration is often regarded as harmful for the home country as it drains the country of human capital.[21] The interaction between education and migration allows to draw inference about the importance of the brain drain with respect to technology diffusion. The importance of trade and FDI does not change significantly in developed and developing countries upon the introduction of the interaction. Migration has now a significant positive effect on diffusion in developed countries, with the overall effect becoming smaller, the higher the educational level in a country. Thus, at the sample mean, a one percent increase in migration increases the relative technology usage by 0.66%. This effect vanishes the higher the educational level of the country, and becomes negative for countries with an educational level beyond the 99th percentile. In contrast, the effect of migration does not depend on a country's educational level in developing countries. A one percent increase in migration raises technology usage relative to the frontier by almost 1.6%, regardless of education. This difference between developed and developing countries can be attributed by the, on average, low educational level in developing countries. According to Benhabib and Spiegel (2005), education has to be above a certain minimum threshold to significantly affect technology diffusion, and most developing countries have not yet reached this threshold. Therefore, the depletion of human capital

[20] UN COMTRADE SITC data show that between 1992 and 2006 developing countries share of total trade in intermediate inputs is only about 28% vs 70% for developed countries.

[21] see Docquier and Rapoport (2012) for an overview

through migration does not affect diffusion in developing countries as it would in developed countries. Rather, migration enhances technology diffusion through information transfers via networks or re-migration, and remittances, which are more pronounced in developing countries relative to developed countries.[22] Thus, there is no evidence of a negative effect in form of a brain drain on technology diffusion in developing countries. Further, the positive effects of migration on technology diffusion outweigh the negative brain drain effect in developed countries with an educational level below the 99th percentile.

Table 3: DOLS Estimation Results

	DOLS with Migration		IV-DOLS		IV-DOLS (Interaction)	
Dep Var: Relative Usage Intensity (t+1)	Developed Countries	Developing Countries	Developed Countries	Developing Countries	Developed Countries	Developing Countries
FDI	0.018***	-0.043***	-0.049	0.377***	-0.035	0.388***
	(0.00)	(0.01)	(0.04)	(0.09)	(0.04)	(0.08)
Trade	0.019	0.309***	1.323***	-3.803***	1.265**	-4.004***
	(0.10)	(0.08)	(0.40)	(0.63)	(0.59)	(0.65)
Education	1.013***	0.310	1.682***	0.163	3.767***	0.284
	(0.17)	(0.19)	(0.31)	(0.13)	(0.70)	(0.27)
Private Investment	0.232**	0.028	-0.050	0.042	0.064	0.042
	(0.09)	(0.06)	(0.07)	(0.10)	(0.06)	(0.10)
Emigration	0.183***	0.254***	0.234	1.444**	3.461***	1.580**
	(0.05)	(0.08)	(0.30)	(0.53)	(0.93)	(0.69)
Emigr$\times$Educ	-	-	-	-	-2.779***	-0.061
	(-)	(-)	(-)	(-)	(0.65)	(0.43)
Country/Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	630	684	630	684	630	684

Estimation is carried out using DOLS with fixed effects, and 2 leads and lags. Standard errors are according to Driscoll and Kraay (1998) to account for heteroskedasticity, serial correlation and cross-sectional dependence. Variables are in logs and defined in TableA.2, Sample includes 25 developed and 46 developing countries between 1973 and 1999; Standard Deviations in parenthesis; *, ** and *** denote 10, 5 and 1 %significance levels.

[22]For example, a study by the World Bank shows that especially in developing countries a majority of foreign students who earned their doctorate in the U.S. return home within 5 years after completing their degree. Further all Top 30 remittance receiving countries are emerging economies

5.2.2 Extreme Bound Analysis

A final check of robustness includes additional explanatory variables. One of the key problems faced by empirical economics is that it is hard to identify the "true" regression. More specifically, it is hard to identify which variables should be included in the regression and which ones should not. A variable can be found to have a significant effect in one specification, but the variable becomes insignificant once we add or omit certain other variables. Levine and Renelt (1992) overcame this problem by using Leamer's (1985) Extreme Bound Analysis (EBA) to identify robust empirical relations. The test considers a pool of N variables that have been identified to be related to the dependent variable. To identify whether a particular variable z is robust, one estimates the regression

$$\gamma = \alpha_j + \theta_t + \beta_{yj}Y + \beta_{zj}Z + \beta_{xj}X_j + \varepsilon \tag{10}$$

where Y is a vector of variables that always appears in the regression, Z is the variable of interest, and $x_j \in X$ is a vector of variables taken from the pool of N potentially influential variables. The model then needs to be estimated for all the possible combinations of $x_j \in X$. The two extreme bounds are defined as the lowest value of $\beta_{zj} - 2\sigma_{zj}$, and the highest value of $\beta_{zj} + 2\sigma_{zj}$. If the lower extreme bound and the upper extreme bound share the same sign, then variable z is said to be significant. This is a rather strict criteria because if there is a single regression for which the sign of the coefficient changes, the variable is not significant. Consequently, Sala-i Martin (1997) developed an alternative criteria to test for robustness. He argues that the robustness criteria should depend on the fraction of the density function lying on each side of the zero. If 95 percent of the density function for the estimates of β_{zj} lie on one side of zero, the variable is significant.[23]

Table 4 shows results for the extreme bound analysis of both Leamer and Sala-I-Martin for Columns 5) and 6) of Table 3 (IV-DOLS: Interaction). The z variable includes either trade, FDI, education, private investment or emigration. The vector Y contains those variables that did not

[23] Sala-i Martin (1997) weighs both the coefficient and standard error by the integrated likelihood ratio to give more weight to the regression that are more likely true. Both Jan-Sturm and de Haan (2005) and Gassebner, Lamla, and Vreeland (2013) conduct their EBA without weights as all specification are equally likely to be "true"

enter z. Other variables that potentially effect technology diffusion are a country's GDP, credit-to-GDP ratio, life expectancy, as well as domestic public investment and U.S. R&D investment. To conduct EBA, a combination of these variables is included in the X-Vector. GDP and the credit-to-GDP ratio might affect technology diffusion as they expand an economy's resource envelope. A larger envelope allows an economy to allocate more resource towards R&D and technology adoption. Public investment can affect technology diffusion in a similar way as GDP and credit. Further, public investment facilitates technology diffusion indirectly by improving existing infrastructure (both educational and transportation). U.S. R&D expenditure affects diffusion as it increases the propensity to innovate in the United States. With the U.S. being among the largest innovators and most open economies, an increasing propensity to innovate facilitates technology diffusion to other countries. Lastly, a country's life expectancy may affect technology diffusion based on a market size argument similar to Acemoglu and Zilibotti (2001): Countries with larger life expectancies are, on average, more educated and wealthier. The larger purchasing power and capital-skill complementarity increases demand for new technology, thus enhancing technology diffusion.

Looking at the sample of developed countries, EBA suggests that all findings of Column 5) in Table 3 are robust, with the exception of trade. The lower and upper bounds are -0.93 and 6.3 respectively, with an average t-value of 1.2. In other words, including combinations of the variables GDP, credit, life expectancy, and public and U.S. R&D investment renders trade insignificant.

Looking at the sample of developing countries, the Sala-I-Martin criteria suggests that all findings of Column 5) in Table 3 are robust. The stricter Leamer criteria confirms these findings with the exception of migration. The average t-value of all combinations of regressions is 2.7 and suggests that, on average, migration significantly increases technology diffusion. However, the lower and upper bounds are -1.75 and 5.2 respectively, thus suggesting that there is at least one specification in which migration does not significantly affect diffusion. Both robustness criteria suggest that the effect of migration is significant, and does not depend on the educational level in the home country.

Table 4: Extreme Bound Analysis

Z-Variables	Avg β	Avg s.e.	Avg t-score	Min β	Min s.e.	Max β	Max s.e.	Leamer	Sala-I-Martin
Developed Countries									
FDI	-0.050	0.034	-1.275	-0.109	0.040	0.025	0.026	Robust	Robust
Trade	0.706	0.574	1.194	-0.003	0.463	1.542	0.667	Fragile	Fragile
Education	3.817	0.652	5.912	2.677	0.690	5.04	0.652	Robust	Robust
Private Investment	0.129	0.054	2.48	0.068	0.060	0.195	0.050	Robust	Robust
Emigration	3.278	0.778	4.314	2.429	0.717	4.122	0.749	Robust	Robust
Emigr×Educ	-2.586	0.554	-4.71	-3.432	0.524	-1.808	0.515	Robust	Robust
Developing Countries									
FDI	0.342	0.057	6.331	0.255	0.050	0.416	0.053	Robust	Robust
Trade	-2.739	0.615	-4.484	-4.146	0.602	-1.543	0.578	Robust	Robust
Education	0.546	0.265	1.63	-0.974	0.242	2.072	0.263	Robust	Robust
Private Investment	0.059	0.087	0.702	0.011	0.095	0.108	0.072	Robust	Robust
Emigration	1.827	0.674	2.712	-0.429	0.661	3.968	0.622	Fragile	Robust
Emigr×Educ	-0.165	0.380	-0.308	-1.541	0.372	1.204	0.350	Robust	Robust

Estimation is carried out using DOLS with fixed effects, and 2 leads and lags. Standard errors are according to Driscoll and Kraay (1998) to account for heteroskedasticity, serial correlation and cross-sectional dependence. Variables are in logs and defined in TableA.2. FDI (IV), Trade (IV), Education (IV), Investment, Emigration (IV) and the Interaction Term are sequentially included in the y-vector with the other variables being included in the z-vector. A combination of the variables credit, life expectation, GDP, US R&D expenditures and public investment are added. Sample includes 25 developed and 46 developing countries between 1973 and 1999;

6 Conclusion

Recent literature has focused on the importance of trade and FDI as channels for technology spillovers across countries. This paper identifies an additional channel, migration, and shows that once included in the estimation, it dominates the long run effect of trade and FDI. In addition to the introduction of migration, this paper contributes to the ongoing literature on technology diffusion by utilizing an advanced measure of technology diffusion to investigate differences between developed and developing countries.

The main findings of the paper indicate that FDI, trade and education have idiosyncratic effects in developed and developing countries. Moreover, the results show that migration significantly increases technology diffusion in both developed and developing countries. However, the positive effect of migration in developed countries is mitigated by a country's educational level. For developed countries with an educational level beyond the 99th percentile, migration even harms diffusion. Theory suggests that migration affects technology diffusion in two opposing ways: On the one hand, the loss of human capital lowers a country's capability of evaluating and implementing new technologies. On the other hand, a larger diaspora accelerates diffusion through remittances, knowledge-sharing and a higher propensity to re-migrate. As suggested by Benhabib and Spiegel (2005), many developing countries have not yet met the minimum educational threshold necessary to significantly attribute to technology diffusion, thus the positive effect of migration is not mitigated by a brain drain in developing countries. Furthermore, the contrasting effects of trade in both developed and developing countries can be attributed to contrasting skill levels in both country groups. As suggested by Acemoglu and Zilibotti (2001), many imported technologies are designed to increase production with the skills of developed countries' workforces. Differences in education create a mismatch between the requirements of these technologies and the skills of developing workers, resulting in low imports of innovative production technologies. Thus, an increase in trade is mostly attributed to higher imports of final goods. However, a high share of final goods imports reduces the need for new technologies in the production sector and forces domestic firms out of the market, thus reducing domestic technology usage.

I test these results for robustness using extreme bounds analysis as suggested by Leamer (1985) and Sala-i Martin (1997). The effects of all 5 variables of interest (FDI, trade, education, private investment and migration) are mostly robust to expanding the set of regressors by all possible combinations of the variables GDP, credit, life expectancy, domestic public investment and U.S. R&D investment.

The findings in this paper reveal some interesting results and hypotheses. Some of these hypotheses, however, require further research since they lie beyond the scope of this paper. For example, the answer as to how migration affects diffusion in developed and developing countries in a positive way is left for future research. Potential reasons could include information transfers through networks and re-migration, or the transfer of remittances. A better understanding by policy makers regarding the dominant channel through which migration affects diffusion is important to implement policies that help to unleash the full potential of migration.

Moreover, future research should put more emphasis on the overall welfare effects of migration on the economy. While this paper attests a positive link between migration and technology diffusion, the effects of migration on the economy as a whole are still ambiguous. Last but not least, future research should examine the effects of technology diffusion on the innovator. On the one hand, increasing technology diffusion leads to countries catching up to the technological frontier, with positive consequences for the leader in the form of increasing purchasing power of developing countries. On the other hand, diffusion reduces the incentive to innovate, potentially resulting in adverse global effects.

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Appendix

Table A.1: List of Technologies

Category	Technology	Definition
Agriculture	Harvester	Number of self-propelled machines that reap and thresh in one operation (per unit of real GDP)
	Irrigated area	Irrigated area as a share of cultivated land
	Tractor	Number of wheel and crawler tractors used in agriculture (per unit of real GDP)
	Pesticides	Metric tons of active ingredients in pesticides used in or sold to the agricultural sector (per unit of real GDP)
	Fertilizer	Metric tons of fertilizer consumed (per unit of real GDP)
Transportation	Aviation I	Civil aviation passenger-KM traveled on scheduled services (per capita)
	Aviation II	Civil aviation ton-KM of cargo carried on scheduled services (per unit of real GDP)
	Rail I	Thousands of passenger journeys by railway (per capita)
	Rail II	Ton-KM of freight carried on railways (excluding livestock and passenger baggage, per unit of real GDP)
	Rail III	Geographical/route lengths of line open at the end of the year (per unit of real GDP)
	Rail IV	Metric tons of freight carried on railways(per unit of real GDP)
	Vehicle I	Number of passenger cars in use (per capita)
	Vehicle II	Number of commercial vehicles, typically including buses and taxis, in use (per unit of real GDP)
Telecommunication	Cellphone	Number of users of portable cell phones (per capita)
	Newspaper	Number of newspaper copies circulated daily (per capita)
	Radio	Number of radios (per capita)
	Telephone	Number of mainline telephone lines (per capita)
	Mail	Number of items mailed/received (per capita)
	Telegram	Number of telegrams sent (per capita)
	TV	Number of television sets in use (per capita)
General Purpose	Internet	Number of people with access to the worldwide network (per capita)
	Computer	Number of self-contained computers designed for use by one person (per capita)
	Electricity	Gross output of electric energy in KwHr (per unit of real GDP)

Definitions are taken from Comin and Hobijn (2009)

Table A.2: List of Variables

Name	Definition	Source
Relative Usage Intensity	Usage intensity of country i at time t relative to technology frontier	CHAT: Author's calculation
FDI	Sum of net FDI Inflow and net FDI Outflow	World Bank
FDI Outflow	Net outflows (new investment outflows less disinvestment) of investment from the reporting economy to the rest of the world, as share of GDP.	World Bank
FDI Inflow	Net inflows (new investment inflows less disinvestment) in the reporting economy from foreign investors, as share of GDP	World Bank
Trade	Sum of exports and imports of goods and services measured as a share of GDP	World Bank
Credit	Growth rate of credit to the private sector as a share of GDP	World Bank
Life Expectancy	Indicates the average number of years a newborn infant would live.	World Bank
Migration	Migration stock of country j, reported by selected destination countries, relative to country j's population*	UN Migration Database
Education	Growth rate of Human Capital per person (index), based on years of schooling (Barro and Lee 2012) and returns to education (Psacharopoulus, 1994)	Penn World Table
GDP per capita	Growth rate of PPP Converted GDP Per Capita (Laspeyres), derived from growth rates of c, g, i, at 2005 constant prices	Penn World Table
Public Investment	Growth rate of public investment as a share of GDP	Penn World Table
Private Investment	Growth rate of private investment as a share of GDP	Penn World Table

* 43 countries included in the Global Migration Database: The 2010 Revision

Table A.3: List of countries

Developed Countries			Developing Countries			
Australia	Germany	New Zealand	Argentina	Egypt	Malaysia	Russia
Austria	Greece	Norway	Bolivia	El Salvador	Mali	Saudi Arabia
Belgium	Ireland	Portugal	Brazil	Ghana	Mexico	South Africa
Canada	Israel	Singapore	Bulgaria	Guatemala	Morocco	Sri Lanka
Czech Republic	Italy	Spain	Cameroon	Honduras	Mozambique	Syria
Denmark	Japan	Sweden	Chile	Hungary	Pakistan	Tanzania
Finland	Korea, Rep	Switzerland	China	India	Panama	Thailand
France	Netherlands	United Kingdom	Colombia	Indonesia	Paraguay	Togo
		United States	Congo, Dem. Rep	Iran	Peru	Turkey
			Ivory Coast	Kenya	Philippines	Uruguay
			Ecuador	Malawi	Poland	Venezuela
					Romania	Zimbabwe

Sample includes 25 developed countries and 46 developing countries between the period 1973 and 1999 for which at least 5 observations were available. Gaps were filled using linear interpolation.

Table A.4: Unit Root Tests

Panel A: Variables in Levels

	Diffusion Lag	FDI	Trade	Emigr	Educ	Private Inv.
IPS-test	18.25	-12.96	-6.73	9.2	2.91	-5.4
	(1.00)	(0.00)	(0.00)	(1.00)	(0.99)	(0.00)
ADF-test	95.15	689.3	293.9	174.23	213.4	277.29
	(1.00)	(0.00)	(0.00)	(0.28)	(0.01)	(0.00)
PP-test	67.1	424.74	226	130.15	125.9	198.7
	(1.00)	(0.00)	(0.00)	(0.97)	(0.99)	(0.03)

Panel B: Variables in First Differences

	Diffusion Lag	FDI	Trade	Emigr	Educ	Private Inv.
IPS-test	-9.84	-24.11	-23.54	-4.2	-1.81	-25.25
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
ADF-test	588.88	895.17	801.43	300.79	217	1084
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
PP-test	1301	3801	1727	217.58	123.65	2473
	(0.00)	(0.00)	(0.00)	(0.00)	(0.99)	(0.00)

The table reports test statistics for IPS and Fisher-type panel unit root tests. p-values are in parenthesis. The H_0 for both tests is that all series are nonstationary. Lags are chosen according to the Akaike Information Criterion. All tests include an individual intercept and trend.

Table A.5: Cointegration tests

Pedroni:			
	Panel PP-Statistic:	-6.47	(0.00)
	Panel ADF-Statistic:	-6.96	(0.00)
	Group PP-Statistic:	-15.08	(0.00)
	Group ADF-Statistic:	-6.92	(0.00)
Kao:			
	ADF	2.19	(0.01)

The H_0 for both tests is no cointegration. Lag length is chosen by the AIC. Both tests include a constant, only the Pedroni test includes an individual trend. Pedroni group-rho, panel-v and panel-rho tests are not reported due to their low power compared to panel-t and group-t tests for low N and low T. See Pedroni (1999) for details.

Table A.6: Summary results for first-stage regressions

	Emigration	FDI	Trade	Education
Individual endogenous regressors:				
Angrist-Pischke χ^2- tests of underidentification:	81.54	103.38	218.56	234.34
	(0.00)	(0.00)	(0.00)	(0.00)
F- statistics:	70.64	42.66	42.11	206.35
	(0.00)	(0.00)	(0.00)	(0.00)
Underidentification test: Kleibergen-Paap rk LM Statistic:	58.12		(0.00)	
Hansen J statistic:	27.61		(0.00)	
Weak-instrument-robust inference:				
Anderson-Rubin Wald test (F-stat):	68.82		(0.00)	
Anderson-Rubin Wald test (χ^2):	904.02		(0.00)	
Stock-Wright LM S statistic:	297.38		(0.00)	

* p-values in parenthesis