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Exploring the Effects of International Wage Differences on Brain Drain

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Abstract

This paper examines how international wage differences affect brain drain by comparing the effects of skill-specific wage differences on low, medium, and high-skilled emigration. Previous literature explores qualitative factors behind migrant flow, but there is little focus on the role of wage differences in individuals' decisions to emigrate. A relatively new data set on emigration rates by education level and a modified gravity model provide a unique analysis of bilateral migration flows. This paper finds that wage differences may have a significant and positive effect on and low-skilled emigration, but a less significant effect on high-skilled emigration or brain drain.

Keywords

Wage, Migration, Education, Brain Drain, International Economics

Cover Page Footnote

Thank you to Dr. Brandon Sheridan, my faculty research mentor, for providing valuable insight and mentorship while I wrote this article.

I. INTRODUCTION

The number of international migrants living abroad has grown considerably since the turn of the century, rising from to 173 million in 2000 to 244 million in 2015 (U.N. 2016). Decreasing transportation and communication costs have expanded employment options for workers on an incredible scale, especially for high-skilled workers able to take advantage of access to sophisticated labor markets in developed countries. While those high-skill migrants enjoy the benefits of globalization, there have long been concerns about the effect of their emigration from their home countries. The emigration of highly skilled workers from developing nations throughout the late 20th and early 21st centuries has caused headline scares of "brain drain." Coined in the 1960s by the British Royal Society, brain drain was first used as a term lamenting the emigration of British scientists from the United Kingdom. More recently, brain drain has come to refer to emigration of the most highly skilled individuals from developing countries (Gibson and McKenzie, 2011a). Formally known as human capital flight or high-skilled emigration, the effects of brain drain have been explored over decades through various schools of thought. The causes of brain drain, however, have long remained largely unexplored and elusive. This paper aims to provide insight on the determinants of brain drain, with a specific focus on the effects of international wage differences.

II. LITERATURE REVIEW

Beginning in the 1960s, the first wave of brain drain research largely found that high-skilled emigration had a neutral economic impact on source countries. Researchers mainly emphasized the benefits of migration and remittances sent home by skilled emigrants (Docquier and Rapoport, 2012). Economists often disregarded claims of losses in developing countries due to brain drain. This view changed, however, as second a wave of research surfaced in the 1970s. Economists began finding negative welfare consequences in developing countries as high-skilled emigration depleted the stock of human capital in source countries. Using an endogenous growth model, Haque and Kim (1995) determined that high-skilled emigration would permanently reduce income per capita and create cross-country differences in economic growth and income.

The pessimistic second wave of research persisted until the late 1990s, when the third and most recent wave of research began to take hold. The new wave placed a larger emphasis on empirical research to strengthen and challenge existing theory, made possible by newfound availability of migration data. Newer literature finds that brain drain does not necessarily deplete the stock of human capital in source countries. In fact, multiple works find brain drain to be beneficial to the source country under certain conditions. Theoretical work by Beine, Docquier, and Rapoport (2001) models a scenario in which the possibility of emigration increases prospects of a higher return to education, thus fostering higher investment in human capital in the source country. Building on this framework, Docquier and Rapoport (2012) define a similar model where a long-run "beneficial brain drain" can occur under two conditions: the probability of high-skilled emigration remaining low and skill price differences generating a strong incentive to attain education.

Beine et al.'s (2001) case of beneficial brain drain has been empirically validated. The same authors conduct an empirical test of their own model and find a positive, significant impact of emigration on gross human capital formation. Their result was reinforced in a later study, which found that doubling the highly high-skilled emigration rate increases the rate of human capital formation by 5% in a set of 27 OECD countries (Beine, Docquier, & Rapoport, 2008). Other case studies concerning small developing countries have provided further micro-evidence that brain drain affects education decisions and acts as a driver of human capital formation (Batista, Lacuesta, and Vicente 2012; Docquier and Rapoport 2012; Samet 2014).

While empirical literature on the effects of human capital flight has flourished in the third wave of research, studies in the other direction are lacking. Docquier and Rapoport (2012) point out that although many empirical papers have found similarities in the determinants of high-skilled emigration and economic growth, the interdependencies between these two forces are in need of greater exploration. In one study, Docquier, Lohest, and Marfouk (2007) find that country size is a key determinant of the skilled emigration rate. This finding helps explain why small island countries have some of the highest rates of brain drain. Other determinants include political stability, human capital stock, post-colonial ties, and geographic distance to destination country groups.

It is important to note that Docquier et al. (2007) do not include variables related to income or wages as a determinant of emigration. This omission is somewhat odd considering that much of the third wave literature refers to returns on human capital investment in monetary terms. The theoretical foundation laid by Beine et al. (2001) implies that workers expect enough of a wage increase from emigration such that migration prospects incentivize them to invest in more human capital. Fan and Yakita (2010) expand upon this assumption by constructing a theoretical model to examine wages as a determinant of both emigration and education decisions of individuals in the source country. They posit that an increase in the foreign skilled wage rate encourages skilled emigration from the source country. Additionally, they argue that the average education level is dependent on the degree of complementarity with the emigration rate. Fan and Yakita's (2010) model has not been empirically validated, again highlighting the scarcity of empirical literature that analyzes wage differences as a factor behind high-skill emigration.

Some authors have studied wage variables, but not as explanatory variables of skilled emigration. Gibson and McKenzie (2011b) find that income gains are not the most significant determinant of emigration decisions. Rather, lifestyle and risk preference variables are more strongly correlated with emigration decisions. Oddly enough, the same authors report in a 2012 paper that migrants themselves receive most of their gains from migration in the form of income (Gibson and McKenzie, 2012). While these results are not necessarily in conflict, they do not paint a clear picture of income's role in high-skilled emigration. Furthermore, the methods used by Gibson and McKenzie do not capture the full extent to which income gains may affect migration decisions. Both of their empirical works from 2011 and 2012 are based on unique surveys conducted with migrants from a select group of five countries. Rather than regress the rate of skilled emigration on different variables, the authors use survey-reported reasons for emigration as dependent variables. While their survey is comprehensive and provides powerful insight into emigration decisions, their results do not seem as strong as what might be gained from a panel regression analysis.

Finally, Grogger and Hanson (2011) do calculate wage differences between source and destination countries. The authors use this measure as an indicator of migrant selectivity and sorting, however, rather than the migration decision itself. It is clear that literature on the determinants of brain drain lacks focus on wage differences as an explanatory variable.

III. Research Question

This paper seeks to answer how international wage differences affect the rate of high-skilled emigration. In doing so, this paper expands upon the existing literature three ways. First, this paper will provide comprehensive analysis that targets the relationship between skill-specific wage differences and high-skilled emigration rates. Previous literature theoretically links relative increases in skilled wages abroad to increased emigration rates, but empirical analysis of this argument is lacking. This study will provide empirical evaluation of the theoretical determinants of brain drain.

Second, this study will make use of recent improvements in data collection related to migration and skill levels. The bulk of influential brain drain literature from the 21st century relies on data from Docquier and Marfouk's (2006) data set on international migration by educational attainment. While this data set consists of two time periods of observation, it is still limited and is mainly used in studies as comparative "before and after" data. Brücker, Capuano, and Marfouk (2013) provide an updated version by expanding the data to include the years 1980 through 2010 in five-year increments. Using an updated and more comprehensive data set ought to provide a fresh, insightful look into the determinants of brain drain. This dataset and others will be explained in more detail later.

Third, this paper will take advantage of the recent availability of bilateral migration data to utilize a modified gravity model as the main framework for study. Modifications of the gravity model can be applied to predict emigration by skill level between source and destination country pairs. Gravity models have seldom been used to analyze the brain drain issue, if at all. This paper will thus expand the existing brain drain literature to include such analysis.

IV. Theoretical Foundation

The theoretical model for this research will be built on a modified gravity model of migration. I will also borrow the framework outlined by Grogger and Hanson (2011) to introduce differenced variables to the gravity equation. I will first explain the gravity model and then outline the intuition behind differenced variables and their application to the gravity model.

The gravity model is most often associated with studies on international trade, but it is also a powerful model for understanding migration. The trade-related gravity model specifies trade as a positive function of the "mass" of two economies and a negative function of the distance between them (Lewer and Van den Berg, 2008). Applied to migration, the population of two countries would be considered their "masses," and distance between the two countries would still constitute a negative function of migration. A basic form of the gravity model of migration appears as follows:

$$M_{ij} = \frac{G P_i^{\beta 1} P_j^{\beta 2}}{D_{ij}^{\beta 3}}. \quad (1)$$

In equation 1, M_{ij} represents migration from country i to country j. P_i and P_j represent the populations of source country i and destination country j, respectively. *G* represents a constant. The denominator $D_{ij}^{\beta 3}$ is the distance between *i* and *j*. Using exponent values β_1, β_2 , and β_3 allow us to estimate the elasticity of each variable. For example, β_1 represents the elasticity of the source population. To preserve the elasticity interpretation provided in the theoretical model, gravity equations are often expressed in log-log format. When expressed in log-log format, these elasticities become the coefficients of each variable. For example, the value of β_1 can be tested against the hypothesis that it is equal to 1.0, which would imply that source population has no effect on migration (Greenwood, 2005). A 1% increase in country *i*'s population would result in a β_1% increase in migration from *i* to *j*.

Equation 2 provides a log-linearized gravity model of migration. It is common to see gravity equations that include variables to represent individual characteristics of countries *i* and *j*. Again, included in these variables are those that represent some measure of country "size," like population. These are represented in equation 2 by X_i and X_j. Extensions of the gravity model usually include other variables related to country pair characteristics, as there are a host of other factors specific to country relationships that may affect migration. These can be either quantitative, such as distance between the countries, or qualitative, which may involve linguistic commonalities or colonial relationships. Quantitative source-destination pair variables are represented in equation 2 by D_{ij}. This variable stands for distance in this instance, but it can also represent other quantitative variables. Qualitative variables are dummy variables represented by z_{ij}.

$$\ln M_{ij} = \beta_0 + \sum_{n=1}^{m} \beta_{in} \ln X_{in} + \sum_{n=1}^{m} \beta_{jn} \ln X_{jn} + \sum_{n=1}^{m} \beta \ln D_{ijn} + \sum_{n=1}^{m} \beta z_{ijn} + e_{ij} \quad (2)$$

Grogger and Hanson's (2011) framework, like many theoretical models applied to brain drain, outline an individual's decision to acquire more or less education based on a function of that individual's utility. In order to keep the model simple, the authors assume that the education decision has already been made, and that it plays a role in utility gains or losses from emigrating. Additionally, it is assumed that workers make their migration decision of whether and where to emigrate so as to maximize their utility. First, let the wage for worker *a* with skill level *s* from source country *i* in destination country *j* be

$$W_{aij}^{s} = \exp\left(\mu_j + \delta_j^2 L_{ai}^2 + \delta_j^3 L_{ai}^3\right). \quad (3)$$

In their equation, Grogger and Hanson (2011) define $\exp(\mu_j)$ as the wage for workers with primary education in destination *j*. The rest of the model builds on wages associated with primary education, meaning the authors assume these wages to be the base wage across countries. Next, δ_j^2 is the return to secondary education in *j*, and δ_j^3 is the return to tertiary education in *j*. Notice that these returns to higher levels of education are dependent on the dummy variable L_{ai}^s, which equals 1 if person *a* from source *i* has schooling level *s*. Essentially, the model stipulates that expected wages build upon the primary-education wages depending on whether a person has achieved secondary or tertiary education.

Emigration poses a variety of costs which are accounted for in Grogger and Hanson's (2011) utility model. The authors assume that these costs consist of two components: a fixed monetary cost of moving from i to j, given by f_{ij}; and a component varying by skill, given by g_{ij}^s. The cost function of emigration would thus read,

$$C_{aij}^s = f_{ij} + \beta g_{ij}^s. \tag{4}$$

Next, Grogger and Hanson (2011) construct a linear-utility equation to model the interaction between wages and costs in terms of an individual's utility received from migration. The utility associated with migration from *i* to *j* (U_{aij}^s) is represented as a function of the difference between the wage earned in country *j* (W_{aj}^s) and migration costs (C_{aij}^s), as well as an unobserved error term:

$$U_{aij}^s = \gamma\left(W_{aj}^s - C_{aij}^s\right) + \varepsilon_{aij}^s. \tag{5}$$

Grogger and Hanson (2011) assume that γ is greater than zero. The source country can theoretically be considered a destination as well, but migration costs would equal zero in this case. In this scenario, the equation would yield the utility associated with staying in the source country, which could then be compared to the utility associated with migration in order to compare the two choices. This, however, is not explored in Grogger and Hanson's (2011) framework.

For the purposes of their study, Grogger and Hanson (2011) suggest examining log odds as a measure of high-skilled emigration. They expand upon equation 5 by expanding costs C_{aij}^s to include fixed and skill-related costs. These are now written individually, which allows for specific expression of the opportunity cost associated with the difference in wages between i and j. The authors examine the log odds of migrating to destination *j* versus staying in source *i* for those with skill level *s*:

$$\ln\left(\frac{E_{ij}^{s}}{E_{i}^{s}}\right) = \beta\left(W_{j}^{s} - W_{i}^{s}\right) - \beta f_{ij} - \beta g_{ij}^{s}. \tag{6}$$

The term E_{ij}^{s} is the population share of education level *s* in source country i that migrates to destination *j*, while E_{i}^{s} is the population share of source *i* that does not migrate (Grogger and Hanson, 2011).

This study seeks to model actual emigration flows among skilled individuals, rather than the log-odds of emigration. In place of log-odds, one could substitute the natural log of migration from source *i* to destination *j*. Education group is still specified with the superscript *s*, and the natural log of migration is represented by the natural log of M_{ij}^{s} in equation 6.1 below.

$$\ln M_{ij}^{s} = \beta\left(W_{i}^{s} - W_{j}^{s}\right) - \beta f_{ij} - \beta g_{ij}^{s} \tag{6.1}$$

The function now specifies the emigration flow of a certain skill group to be a function of the opportunity cost associated with wages, the fixed monetary cost of emigration, and other costs varying by skill level. The structure of Grogger and Hanson's (2011) model is the same except for the dependent variable, which gives their model a new focus and purpose.

Equation 6.1 can now be applied to equation 2 to introduce differenced variables to the gravity model. Because the fixed monetary cost of emigration f_{ij} is purely theoretical, we can replace this variable with other determinants of emigration costs not associated with skill level. These variables usually include a mix of variables represented by *X* and *z*, but are most easily conceptualized with the fact that distance between *i* and *j* is fixed. Skill related costs are difficult to measure exactly, but can be captured by a variety of variables, including linguistic ability. Thus, g_{ij}^{s} is also accounted for with variables represented by *X* and *z*. The only remaining part of equation 6.1 is the wage difference, which is now incorporated and transformed into log form in equation 7 below.

$$\ln M_{ij}^{s} = \beta_0 + \beta_1 \ln\left(W_{j}^{s} - W_{i}^{s}\right) + \sum_{n=1}^{m} \beta \ln X_i + \sum_{n=1}^{m} \beta \ln X_j + \sum_{n=1}^{m} \beta D_{ij} + \sum_{n=1}^{m} \beta z_{ij} + e_{sh} \tag{7}$$

The theoretical equation is now set up nicely for empirical evaluation. Based on these parameters, it is expected that a positive wage difference for high-skilled workers will have a positive effect on high-skill emigration from the source country to the destination country.

V. DATA

Data on emigration flow from source countries to destination countries is provided by Brücker, Capuano, and Marfouk (2013) (henceforth BCM). The authors list migrant stocks for the years 1985, 1990, 1995, 2000, 2005, and 2010. The data set breaks down these migration flows by education level, gender, and country of origin. Emigration stocks are broken down into three categories corresponding to education level: primary, secondary, and tertiary. In the remainder of this paper, individuals with tertiary education will be considered to be high-skilled, those with only secondary education to be medium-skilled, and those with only primary education to be low-skilled.[1] Only the 28 OECD countries are recorded as destination countries.

Data on independent variables comes from two distinct data sets. First, the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) provides a "gravity" data set assembled by Head and Mayer (2013). This data set captures many qualitative variables and indicators specific to source-destination pairs. These include dummy variables for border contiguity, common language, and colonial relationships, among others. Weighted distance is also recorded per source-destination pair. Second, the World Development Indicators (WDI) provide various economic indicators like GDP growth, income quintiles, and demographic variables like population size and life expectancy (The World Bank, 2017).

Unfortunately, neither CEPII nor WDI offer a measure of wage by education level. Instead, I use data on monthly occupational wages assembled by Freeman and Oostendorp (2012). Their data is based on the International Labor Organization (ILO) October Inquiry, which they cite as the most comprehensive international occupational wage survey. The authors standardize their data to make it more widely applicable to all workers, including standardizations for sex, age, and hourly versus monthly wages. Wage values are originally reported in nominal U.S. dollar amounts but are converted to real values using a base year of 2010 for the purposes of this study. For all further data and calculations involving occupational wage data, real U.S. dollar values are used.

To use the monthly occupational wage data as a proxy for data on wages by education level, they must be grouped in such a way that corresponds with

[1] No data is provided for individuals with no education.

education levels. For this purpose, quintiles of occupational wages based on country and year are constructed. For each year and within each country, all reported occupational wages are assigned a quintile bucket based on its value. Quintiles are numbered one through five, with one being the lowest and five being the highest.[2] The values within each quintile are averaged to provide a single quintile wage for each year per country. These highest, middle, and lowest quintile wages are then assumed to correspond with the average wage of individuals with tertiary, secondary, and primary education, respectively. The only exception is that when predicting total emigration, total GDP per capita is used as the wage proxy, rather than an occupational wage measure.

Time and data constraints do limit these variables. First, using only the first, third, and fifth quintiles inherently leaves out wage observations in the second and fourth quintiles. These could have been included by creating an average between the first and second, second and third, and so on. Still, education levels between these quintiles are likely different, and this study is aiming to find unique results related to each education level. While some data is omitted by leaving out the second and fourth quintiles, it is more likely that the wages observed are associated with the three targeted education levels. Additionally, data constraints prevent the creation of an appropriate occupational wage measure to test against total emigration. Multiple "averages of averages" would have to be used to construct this variable, which would make it far less trustworthy than simply using GDP per capita.

The assumption that the first, third, and fifth quintiles correspond to primary, secondary, and tertiary levels of education requires justification. For this, it is useful to examine which occupations' wages tend to fall into these selected quintiles. Evaluating whether the occupations in each quintile correspond to tertiary, secondary, and primary education levels ought to shed light on the strength of this assumption. First, Table 1 lists the top 20% most frequent occupations that appear in the fifth quintile (Q5). It is well known, or reasonable to assume, that many of the occupations appearing here require highly specialized education or tertiary degrees. The occupations listed contain 62% of all Q5 wage observations, suggesting that the Q5 occupational wage measures are a relatively good proxy for wages of tertiary educated individuals.

Next, Table 2 lists the top 20% most frequent occupations that appear in the third quintile (Q3). The distribution of occupations is more widespread here, as only

[2] The "highest" quintile wages lie between the 80th and 100th percentiles, the "middle" quintile wages lie between the 40th and 60th percentile, and the "lowest" quintile wages lie between zero and the 20th percentile.

39% of all Q3 wage observations are contained in the top 20% most frequent occupations. Still, the occupations found here are commonly characterized as middle-class jobs. These jobs rarely require tertiary education, and most require secondary education. Thus, the Q3 occupational wage measures are a fair proxy for wages of secondary educated individuals.

Finally, Table 3 lists the top 20% most frequent occupations in the first quintile (Q1). These contain 55% of all Q1 wage observations, and it is easy to see that most jobs listed do not require tertiary or secondary education. It is reasonable to assume that these jobs could be held by those with only primary education, making the Q1 occupational wage measures a good proxy for wages of primary educated individuals.

TABLE 1: Occupations in the Fifth Quintile

Occupation Name	Percentage	Cumulative Percentage
General physician	3.62%	3.62%
Power distribution and transmission engineer	3.41%	7.03%
Accountant	3.40%	10.43%
Air transport pilot	2.86%	13.29%
Teacher (third level)	2.85%	16.14%
Dentist (general)	2.78%	18.92%
Teacher in languages and literature (third level)	2.58%	21.50%
Chemical engineer	2.42%	23.92%
Journalist	2.36%	26.28%
Computer programmer	2.22%	28.50%
Air traffic controller	2.13%	30.63%
Flight operations officer	1.94%	32.57%
Teacher in languages and literature (second level)	1.91%	34.48%
Computer programmer	1.88%	36.36%
Aircraft engine mechanic	1.85%	38.21%
Mathematics teacher (second level)	1.78%	39.99%
Government executive official – central	1.78%	41.77%
Aircraft cabin attendant	1.75%	43.52%
Technical education teacher (second level)	1.70%	45.22%
Ship's chief engineer	1.61%	46.83%
Petroleum and Natural Gas Engineer	1.57%	48.40%
Supervisor or general foreman	1.51%	49.91%
Professional nurse (general)	1.46%	51.37%
Insurance agent	1.37%	52.74%
Power-generating machinery operator	1.28%	54.02%
Bank teller	1.28%	55.30%
Govt. executive official – regional or provincial	1.25%	56.55%
Govt. executive official – local authority	1.21%	57.76%
Supervisor or general foreman	1.19%	58.95%
Clerk of works	1.13%	60.08%
Physiotherapist	1.13%	61.21%
Chemistry technician	1.12%	62.33%

TABLE 2: Occupations in the Third Quintile

Occupation Name	Percentage	Cumulative Percentage
Construction carpenter	1.68%	1.68%
Automobile mechanic	1.66%	3.34%
Automobile mechanic	1.63%	4.97%
Printing pressman	1.59%	6.56%
Plumber	1.50%	8.06%
Welder	1.49%	9.55%
Building electrician	1.46%	11.01%
Machine compositor	1.34%	12.35%
Motor bus driver	1.32%	13.67%
Book-keeper	1.27%	14.94%
Stock records clerk	1.26%	16.20%
Hand compositor	1.25%	17.45%
Building painter	1.22%	18.67%
Hotel receptionist	1.19%	19.86%
Bricklayer (construction)	1.19%	21.05%
Office clerk	1.15%	22.20%
Constructional steel erector	1.13%	23.33%
Stenographer-typist	1.11%	24.44%
Post office counter clerk	1.11%	25.55%
Metalworking machine setter	1.09%	26.64%
Urban motor truck driver	1.08%	27.72%
Long-distance motor truck driver	1.08%	28.80%
Bookbinder (machine)	1.07%	29.87%
Telephone switchboard operator	1.07%	30.94%
Stenographer-typist	1.05%	31.99%
Ambulance driver	1.05%	33.04%
Dairy product processor	1.04%	34.08%
Grain miller	1.04%	35.12%
Cook	1.04%	36.16%
Mixing- and blending-machine operator	1.03%	37.19%
Machinery fitter-assembler	1.02%	38.21%
Clerk	1.02%	39.23%

TABLE 3: Occupations in the First Quintile

Occupation Name	Percentage	Cumulative Percentage
Sewing-machine operator	2.97%	2.97%
Laborer	2.78%	5.75%
Room attendant or chambermaid	2.65%	8.40%
Laborer	2.61%	11.01%
Waiter	2.59%	13.60%
Laborer	2.27%	15.87%
Salesperson	2.24%	18.11%
Field crop farm worker	2.10%	20.21%
Laborer	1.88%	22.09%
Garment cutter	1.87%	23.96%
Packer	1.79%	25.75%
Laborer	1.74%	27.49%
Shoe sewer (machine)	1.74%	29.23%
Baker (oven man)	1.71%	30.94%
Leather goods maker	1.68%	32.62%
Laborer	1.65%	34.27%
Cash desk cashier	1.62%	35.89%
Clicker cutter (machine)	1.57%	37.46%
Thread and yarn spinner	1.56%	39.02%
Plantation worker	1.55%	40.57%
Cloth weaver (machine)	1.53%	42.10%
Refuse collector	1.52%	43.62%
Laster	1.51%	45.13%
Cook	1.46%	46.59%
Laborer	1.40%	47.99%
Forestry worker	1.24%	49.23%
Laborer	1.24%	50.47%
Sawmill sawyer	1.17%	51.64%
Tanner	1.14%	52.78%
Hotel receptionist	1.13%	53.91%
Wooden furniture finisher	1.10%	55.01%

Unfortunately, the incompleteness of the Freeman and Oostendorp data set limits the available degrees of freedom so much that it cannot be used in a regression analysis with the BCM data without some manipulation. Constructing five-year averages of quintile occupational wages by country and year makes the data much more complete and useful. These averages include the target years reported in the BCM database and the four years prior. For example, the value of Q5 wages in 1985 has been recalculated as an average of Q5 wage observations from 1981 through 1985. This calculation increases the degrees of freedom substantially, and makes the data set useful when dealing with the timeframe restrictions of the BCM data set. The proxy of GDP per capita is not transformed into five-year wage averages, as data for this variable is very complete.

Finally, the five-year wage averages specific to each quintile are subtracted between source-destination pairs to create a skill-specific wage difference. Each wage difference is calculated as the destination wage minus the source wage. To provide more information on wage differences as the variable of interest, Table 4 provides summary statistics for wage differences across the three selected quintiles, as well as for the total population.[3] Recall that monthly wages are used in this study. Wages in each skill category follow an approximately normal distribution, though perhaps showing a slight leftward skewness. It is also important to note that the mean and median wage differences are not close to zero. This finding is noteworthy, because it means that there is a high likelihood that wage differences among source-destination pairs are not trivial. In other words, it is reasonable to assume that something like a 10% change in a wage difference is not so small as to go unnoticed by a reasonable individual making their emigration decision.

TABLE 4: Summary Statistics of Occupational Wage Differences

Wage Differences (5-year Averages)	(1) N	(2) Mean	(3) Median	(4) St. dev	(5) Min	(6) Max
Low-Skill	55,505	775	810	1,161	-4,876	5,044
Medium-Skill	53,850	931	956	1,501	-6,181	6,374
High-Skill	54,625	1,360	1,331	2,569	-14,973	10,641
GDP per Capita	252,850	19,208	18,918	24,156	-131,386	111,742

The negative minimum values in table 4 above do not indicate negative wages. Again, the table is related to wage differences between the destination and source countries. When the occupational wage in the source country is greater than that of the destination, the value will appear negative. These negative observations are

[3] A more detailed table that includes a distribution across percentiles can be found in Appendix A.

included in the regression analysis, but the fact that they are far from zero still indicates that wage differences are not trivial

VI. Empirical Model

A multivariate regression with robust standard errors is used to test the relationship between skill-related wage differences and skilled emigration. It is important to note that SD pairs are unique to the direction of emigration recorded in the data. For example, the SD pair Germany-Austria is different than Austria-Germany. Source and destination specific data are used to create wage difference. Other variables used in this model include the populations of the source and destination countries (POP), average life expectancy in both countries (LE)[4], and stock of international migrants in the destination country (MIG). These variables, along with weighted distance between the source and destination countries (DIST), will be transformed to their natural log. Other dummy variables account for the effects of various characteristics of SD pairs, and will not be logged. These variables indicate contiguity (CONTIG), whether the destination country is an EU member (DEU), linguistic commonality (LANG), religious commonality (RELIG) [5], and whether the countries have had colonial ties after 1945 (COL). The regression would appear in written form as follows:

$$\begin{aligned} \ln M_{ij}^{s} &= \ln\beta_0 + \beta_1 \ln(\mathrm{OCCWAGE})_{ij}^{s} + \beta_2(\mathrm{POP})_i + \beta_3(\mathrm{POP})_j \\ &+\beta_4 \ln(\mathrm{LE})_i + \beta_4 \ln(\mathrm{LE})_j + \beta_5 \ln(\mathrm{MIG})_j + \beta_6 \ln(\mathrm{DIST})_{ij} + \beta_7(\mathrm{DEU})_j \\ &+\beta_8(\mathrm{CONTIG})_{ij} + \beta_9(\mathrm{LANG})_{ij} + \beta_{10}(\mathrm{RELIG})_{ij} + \beta_{11}(\mathrm{COL})_{ij} + e. \end{aligned} \tag{8}$$

If the coefficient β_1 is statistically significant, then it can be interpreted as the elasticity of high-skilled emigration. In other words, a 1% change in the relevant skilled wage difference would cause a β_1% change in emigration from source to destination. A positive wage difference ought to cause higher (positive) emigration from the source country to the destination country. In order to delineate effects unique to the brain drain phenomenon, as opposed to emigration of other skill groups, I conduct tests using emigration of high, medium, and low skilled groups as dependent variables, as well as total emigration. All regressions are calculated to include robust standard errors.

There is some potential for reverse causality or endogeneity with regards to wage related variables. Migrant flows may decrease wages in the destination

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[4] This measure is intended to serve as a proxy for population health and standard of living.

[5] Linguistic commonality is defined as each country sharing a language spoken by at least 9% of the population in each. The same is true of religious commonality in regards to sharing a religion.

country and increase wages in the source country. The use of five-year wage averages, however, ought to mitigate the risk of these econometric issues. Furthermore, empirical evidence in labor economics indicates that these flows have essentially no impact on a destination country's wages, and only a positive impact on the source country's wages (Mayda 2010). If anything, the effect of wage differences may be underestimated.

VII. Results

The results of the model can be seen in Table 5. Overall, these results suggest that wage differences are insignificant for high- and medium-skilled emigration. The negative coefficient on fifth quintile wage differences is unique, but it is difficult to interpret as the coefficient is not statistically significant. This insignificant result is consistent with previous literature, which has suggested that wage or income related variables are not the most important factor behind high-skilled emigration.

Another result indicating some uniqueness to high-skill emigration is the relatively small effect of contiguity between source and destination countries. This factor is more important for medium- and low-skill emigration, which may result from relatively low costs of movement between contiguous countries. It is reasonable to think that individuals with higher skills, and perhaps higher incomes, are able to more freely choose where they want to migrate, and actually reach that destination. Those with middle and lower incomes would likely find job opportunities across a border to be easier to attain than those in distant countries. This interpretation is strengthened when observing the weighted distance variable, which also has the weakest negative effect on high-skilled emigration.

This model shows the size of the destination's migrant stock to be a significant and positive factor across all emigration categories. This makes sense as countries with higher migrant stocks are more likely to be open to immigrants. Additionally, the coefficients on common language, common religion, and colonial relationships are all positive. It is not surprising that these variables are significant and positive for all categories of emigration, as these source-destination pair qualities would make migration between the source and destination easier across all skill levels.

The disparities between the coefficients on source and destination life expectancy tell an interesting story. Higher source life expectancy appears to be associated with higher emigration flows. Seeing as this is relatively consistent across all categories of emigration, this could simply suggest that healthier countries tend to have more emigrants. Destination life expectancy has a notably strong pull effect on high- and medium-skilled emigrants, suggesting that these individuals are attracted to countries with high health standards. This finding is also consistent with previous literature, as other authors have found lifestyle factors to be important to high-skilled emigrants.

In light of past literature, there may be some confusion surrounding the interpretation of the source country population coefficient in light of past literature. Recall that Docquier et al. (2007) found that source countries with small populations had higher rates of brain drain. In their model, this effect appears as negative, representing an inverse relationship. The coefficients in this study for source country population are positive, however, because the dependent variable does not represent a rate of emigration, but rather a flow. The positive effect indicates that larger source countries have higher amounts of emigrants, which makes sense.

A variable that yields non-intuitive results is the dummy variable indicating whether the destination is an EU country. It is strange that EU membership among destination countries seems to have a negative effect on the emigration flow from source countries, especially since EU nations tend to be modern, democratic, and wealthy. One potential explanation could be that these nations also have more restrictive immigration policies, which would certainly limit the flow of migrants into those countries.

TALBE 5: Modified Gravity Model

VARIABLES	(1) High-Skill	(2) Medium-Skill	(3) Low-Skill	(4) Total
Q5 Occupational Wage Diff	-0.0263			
	(0.0346)			
Q3 Occupational Wage Diff		0.0260		
		(0.0352)		
Q1 Occupational Wage Diff			0.102**	
			(0.0397)	
GDP per Capita Diff				0.103***
				(0.0255)
Source Pop	0.757***	0.728***	0.791***	0.836***
	(0.0135)	(0.0140)	(0.0142)	(0.00819)
Destination Pop	1.005***	0.933***	0.810***	1.015***
	(0.0192)	(0.0213)	(0.0224)	(0.0126)
Source LE	5.026***	4.935***	5.284***	5.246***
	(0.196)	(0.212)	(0.218)	(0.123)
Destination LE	14.70***	10.57***	5.873***	7.039***
	(1.487)	(1.566)	(1.647)	(0.824)
Destination Migrant Stock	0.719***	0.350***	0.437***	0.522***
	(0.0398)	(0.0425)	(0.0442)	(0.0260)
Weighted Distance	-0.973***	-1.127***	-1.147***	-1.185***
	(0.0378)	(0.0402)	(0.0425)	(0.0241)
Destination is EU	-1.300***	-1.236***	-0.657***	-1.450***
	(0.0668)	(0.0687)	(0.0710)	(0.0380)
Contiguity	0.272*	0.698***	0.529***	0.632***
	(0.162)	(0.184)	(0.193)	(0.158)
Common Language	1.932***	1.640***	1.446***	1.515***
	(0.0856)	(0.0984)	(0.110)	(0.0503)
Common Religion	0.343**	0.666***	0.434**	0.855***
	(0.160)	(0.164)	(0.171)	(0.0812)
Colonial Relationship	2.529***	2.143***	3.376***	2.997***
	(0.149)	(0.181)	(0.181)	(0.108)
Constant	-101.3***	-79.90***	-60.63***	-68.52***
	(6.171)	(6.462)	(6.786)	(3.418)
Observations	3,608	3,585	3,757	14,522
R-squared	0.758	0.697	0.659	0.654

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

VIII. Robustness Check

In order to check the robustness of the main model and evaluate the validity of using occupational wages, a different proxy for wage differences by education group is used: income per capita of the first, third, and fifth income quintiles. Quintiles are categorized just as before, with Q1 being the lowest and Q5 being the highest.[6] All other variables from the main model remain, including the log transformation of the dependent variable.

Following intuition used by Grogger and Hanson (2011), income per capita by quintile for each country in a given year is calculated using income share per quintile, S.[7] All GDP measures are recorded in 2010 U.S. dollars, meaning all wage proxy values are real and directly comparable to one another. The monetary value of a quintile's total wealth is calculated by multiplying S and the source country GDP, Y_i. That value can then be put into per capita terms by dividing it by the population of one income quintile, which is one-fifth of the total population P_i. The per capita income of quintile q in country i is denoted as y_i^q, which is then assumed to equal the per capita income of the relevant skill level s.

$$y_i^q = \frac{S * Y_i}{0.2(P_i)} = y_i^s \tag{9}$$

Five-year averages of per capita income by skill level are constructed in the same fashion as the occupational wage variables. By utilizing income share per quintile, this wage proxy accounts for some degree of income inequality. If one were to simply divide GDP per capita by five, it would inaccurately assume that the richest and poorest individuals in a country receive exactly the same share of total income. Total GDP per capita will continue to be used as the wage proxy for regressions predicting total emigration and is similarly not transformed into a five-year average due to the completeness of the data. These proxy measures related to income will be referred to as "wages" for the remainder of this paper.

Similar to Table 4, Table 6 below provides summary statistics for the new wage difference proxies across the three selected quintiles, as well as for the total

[6] The "highest" quintile incomes lie between the 80th and 100th percentiles, the "middle" quintile incomes lie between the 40th and 60th percentile, and the "lowest" quintile incomes lie between zero and the 20th percentile.
[7] Income share per quintile is the percentage of a country's income earned by a specific quintile of residents. This measure is provided by WDI in terms of percentage of total income or consumption in a given year.

population.[8] These summary statistics pertain to the five-year averages of quintile income per capita. Wages in each skill category follow an approximately normal distribution. Again, it is easy to see that the newly estimated wage differences are not trivial since the mean and median values are quite larger than zero. It is reasonable to assume that something like a 10% change in these wage differences would not be so small as to go unnoticed by emigrants.

TABLE 6: Summary Statistics of Wage Differences based on Quintile Income per Capita

Wage Differences (5-year Averages)	(1) N	(2) Mean	(3) Median	(4) St. dev	(5) Min	(6) Max
Low Skill	62,275	11,111	9,434	14,600	-61,868	65,493
Medium Skill	62,275	20,281	19,558	24,367	-84,936	90,634
High Skill	62,275	46,208	45,809	54,457	-187,329	210,354
GDP per Capita	252,850	19,208	18,918	24,156	-131,386	111,742

To further assess the validity of this wage proxy, Table 7 provides the correlation coefficients between occupational wage differences and the corresponding quintile income per capita differences.[9] These correlation coefficients pertain to the five-year averages of these measures. It is apparent that the wage difference measures are highly correlated. Since the occupational wage variables were deemed to be strong proxies for wages by education level, the same can be said for quintile income per capita.

TABLE 7: Correlation between Proxies for Wages

Wage Proxy Variables (5-year Averages)	Q5 Income per Capita Difference	Q3 Income per Capita Difference	Q1 Income per Capita Difference
Q5 Occupational Wage Difference	0.7811		
Q3 Occupational Wage Difference		0.7998	
Q1 Occupational Wage Difference			0.7545

[8] A more detailed table that includes a distribution across percentiles can be found in Appendix B.
[9] A more detailed correlation table can be found in Appendix C

IX. Robustness Check Results

The results of the robustness check can be found in Table 8 on the next page. Here, the coefficients on the new wage proxy variables are somewhat different than those for occupational wages. The wage results are significant across all categories of emigration, but negative only for high-skilled emigration. Compared to the insignificant wage results in the main model, this finding provides an alternative interpretation of wage effects on emigration. The differing results highlight the fact that the wage proxies used in this paper are not perfect, and future research ought to explore better wage proxies. In general, this model strengthens the idea that wage differences are more important for emigrants of lower skill levels.

Aside from wage variables, the vast majority of coefficients in the robustness check echo the results of the main model. Border contiguity is again shown to be far less significant for high-skilled emigration than for other emigration categories. This model suggests that the negative effect of EU destinations is even larger than what was seen earlier, but the negative effect remains consistent. In contrast, the results pertaining to destination life expectancy and destination migrant stock are quite different and more varied than in the main model. It should be noted that the R squared values are higher in the main model than they are in these robustness check regressions, meaning that coefficients were probably more accurately estimated in the main model.

TABLE 8: Modified Gravity Model using Income Per Capita by Quintile

VARIABLES	(1) High Skill	(2) Medium Skill	(3) Low Skill	(4) Total
Q5 Income Per Cap Diff	-0.116***			
	(0.0357)			
Q3 Income per Cap Diff		0.142***		
		(0.0380)		
Q1 Income per Cap Diff			0.175***	
			(0.0395)	
GDP per Capita Diff				0.103***
				(0.0255)
Source Pop	0.834***	0.799***	0.794***	0.836***
	(0.0167)	(0.0178)	(0.0180)	(0.00819)
Destination Pop	0.951***	0.882***	0.830***	1.015***
	(0.0198)	(0.0225)	(0.0234)	(0.0126)
Source LE	5.910***	6.352***	6.434***	5.246***
	(0.206)	(0.222)	(0.222)	(0.123)
Destination LE	0.767	3.708**	-1.906	7.039***
	(1.598)	(1.789)	(1.848)	(0.824)
Destination Migrant Stock	0.788***	-0.0181	0.198***	0.522***
	(0.0420)	(0.0495)	(0.0536)	(0.0260)
Weighted Distance	-1.056***	-1.202***	-1.214***	-1.185***
	(0.0374)	(0.0402)	(0.0416)	(0.0241)
Destination is EU	-1.675***	-1.484***	-0.989***	-1.450***
	(0.0606)	(0.0641)	(0.0687)	(0.0380)
Contiguity	0.277	0.623***	0.758***	0.632***
	(0.199)	(0.221)	(0.230)	(0.158)
Common Language	1.411***	1.241***	1.002***	1.515***
	(0.0818)	(0.0940)	(0.0966)	(0.0503)
Common Religion	0.395***	0.784***	0.699***	0.855***
	(0.115)	(0.129)	(0.137)	(0.0812)
Colonial Relationship	2.541***	1.899***	3.256***	2.997***
	(0.181)	(0.193)	(0.211)	(0.108)
Constant	-42.74***	-55.84***	-31.63***	-68.52***
	(6.909)	(7.742)	(8.038)	(3.418)
Observations	4,253	4,206	4,182	14,522
R-squared	0.708	0.633	0.601	0.654

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

X. Conclusion

Brain drain is a contentious issue for politicians and economists alike. The bulk of literature has attempted to explain the effects of brain drain through theory and empirical evidence. Thorough research in this area has allowed for much development on the effects of brain drain. Research on brain drain's causes, however, is heavily lacking. Many studies link brain drain to qualitative country-pair characteristics, but very few explicitly examine the role of wages.

This paper attempts to answer the question: How do international wage differences affect the rate of high-skilled emigration? A modified gravity model tests the effects of skill-related wage differences on high, medium, low-skilled, and total emigration. While previous studies have relied on data from only 1990 and 2000, this paper uses an updated data set spanning 1980 to 2010. Although income per capita estimates act as proxies for wage differences, this paper focuses on the factor of wage differences more than most studies in relevant literature. Comparing the effect of this variable, among others, across different skill categories of emigration also helps highlight characteristics unique to the brain drain phenomenon, as opposed to common factors of emigration related to different skill groups and populations as a whole.

Using proxies based on occupational wages, this study suggests that high-skill wage differences between source and destination countries are not a significant factor of high-skill emigration. This result is consistent with previous literature and reflected in the robustness check, which utilizes a different wage proxy based on income by quintile. The insignificance of wage differences may be unique to brain drain, as wage effects tend to positively and significantly affect medium-skilled, low-skilled, and total emigration. In addition, border contiguity and weighted distance are far less significant factors behind high-skilled emigration than for medium skilled, low skilled, and total emigration.

Future research should continue to focus on the role of wages and income in the brain drain phenomenon. The wage proxies used in this paper are not perfect, and when viewed alone, could lead researchers to different conclusions. Better data collection in the future ought to yield data on wages by education level, but until then economists ought to develop a more accurate and consistent proxy variable. Expanding the set of control variables is also desirable. Including a control for the strictness of destination immigration policy would likely improve the models used in this paper, and perhaps explain why EU membership among destination countries seems to discourage migration in their direction. A variable controlling for political stability would also yield valuable information and would probably show significant. Unfortunately, time and data restrictions prevented the inclusion of these variables in this study. Finally, future studies may be able to improve upon the empirical methods used in this paper. Methods to increase degrees of freedom would be advantageous to reevaluating results found here. It would probably be beneficial to construct an occupational wage variable that could be used in the regression for total emigration, rather than using GDP per capita, as it would be more comparable to the other wage proxies. Still, this study provides a good starting point for future researchers to pin down the effects of wage differences on brain drain.

Appendix A: Expanded Summary Statistics of Occupational Wage Differences

Wage Differences (5-year Averages)	(1) N	(2) Mean	(3) St. Dev	(4) Min	(5) Max	(6) Skewness	(7) Kurtosis
Low-Skill	55,505	774.8	1,161	-4,876	5,044	-0.252	4.196
Medium-Skill	53,850	931.5	1,501	-6,181	6,374	-0.311	4.065
High-Skill	54,625	1,360	2,569	-14,973	10,641	-0.384	4.780
GDP per Capita	252,850	19,208	24,156	-131,386	111,742	-0.0756	4.976

Wage Differences (5-year Averages)	(8) p1	(9) p5	(10) p10	(11) p25	(12) p50	(13) p75	(14) p90	(15) p95	(16) p99
Low-Skill	-2,348	-1,220	-587.3	73.03	810.3	1,581	2,092	2,467	3,420
Medium-Skill	-3,117	-1,692	-874.8	31.74	955.7	1,972	2,690	3,117	4,044
High-Skill	-5,418	-2,939	-1,760	-75.03	1,331	3,070	4,580	5,423	6,720
GDP per Capita	-48,052	-21,264	-7,417	5,683	18,918	33,242	45,544	56,997	87,890

Appendix B: Expanded Summary Statistics of Wage Differences based on Quintile Income per Capita

Wage Differences (5-year Averages)	(1) N	(2) mean	(3) sd	(4) min	(5) max	(8) skewness	(9) kurtosis
Low-Skill	62,275	11,111	14,600	-61,868	65,493	0.195	5.303
Medium-Skill	62,275	20,281	24,367	-84,936	90,634	-0.107	4.513
High-Skill	62,275	46,208	54,457	-187,329	210,353	-0.115	4.534
GDP per Capita	252,850	19,208	24,156	-131,386	111,742	-0.0756	4.976

Wage Differences (5-year Averages)	(11) p1	(12) p5	(13) p10	(14) p25	(15) p50	(16) p75	(17) p90	(18) p95	(19) p99
Low-Skill	-28,513	-11,755	-3,096	3,031	9,434	18,899	28,273	36,995	58,127
Medium-Skill	-47,579	-21,581	-4,855	5,600	19,558	35,882	43,630	61,451	86,007
High-Skill	-109,038	-49,498	-10,523	15,342	45,809	80,126	101,057	143,116	198,106
GDP per Capita	-48,052	-21,264	-7,417	5,683	18,918	33,242	45,544	56,997	87,890

Appendix C: Correlation between Occupational Wage and Quintile Income per Capita Differences

Wage Variables	Q5 Inc/Cap Diff	Q3 Inc/Cap Diff	Q1 Inc/Cap Diff	Q5 Occ. Wage Diff	Q3 Occ. Wage Diff	Q1 Occ. Wage Diff
Q5 Inc Cap Diff	1					
Q3 Inc Cap Diff	0.9831	1				
Q1 Inc Cap Diff	0.9253	0.9565	1			
Q5 Occ Wage Diff	0.7811	0.7753	0.6945	1		
Q3 Occ Wage Diff	0.784	0.7998	0.7421	0.9742	1	
Q1 Occ Wage Diff	0.7715	0.8006	0.7545	0.9544	0.9915	1

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