Resource Shocks and Human Capital Stocks - Brain Drain or Brain Gain?

DANIEL STEINBERG*

University of Tübingen

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Abstract

Based on the paradox of plenty, resource abundant countries tend to be vulnerable for lower economic prosperity along with instable political institutions as well as corruption. This paper sheds light on the relationship between resource abundance and the selectivity of migration. First, we combine a Dutch-Disease-Model with a Roy-Borjas-Model in order to elaborate on the relationship between resource shocks and migrant selectivity theoretically. Thereby, we predict that resource booms give rise to brain drain effects which are mediated through income inequality effects. Second, we provide empirical evidence for the effect of resource shocks on migrant selectivity based on a structural equation model in order to disentangle effects on income inequality and migrant selectivity. Our results show that resource shocks, especially oil booms, strengthen brain drain effects in a sample with 113 countries between 1910-2009.

Keywords: Resources, Income Inequality, International Migration
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*Department of Economics, Melanchthonstr. 30, 72074 Tübingen, Germany, email: Daniel.Steinberg@uni-tuebingen.de.

1 Introduction

"One of the surprising features of economic life is that resource-poor economies often vastly outperform resource-rich economies in economic growth."

– Jeffrey Sachs and Andrew Warner (1985)

Whether the detection of resources is a curse or a blessing for economic development has been subject to numerous studies. In their pioneering paper, Sachs and Warner (1995) delivered evidence that the exploration and exploitation of natural resources is an impediment to economic prosperity based on a sample of 79 developing countries. This disparity between natural and economic wealth, known as the "resource curse" (Auty (1993)), is in line with the findings of several other authors (Gelb (1988) and Gylfason et al. (1999)). In general, the effect appears to be particularly relevant for countries which are prone to corruption and government inefficiencies (Van der Ploeg (2011)).

Gylfason (2001) devoted another paper to the question, whether resource abundance crowds out educational investments and concludes that "public expenditure on education relative to national income, expected schooling for girls, and gross secondary school enrollment are all shown to be inversely related to the share of natural capital in national wealth across countries" (p. 847). Despite unprecedented research, most of the studies regarding the resource curse focus on the relationship between resource abundance and economic prosperity. Some models indicate that resource shocks have an impact on income inequality, subsequently (Leamer et al. (1999), Goderis and Malone (2011), Gylfason and Zoega (2003)), while the effect depends qualitatively on ethnic fractionalizations (Fum and Hodler (2010)).

According to Fum and Hodler (2010), "natural resources raise income inequality in ethnically polarized societies, but reduce income inequality in ethnically homogenous societies" (p. 360). However, there are still some open questions. Whilst Gylfason (2001) dedicates his paper to the effects of resource booms on educational investments of local residents, we relate resource shocks to the selectivity of emigrating individuals. Specifically, we raise the following questions: What do we theoretically expect for the effect of resource shocks on the selectivity of emigrating individuals? Is the impact of resource abundance on migrant selectivity mediated through the effect on inequality as Borjas (1987) suggests? Do the effects differ with respect to specific country characteristics?

In order to tackle these questions, I complement a theoretical analysis with an empirical investigation. In the theoretical part, I proceed in three steps. First, I make use of classical dutch-disease-models (Corden and Neary (1982), Corden (1984), Torvik (2001), Ismail (2010)) which examine the effect of resource shocks on the exchange rate.[1] Second, I rely on Stolper and Samuelson (1941) showing that an appreciation of the exchange rate impinges on the income distribution in the respective country. According to Stolper and Samuelson (1941), output price changes transmit into input price variations of respective factors of production. For instance, a rise in the commodity price entails an increase of the price of the production factor used disproportionately in the production process and a decline of the price of the other factor of production. This might lead to a dispersion or a contraction of income distributions between high and low skilled labor. Third, we complement our framework with a Roy-Borjas-model (Roy (1951), Borjas (1987)) proving that inequality effects translate into brain drain effects. Based on Borjas (1987), relative skill premia between source and host countries determine the selectivity of migration. Provided that skill premia in the destination country exceed skill premia in the source country, migrants are on average positively selected if income correlations across countries are sufficiently high.

Specifically, I propose an economy with two sectors, the (tradable) manufacturing sector, M, as well as the (non-tradable) service sector, S, while prices for manufacturing goods are exogenously given (small open economy). In order to separate within-country-mobility from between-country-migration, I analyze the impact of resource booms on migrant selectivity sequentially. On the first stage, the economy experiences a resource boom which induces intersectoral mobility. On the second stage, I allow for international migration based on relative skill premia. Several parts of the framework are related to Ismail (2010), Goderis and Malone (2011) as well as Bougheas and Nelson (2012) but with exogenous income shocks put into the budget constraint.

In the empirical part, I apply several econometric technics in order to test our theoretical predictions. Apparently, (quasi-)experimental research designs are not appropriate in order to verify the predictions raised in the theoretical section. This is due to the fact that treatment and control groups are not totally separable. In particular, if an individual emigrates from country A to B in the course of an oil boom in A or B than the migration from A to C is treated as well and not a potential control group. Therefore as a baseline setup, I construct a simple panel model which explains emigrant selectivity by oil income

[1] Additional Dutch disease models are provided by Alexeev and Conrad (2009), Bjornland (1998), Krugman (1987), Lama and Medina (2012).

per capita and a set of covariates. As main covariates, I consider relative skill premia between source and destination countries along with the number of migrants from the same country of origin in each host country. Whereas the former provides a test of the Roy-Borjas-model, the latter captures community effects which impinge on the costs of migration. I expect a trade-off between the selectivity and the quantity of migration as high-skilled individuals are adaptable even in the absence of communities. Conversely, low skilled individuals have to rely on the community in order to overcome language barriers and to find appropriate labor market positions. In addition, we include distances between source and destination countries as well as colonial ties and dummies for common languages which capture cultural disparities. In parallel, we account for poverty constraints impinging on migration decisions which were shown to to be relevant in the literature (Belot and Hatton (2012)).

The baseline framework is estimated with pooled OLS along with fixed and random effects estimators taking into account several robustness checks. In order to account for partial adjustments in migrant selection, I construct a dynamic panel model while relying on estimators provided by Anderson and Hsiao (1981), Blundell and Bond (1998) and Arellano and Bond (1991). As an extension, I construct a structural equation model which disentangles the effect of resource booms on income inequality and migrant selectivity. All models rely on census data (Ruggles et al. (2010)) based on 113 source and 26 destination countries between 1910 and 2009. Basically, the results are consistent with the theoretical predictions. Oil shocks lead to a contraction of the income distribution and, thereby, foster brain drain effects. But whether the effects are mediated through distributional effects is not clear cut.

Finally, we encounter two main issues. First, bilateral migration streams are not exogenous. Rather, migrants base their migration decision on a multilateral comparison of source countries with all potential destination countries. Hence, migration decisions are not exclusively based on push and pull factors in actual source and host countries but also on pull factors in potential destination countries. Therefore, we scrutinize the methodology of recent papers which explain the quantity of migration bilaterally based on push and pull factors in source and destination countries.[2] However, we explicitly account for the selectivity of migration which legitimizes a bilateral approach. Second, a battery of countries implemented restrictive migration policies in the course of the 20th century which impinged on the quantity was well as the selectivity of migration. Although

[2] Third-country-effects particularly impinge on the quantity of migration and have to be analyzed based on conditional logit models.

individuals already resolved to emigrate, they might face implicit or explicit restrictions which affect the choice of the destination country as well. I conduct robustness checks in order to prove, whether migrant restrictions have a serious impact on our results.

The article is organized as follows. In section 2 we set out the theoretical model which relates resource shocks, income inequality and migrant selectivity. In section 3 we are concerned with an empirical test of the theoretical model and implement several empirical strategies to confront theoretical predictions with data. Section 4 concludes.

2 Theory

2.1 Assumption

In order to examine the impact of resource shocks, especially oil abundance, on migrant selectivity, we proceed in three steps. In a first step, a country experiences a resource windfall. This shock exclusively induces intersectoral within-country mobility while international migration is totally restricted. In a second step, we dispense with migration restrictions and allow for migration across countries. Finally, we illuminate the selectivity of those who migrated across countries. This trichotomy enables us to isolate the effect of resource shocks on migrant selectivity while taking into account inequality effects as an intermediary.

The economy comprises two sectors, manufacturing goods, M, which are tradable as well as services, S, which are non-tradable. Since the economy faces exogenous world prices for the manufacturing good, the country can be characterized as a small open economy. Both sectors employ high-skilled labor, H, as well as low-skilled labor, L, even though the share of low-skilled labor in the service sector offsets the share of low-skilled labor in the manufacturing sector. This assumption is particularly relevant for developing countries in which the tertiary sector is not as sophisticated as in developed countries. However, in our framework, services only capture basic services which are non-tradable while tradable and sophisticated business services are part of the tradable sector. In both sectors, we abstract from capital in the production process. Although this assumption is restrictive, however, it simplifies the derivation of distributional effects.

Basically, we combine the Rybczynski-theorem (Rybczynski (1955)) with the Stolper-Samuelson-theorem (Stolper and Samuelson (1941)) in order to prove that resource windfalls impinge on income inequality domestically. According to the Rybczynski theorem, if a production factor is augmented, the production of the good which uses this factor intensively increases relative to the output of the other good. A dutch disease comes across resource movements from the manufacturing to the service sector which directly affect the size of the tradable relative to the non-tradable sector.

According to Stolper and Samuelson (1941), output price changes translate into respective factor price changes which more than compensate the initial output price shift such that income distributions are dispersed or contracted. If the relative price of non-tradables compared to tradables increases (the price of tradables is exogenously given), the price of the production factor used intensively in the non-tradable sector, low-skilled labor, increases whereas the price of the production factor used less intensively in the non-tradable sector, high-skilled labor, decreases. Moreover, subsequent factor price changes exceed initial output price shifts such that the dutch disease translates into real changes of economic inequality. We will come back to both theorems in more detail below. Meanwhile, we set out the basic framework formally.

Suppose that firms in each sector, $i = M, S$, solve the following optimization problem:

$$\max_{L,H} \pi_i = p_i A_i L^{\alpha_i} H^{\beta_i} - w_H H_i - w_L L_i$$

After maximizing profits, they wind up with

$$w_L = p_i \alpha_i L_i^{\alpha_i - 1} H_i^{\beta_i} \tag{1}$$

$$w_H = p_i \beta_i H_i^{\beta_i - 1} L_i^{\alpha_i} \tag{2}$$

I henceforth posit a representative household for low-skilled as well as for high-skilled labor maximizing a simple Cobb-Douglas utility function ($0 < \xi < 1$) subject to the budget constraint:

$$\max_{S,M} U = M^{\xi} S^{1-\xi}$$

s.t.

$$pS + M = Y$$

In analogy to Torvik (2001) and Goderis and Malone (2011), we assume oil shocks, χ, which are measured in productivity units of the non-tradable sector, A_S. Therefore, income equals the value of sum of the production in the traded and non-traded sector along with resource income:

$$Y = pA_S L^{\alpha_S} H^{\beta_S} + A_M L^{\alpha_M} H^{\beta_M} + A_S \chi \tag{3}$$

Since, in a first step, high-skilled labor and low-skilled labor are mobile intersectorally but immobile internationally, the following full-employment conditions have to hold for high-skilled labor, H, and low-skilled labor, L:

$$a_{MH}Y_M + a_{SH}Y_S = H \tag{4}$$

and

$$a_{ML}Y_M + a_{SL}Y_S = L \tag{5}$$

where $a_{ij} = \frac{j}{Y_i}$, $i = M, S$, $j = H, L$. Each equation states the average amount of low skilled labor and high skilled labor which is necessary to produce one unit of output.

In addition, perfect competition induces zero profits in both sectors. This implies in the light of the dual approach that prices equal unit cost functions. Namely, we derive for the production technologies above:

$$p_M = \left[w_L^{\frac{\alpha_M}{\alpha_M+\beta_M}} \left(\frac{\alpha_M w_H}{\beta_M} \right)^{\frac{\beta_M}{\alpha_M+\beta_M}} + w_H^{\frac{\beta_M}{\alpha_M+\beta_M}} \left(\frac{\beta_M w_L}{\alpha_M} \right)^{\frac{\alpha_M}{\alpha_M+\beta_M}} \right] = c_M(w_L, w_H, Y_M = 1) \tag{6}$$

and

$$p_S = \left[w_L^{\frac{\alpha_S}{\alpha_S+\beta_S}} \left(\frac{\alpha_S w_H}{\beta_S} \right)^{\frac{\beta_S}{\alpha_S+\beta_S}} + w_H^{\frac{\beta_S}{\alpha_S+\beta_S}} \left(\frac{\beta_S w_L}{\alpha_S} \right)^{\frac{\alpha_S}{\alpha_S+\beta_S}} \right] = c_S(w_L, w_H, Y_S = 1) \tag{7}$$

In making use of the assumptions above, we proceed with a proof relating resource booms and the selectivity of migration.

2.2 Resource Shocks and Migrant Selectivity

Proposition*: A resource windfall, $\chi > 0$, gives rise to brain drain (brain gain) effects if $\alpha_S > \alpha_M$ ($\alpha_S < \alpha_M$), mediated through a contraction (dispersion) of the income distribution.*

Proof: In order to prove the proposition above, we proceed in three steps. First, we follow Torvik (2001) and Ismail (2010) in order to derive the spending effect arising from a dutch disease. Second we apply the Stolper-Samuelson theorem (Stolper and Samuelson (1941)) in order to derive inequality effects. Finally, we make use of the Roy-Borjas model in order to relate relative income inequality and migrant selectivity.

Regarding the first step, solving the household optimization problem yields:

$$M = \xi Y \tag{8}$$

as well as

$$S = \frac{(1-\xi)Y}{p} \tag{9}$$

In the light of the production technologies and the market clearing conditions for services, $S = Y_S$, we further get for the relative price of services in terms of manufacturing goods:

$$p = \frac{(1-\xi)(A_M L^{\alpha_M} H^{\beta_M} + A_S \chi)}{\xi A_S L^{\alpha_S} H^{\beta_S}} \tag{10}$$

which is the same expression as in Torvik (2001). While the price of the manufacturing good is exogenously determined on the world market, the price of services is determined endogenously. Based on the equation above, resource windfalls have a positive impact on the price of non-tradables in terms of tradables, which can be interpreted as an appreciation as part of a dutch disease.

Regarding the second step, we analyze the distributional effects emerging from an appreciation. Put in terms of Stolper and Samuelson (1941), the spending effect as part of the dutch disease transmits into a contraction of the real wage gap between high and low skilled labor. Alternatively, Goderis and Malone (2011) derive inequality effects arising from oil booms based on GINI coefficients and account for dynamic adjustments but the results are mainly consistent. In order to prove the Stolper-Samuelson theorem in this framework, I relate output prices to input prices following the framework of Feenstra (2003) under consideration of Jones (1965).

Totally differentiating the zero profit conditions stated above yields:

$$\frac{\Delta p_i}{p} = \left(\frac{\partial c_i}{\partial w_H} \bigg/ \frac{c_i}{w_H} \right) \frac{\Delta w_H}{w_H} + \left(\frac{\partial c_i}{\partial w_L} \bigg/ \frac{c_i}{w_L} \right) \frac{\Delta w_L}{w_L} \tag{11}$$

Taking into account that $\hat{p} = \ln p = \frac{\Delta p}{p}$, we further get

$$\hat{p}_i = \left(\frac{\partial c_i}{\partial w_H} \bigg/ \frac{c_i}{w_H} \right) \hat{w}_H + \left(\frac{\partial c_i}{\partial w_L} \bigg/ \frac{c_i}{w_L} \right) \hat{w}_L \tag{12}$$

The coefficients can be interpreted as the cost elasticities of factor price changes. In each sector, they depend implicitly on the relative amount of the production factors. If we put the expression in matrix notation while being more explicit, we wind up with

$$\begin{bmatrix} \hat{p}_M \\ \hat{p}_S \end{bmatrix} = \begin{bmatrix} \frac{\beta_M}{\alpha_M+\beta_M} & \frac{\alpha_M}{\alpha_M+\beta_M} \\ \frac{\beta_S}{\alpha_S+\beta_S} & \frac{\alpha_S}{\alpha_S+\beta_S} \end{bmatrix} \times \begin{bmatrix} \hat{w}_H \\ \hat{w}_L \end{bmatrix} \tag{13}$$

Isolating factor prices on the left-hand-side of the equation, yields an expression which describes factor prices as a function of output prices.

$$\begin{bmatrix} \hat{w}_H \\ \hat{w}_L \end{bmatrix} = \frac{1}{\mid \lambda \mid} \begin{bmatrix} \frac{\alpha_S}{\alpha_S+\beta_S} & -\frac{\alpha_M}{\alpha_M+\beta_M} \\ -\frac{\beta_S}{\alpha_S+\beta_S} & \frac{\beta_M}{\alpha_M+\beta_M} \end{bmatrix} \times \begin{bmatrix} \hat{p}_M \\ \hat{p}_S \end{bmatrix} \tag{14}$$

If we assume constant returns to scale, $\alpha_S + \beta_S = 1$ and $\alpha_M + \beta_M = 1$, we wind up with

$$\begin{bmatrix} \hat{w}_H \\ \hat{w}_L \end{bmatrix} = \frac{1}{\mid \lambda \mid} \begin{bmatrix} \alpha_S & -\alpha_M \\ -\beta_S & \beta_M \end{bmatrix} \times \begin{bmatrix} \hat{p}_M \\ \hat{p}_S \end{bmatrix} \tag{15}$$

with the determinant given by:

$$\mid \lambda \mid = \alpha_S \beta_M - \alpha_M \beta_S \tag{16}$$

This equation says that if high-skilled labor exceeds low-skilled labor in manufacturing, the opposite has to be the case in the service sector as the production factors are exclusively mobile across sectors. Formally,

$$\mid \lambda \mid = \alpha_S - \alpha_M = \beta_M - \beta_S \begin{cases} > 0 & \text{if } \alpha_S > \alpha_M \Leftrightarrow \beta_M > \beta_S \\ < 0 & \text{if } \alpha_S < \alpha_M \Leftrightarrow \beta_M < \beta_S \end{cases} \tag{17}$$

Based on the previous expression, we can relate output price changes, $\hat{p} = \hat{p}_S - \hat{p}_M > 0$, to input-price-responses $\hat{w} = \hat{w}_H - \hat{w}_L$, which is similarly stated in Feenstra (2003):

$$\hat{w}_H - \hat{w}_L = \underbrace{\frac{\hat{p}_M(\alpha_S - \alpha_M) + (\hat{p}_M - \tilde{p}_S)\alpha_M}{\alpha_S - \alpha_M}}_{<\hat{p}_M, \alpha_S > \alpha_M} - \underbrace{\frac{\hat{p}_S(\beta_M - \beta_S) - (\hat{p}_M - \hat{p}_S)\beta_S}{\beta_M - \beta_S}}_{>\hat{p}_S, \beta_M > \beta_S} \tag{18}$$

$$\hat{w}_H - \hat{w}_L \begin{cases} < 0 & \text{if } \alpha_S > \alpha_M \Leftrightarrow \beta_M > \beta_S \\ > 0 & \text{if } \alpha_S < \alpha_M \Leftrightarrow \beta_M < \beta_S \end{cases} \tag{19}$$

According to equation (18), a dutch disease, $\hat{p} = \hat{p}_S - \hat{p}_M > 0$, gives rise to distributional effects. Qualitatively, inequality effects depend on the share of low-skilled labor in the service sector compared to the share of low-skilled labor in the manufacturing sector. In particular, if the share of low-skilled labor in the service sector offsets the share of low-skilled labor in the manufacturing sector, $\alpha_S > \alpha_M$, a dutch disease translates into a less dispersed income distribution. Quantitatively, an appreciation leads to factor price shifts which outweigh the initial output price variation. Hence, the dutch disease translates into distributional effects in real terms. This is an application of the Stolper-Samuelson-theorem. According to Stolper and Samuelson (1941), a rise in the output price increases the price of the production factor used intensively in the production process and reduces the price of the other production factor. Additionally, Stolper and Samuelson (1941) claim that factor price movements exceed output price shifts (magnification effect).

The evidence for the Stolper-Samuelson theorem is generally mixed. While Krueger (1997) along with Sachs and Shatz (1994) find empirical support for the Stolper-Samuleson theorem, Baldwin and Cain (1997) could not find significant effects of trade on income inequality. In specific country contexts, Beyer et al. (1999), Chiquiar (2008), Robertson (2004) and Gonzaga et al. (2006) provide support in favor of the Stolper-Samuelson theorem.

In a final step, we bride the gap between resource shocks and migrant selectivity by making use of the Roy-Borjas-model (Borjas (1987), Roy (1951)). Since we already confirmed the distributional effects of resource booms, it is just pending to illuminate the relationship between relative income contraction and migrant selectivity. Thereby, I rely on seminal contributions of Borjas (1987) and dispense with the assumption of migrant restrictions. I posit a world comprised by two countries, a resource rich country, R, and a resource scarce country, S, while migration between R and S is an option. In each country, $k \in \{R, S\}$, the logarithm of the aggregate income $\tilde{Y}_k$, is given by a deterministic component, μ_k, and a stochastic component, ϵ_k, according to the following function:

$$\hat{Y}_k = \mu_k + \epsilon_k$$

The stochastic components are normally distributed with zero mean and a variance given by σ_k. The correlation coefficient between stochastic components across countries is denoted by ρ_{RS}:

$$\epsilon_k \sim N(0, {\sigma_k}^2) \tag{21}$$

$$\rho_{R,S} = corr(\epsilon_R, \epsilon_{S \neq R}) = \frac{\sigma_{RS}}{\sigma_R \sigma_S} \tag{22}$$

The decision for bilateral migration from R to S, $M_{RS} = \hat{Y}_S - \tilde{Y}_R - \pi_{RS}$, depends on the wages in the resource abundant country, Y_R, relative to the wages in the resource scarce country, Y_S, while taking into account migration costs given by π_{RS}. Based on the notation above, we can derive the probability of migration from the resource abundant country, R, to the resource scarce country, S, as follows:

$$P_{RS} = P(M_{RS} > 0) \tag{23}$$

Plugging in the expressions above for M and Y yields:

$$P_{RS} = P(\epsilon_S - \epsilon_R > -\mu_S + \mu_R + \pi_{RS}) \tag{24}$$

or equivalently

$$P_{RS} = 1 - \Phi\left(\frac{-\mu_S + \mu_R + \pi_{RS}}{\sigma_{\epsilon_s - \epsilon_R}}\right) \tag{25}$$

where Φ denotes the cumulative distribution function of a normally distributed variable. According to the previous equation, the probability of migration from country R to S is positively affected by mean income in country S and decreases with mean income in country R. Additionally, migration costs from R to S impinge negatively on the probability of migration.

Analogous to Borjas (1987), we can compare expected wages if the individual migrates with the counterfactual of expected wages if the same individual would not have been migrated:

$$E(\hat{Y}_S|M_{RS} > 0) = \mu_S + \rho_{S\epsilon_S - \epsilon_R}\sigma_S \left(\frac{\phi(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S - \epsilon_R}})}{\Phi\left(\frac{-\mu_R+\mu_S-\pi_{RS}}{\sigma_{\epsilon_S - \epsilon_R}}\right)}\right) \tag{26}$$

$$E(\hat{Y}_R|M_{RS} > 0) = \mu_R + \rho_{R\epsilon_S - \epsilon_R}\sigma_R \left(\frac{\phi(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S - \epsilon_R}})}{1 - \Phi\left(\frac{-\mu_R+\mu_S+\pi_{RS}}{\sigma_{\epsilon_S - \epsilon_R}}\right)}\right) \tag{27}$$

where ϕ denotes the probability density function of a normally distributed random variable. Following Borjas (1987), we can equivalently state

$$E(\hat{Y}_S|M_{RS} > 0) = \mu_S + \frac{\sigma_R\sigma_S}{\sigma_{\epsilon_S - \epsilon_R}}\left(\frac{\sigma_S}{\sigma_R} - \rho\right)\left(\frac{\phi(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S - \epsilon_R}})}{1 - \Phi\left(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S - \epsilon_R}}\right)}\right) \tag{28}$$

$$E(\hat{Y}_R|M_{RS} > 0) = \mu_R + \frac{\sigma_R\sigma_S}{\sigma_{\epsilon_S - \epsilon_R}}\left(\rho - \frac{\sigma_R}{\sigma_S}\right)\left(\frac{\phi(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S - \epsilon_R}})}{1 - \Phi\left(\frac{-\mu_R+\mu_S+\pi_{RS}}{\sigma_{\epsilon_S - \epsilon_R}}\right)}\right) \tag{29}$$

If we assume that $\frac{1}{\rho} < \frac{\sigma_S}{\sigma_R} > 1$, individuals migrating from R to S are positively selected compared to the average skills in R. According to this inequality, the attraction of a positive selection is based on two conditions. First, skill premia across countries are sufficiently correlated. Particularly, individuals in the upper tail of the income distribution in the source country are supposed to be in the upper tail of the income distribution in the destination country as well. Second, skill premia in the resource scarce country have to offset skill premia in the resources abundant country. In contrast, if it holds that $\frac{1}{\rho} < \frac{\sigma_R}{\sigma_S} > 1$, than individuals migrating from R to S are adversely selected relative to average skills in R. This holds under the assumption that the income distribution in R is more dispersed compared to the S.

Therefore, if resource booms lead to less dispersed income distributions, as shown above, they lay the ground for brain drain effects in the light of Borjas (1987). By now, we assumed that the world is comprised by just two countries while just one country experiences a resource windfall. However, migration decisions are affected by push and pull factors in source and destination countries. For instance, the destination country can be resource abundant to some extend as well. In this case, inequality effects arising from resource booms in the source country have to outweigh inequality effects in the destination country in absolute value.[3]

Studies relating relative skill premia and the selectivity of migration come to different results and mainly focus on bilateral migration patterns between Mexico and the US. Borjas (1987) analyzes migration patterns between the US and Mexico based on census data from 1970 and 1980 and concludes that comparatively high earnings-skill-ratios are attributable to migrants from regions characterized by low income inequality. Similarly, Moraga (2011) sheds light on bilateral migration between the same countries showing that between 2000 and 2004 Mexican emigrants had less schooling compared to individuals left behind. This indicates that migrants were on average adversely selected. Diametrically opposed and contradictorily to Borjas (1987), Chiquiar (2005) finds that Mexicans in the US are on average positively selected based on Mexican and US census data from 1990 and 2000. But according to Moraga (2011), these results are due to a sample selection bias. Kaestner and Malamud (2014) concludes that migrants from Mexico to the US are neither positively nor negatively selected, rather their educational background is similar to Mexican residents. Consistently, Orrenius and Zavodny (2005) found that migrants from Mexico to the US are not adversely selected while referring to data from the Mexican Migration Project. But illegal migrants are selected from the lower tail of the educational distribution. Belot and Hatton (2012) investigate migrant selection in a sample comprising 70 source and 21 host countries. Regarding these countries, migration costs arising from colonial ties and distances between source and destination countries appear to be much more important in explaining migrant selectivity. Relative income dispersion

[3]We will control for push and pull factors in our empirical framework below.

is significant only if poverty constraints are considered. Stolz and Baten (2012) test the Borjas model in the era of mass migration and cannot falsify the theoretical predictions.

To sum up, the theoretical framework suggests the following predictions. First, resource booms give rise to a dutch disease coming across an appreciation of the exchange rate. Second, the appreciation of the exchange rate translates into a less dispersed income distribution which, ceteris paribus, strengthens brain drain effects.

In order to verify or falsify theoretical predictions, I proceed with several econometric models in section 3.

3 Evidence

3.1 Empirical Framework and Data

Our empirical framework mainly draws upon longitudinal data based on Ruggles et al. (2010) which capture migration patterns among 113 countries between 1910 and 2009, commonly known as IPUMS (Integrated Public Use Microdata Series).[4] In the baseline regression we posit the following equation of interest which relates the selectivity of emigration and oil income per capita along with several additional covariates, denoted as $\boldsymbol{X}_{ijt}$.

$$SELECTIVITY_{ijt} = \alpha_{ij} + \chi_t + \phi RESOURCES_{ijt} + \boldsymbol{X}'_{ijt}\xi + \epsilon_{ijt} \tag{30}$$

In line with Grogger and Hanson (2011) as well as Stolz and Baten (2012), we collapse our data set for source-destination country pairs, ij, and aggregate data by decades.[5] Hence, α_{ij} captures country pair fixed effects while χ_t indicates time fixed effects. Whilst the former accounts for variables which differ between country pairs but are time invariant, the latter captures variables that change over time but are invariant across states. The SELECTIVITY of migration is determined for 2.1 million individuals migrating from 113 source to 23 destination countries as the difference between the years of schooling of emigrants compared to the average years of schooling in the source country, respectively. Basically, the definition of migrant selection is far from clear cut in the literature. The definitions range from actual wages relative to the wages of non-migrants (Borjas (1987),

[4]Data on migrant selection were descriptively assembled by Monschauer (2013) based on Ruggles et al. (2010) in the course of his bachelor thesis supervised at our chair.

[5]Thereby, as migrant selectivity is quite persistent over time, we do not exclude decades which comprise occasional missing values, especially in the first decade. However, this does not produce artificial variation, as we calculate the mean of migrant selectivity by decades.

Kaestner and Malamud (2014)) over potential wages predicted by education, age and marital status (Chiquiar and Hanson (2002)) to various educational measures (Stolz and Baten (2012), Belot and Hatton (2012)) relative to the average in the source country, respectively. Hence, our selectivity measure is consistent with the latter. We take into account 73 censuses based on IPUMS from which we draw information on the years of schooling of migrants and their place of birth as well as the country and place of residence. Additionally, we make use of recently collected data from Barro and Lee (2012) in order to account for the average years of schooling in each source country. Besides of recent census data, Barro and Lee (2012) rely on historical school enrollment rates. The Barro and Lee (2012) sheets date back to 1950 and indicate the education for 5 year age cohorts between 20 and 65 years for half of a decade. Through taking into account the old cohorts in 1950, we can retrace the years of schooling until 1910.

To account for the dynamics of migration, I rely on the assumption that the average age of migrants is 25 which is consistent with data from the United Nations which state that modal migration ages are between 23 and 27 years (United Nations (2011)). Most of the individuals migrate between countries with similar economic backgrounds. The United States are the only highly-developed, industrialized country representing a host country in the data set. Therefore, we are not able to account for migration patterns into high income european countries.

As the years of schooling are only captured retrospectively, the data set provides no information on whether the education of migrants was actually acquired in the country of origin or the country of destination. However, since most of the migrants arrive in the destination country at ages between 23 and 27, the problem appears to be negligible. Furthermore, the sign of a potential bias is indeterminate. If migrants are positively selected compared to the source country, they might acquire less education in the host country relative to a counterfactual in which these individuals would not have been migrated.

Another potential pitfall that has to be addressed is that migrants face restrictions regarding the choice of the destination country. Especially in the 20th century, industrial countries implemented several restrictions which acted as an impediment for the free movement of people. These restrictions often imply the conditionality of a right of residence. Permissions might be conditioned on a recent employment contract with an income exceeding a certain threshold or certain additional criteria. Particularly, migrant restrictions are apparent in the United States as the only high income industrial destination country in our data set. Additionally, we do not capture illegal migration streams which are expected to be negatively selected on average at least in comparison with the destination country. This might induce an upward bias in our migrant selectivity data. In order to account for migrant restrictions and additional unobserved heterogeneity we control for country pair and time fixed effects.

By means of a kernel density estimator, we show that migrant selectivity is approximately normally distributed. The density estimation depicted below is based on an Epanechnikov Kernel and a bandwidth given by 0.6087. This is the optimal bandwidth minimizing the mean integrated squared error (MISE) if migrant selectivity would follow a Gaussian distribution and the Kernel used is normally distributed as well.[6]

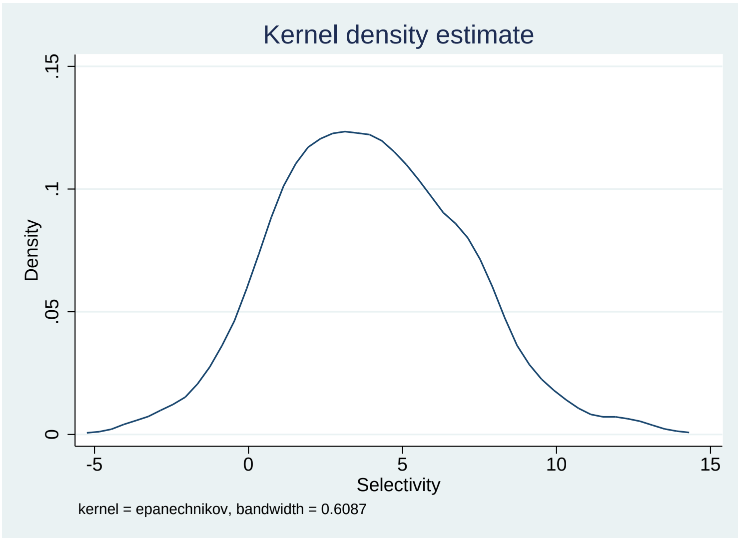

Figure 1: Kernel density estimation migrant selectivity

The independent variable RESOURCES captures income generated in the oil sector based on Haber and Menaldo (2011). More precisely, resource incomes are measured in terms of

[6] I estimate the density of migrant selectivity using a non-parametric approach which is standard. In the univariate case I have: $\hat{f}(x) = \frac{1}{nh_n}\sum_{i=1}^{n} K\left(\frac{x-x_i}{h_n}\right)$ where K is the density, n the number of observations, h_n the bandwidth and x_i indicates migrant selectivity. The criteria for choosing the optimal bandwidth is the commonly used MISE (Mean Integrated Square Error) which is given by $MISE = E\left[\int \left(\hat{f}(x) - f(x)\right)^2 dx\right] = \int V\left[\hat{f}(x)\right] dx + \int Bias\left[\hat{f}(x)\right]^2 dx \approx \frac{1}{nh}\left(\int K(v)^2 dv\right) + \frac{1}{4}k_2^2 h^4 \int f''(x)^2 dx$. Note that there is an inherent trade off in the minimization as for the variance to be small we would like to choose a large bandwidth whereas for the bias to be small we would like the bandwidth to be as small as possible. In order to find the optimal bandwidth, I minimize the asymptotic MISE over the bandwidth h, which yields: $h_{optimal} = \frac{1}{n^{\frac{2}{5}} k_2^{\frac{2}{5}}} \frac{\left(\int K(v)^2 dv\right)^{\frac{1}{5}}}{\left(\int f''(x)^2 dx\right)^{\frac{1}{5}}}$. Finally to find K, we need to plug the optimal bandwidth into the asymptotic MISE and minimize that same asymptotic MISE over K. This yields $K_{optimal}(t) = \frac{3}{4\times 5^{\frac{1}{2}}}\left(1 - \frac{1}{5}t^2\right) 1(t^2 \leq 5)$ which is called the Epanechnikov kernel.

prices from 2007 (constant prices determined on the world market) and relative to population size - an approach which is also consistent with Hamilton and Clemens (1999). Additionally, the procedure is superior to a specification which captures the gross domestic product in the denominator (Fum and Hodler (2010), Hodler (2006), Brunnschweiler and Bulte (2008)). The latter would be more of an indicator for resource dependence and not necessarily for resource abundance. In the curse of further robustness checks we additionally rely on resource income generated by oil, natural gas, coal, precious metal, and industrial metal industries. In contrast to the other covariates, the difference of oil income per capita between source and destination countries is intentionally not given in logs but in million USD. Since we are interested in the relationship between resource income per capita and migrant selectivity, our main coefficient of interest is ϕ. Consistently with our theoretical predictions, we expect the selectivity of emigrating individuals to be positively related to the abundance of natural resources. Resource windfalls are expected to reduce income inequality which gives rise to brain drain effects. However, resource abundance can act as push and pull factors in migration decisions. Hence, I build differences in resource incomes between source and destination countries.

The covariates, $\boldsymbol{X}_{ijt}$, are inspired by Belot and Hatton (2012) along with Stolz and Baten (2012). Similarly to Stolz and Baten (2012), I claim that in order to emigrate, individuals need a certain amount of income. Hence, we control for GDP in the source country in order account for poverty constraints which serve as an impediment to emigration. The income required increases with the distance between the source and destination country even though the distance is not exogenous due to self-selection. In particular, we assume that high skilled individuals can overcome poverty constraints more easily. In order to reduce potential feedback effects, I consider the gross domestic product in the previous period. In general, gross domestic products capture additional resource income as well. However, resource income is measured in constant prices whilst GDP is measured in nominal terms before we take the logarithm. Therefore, perfect collinearity is ruled out between these variables.

Additionally, we approximate network effects of migration by accounting for the number of people who moved previously from the same country of origin to the respective destination country. According to Cohn (2009), migration costs decrease in the course of friends and relatives already hosted in a specific destination. If communities consist of people from the same country of origin, individuals share a similar cultural background. Therefore, it is much easier to gather information regarding job positions, to initiate relationships and to overcome language barriers. Consistently with Chiquiar (2005), Belot and Hatton (2012) and McKenzie and Rapoport (2010), I expect a selectivity-quantity tradeoff in migration. In essence, the selectivity of migration decreases with the size of the community in the residence country. Whilst the most skilled individuals are very adaptable even in the absence of any community effects, low-skilled individuals have to rely on networks in order to succeed. This theory is in line with the scatter plot displayed below.

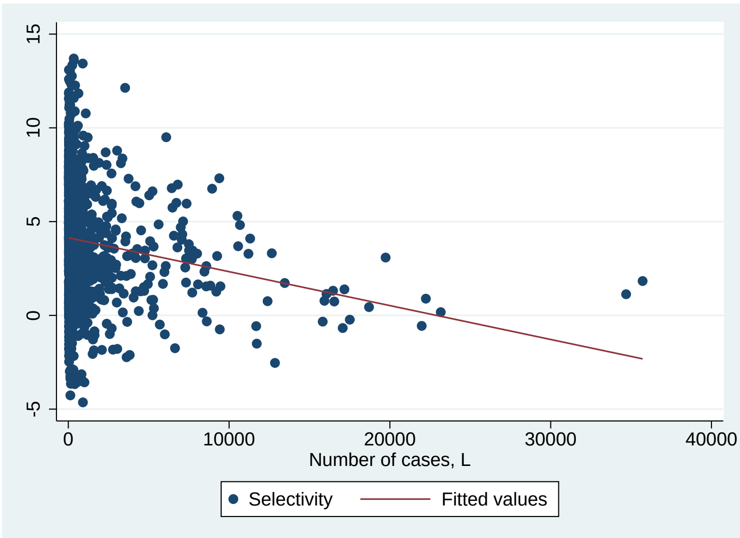

Figure 2: Quality-Quantity Trade-Off in Migration

As community effects can be approximated by measures of cultural proximity, we additionally take into account a dichotomous variable which is 1 if languages in source and destination countries coincide and 0 otherwise. Consistently, we add a dummy variable for colonial ties between source and host countries which is 1 if source and destination countries have a colonial tie and 0 otherwise. We expect both variables, the common languages as well as colonial ties, to be negatively correlated with the selectivity of migration since low-skilled workers are more likely to self-select into countries which are culturally proximal. These self-selection effects lead to the endogeneity of bilateral migration patterns but we directly account for self-selection with our dependent variable. Variables capturing cultural proximities are standard in gravity trade models which relate the number of tradable goods to push and pull factors in country i and j, respectively (Anderson and Van Wincoop (2002)). Since these variables affect the costs of migration, they necessarily impinge on the selectivity of migration as well. Higher migration costs are more easily borne by high-skilled individuals.

Variables which are common in gravity models as well are distances between source and destination countries, which are more easily borne by high-skilled individuals as well. Hence, we expect the effect of migration costs on migrant selectivity to be positive. Moreover, civil wars accounted in the data set severely act as push factors for migration. Wars are extreme events which massively depress the quality of life and, thereby, induce strong incentives to emigrate. Przeworski et al. (2000) accounts for the number of civil wars by country.

As Acemoglu et al. (2001) already pointed out, the quality of political institutions has a significant impact on economic development. Since these institutions might also be condusive for the selectivity of migration, we account for the openness of democracy. By means of a polity IV variable, available, for instance, in Przeworski et al. (2000), which ranges from 0 for low institutional quality to +10 for high institutional quality we capture these effects. As democracy serves as a push and pull factor we account for the difference in democracy between source and destination countries.

3.2 Descriptive Statistics

Before we succeed with our statistical analysis, I provide a descriptive overview capturing all the variables I make use of in the econometric analysis below. Specifically, table 3 displays the mean, the standard deviation as well as the minimum and maximum for each variable included in the data set described above. Based on the descriptives, we capture 1,780 cases of migrant selection. Migrants are randomly selected based on census data which are representative, at least on a national level. However, the dataset does not capture all of the migrants but a random sample for bilateral migration patterns between 113 source and 26 destination countries. Whether our results are externally valid even beyond countries included in our analysis is further discussed below. In the second table, we display the number of migration patterns for a set of countries included in our data set. Regarding emigration, we rely on 141 cases in Rwanda to 178,218 cases in Colombia. Conversely, regarding immigration countries range from Jamaica with 1,250 cases to the United States with 808,279 cases, respectively.

Variable	N	Mean	SE	Min	Max	Source
GDP	2453	8271.742	7147.458	260.366	30578.49	Haber and Menaldo (2011)
GDP growth	2,108	1.89	1.97	-11.71	9.74	Haber and Menaldo (2011)
Gini	872	39.7865	8.72204	15.42	62.8	Baten and Mumme (2010)
Migrant Selection	1,780	3.9435	3.022	-4.6283	13.697	Ruggles et al. (2010), Barro and Lee (2012)
Total Oil Income per Capita	1,748	161.3509	1,070.096	0	33,032.62	Haber and Menaldo (2011)
Total Resource Income per Capita	2332	256.3892	1059.265	0	33304.23	Haber and Menaldo (2011)
Population Size	1,751	7.33e+07	1.84e+08	69,000	1.21e+09	Haber and Menaldo (2011)
Civil War	1,756	0.0895	0.2856	0.00	1.00	Przeworski et al. (2000)
Democracy	1,668	5.5631	3.540	0.00	10.00	Przeworski et al. (2000)
Colonial Tie	1,706	.0539	.22594	0	1	Mayer and Zignago (2011)
Distance	1,686	7,635.419	4595.056	0	18,703.86	Mayer and Zignago (2011)
Manufacturing/Exports	1227	39.4177	31.00289	.0016561	96.3141	International Monetary Fonds (2015)
Inflation	2307	24.63757	19.60215	0	73.149	International Monetary Fonds (2015)
Educational Inequality	2382	38.00002	21.58666	4.692087	99.4337	International Monetary Fonds (2015)

Table 1: Descriptive Statistics and Data Sources

Country	Em	Im	Country	Em	Im	Country	Em	Im	Country	Em	Im	Country	Em	Im
Afghanistan	686	n.d.	Costa Rica	3886	28973	Iraq	2068	n.d.	Mozambique	30923	n.d.	Sudan	2519	n.d.
Albania	794	n.d.	Cuba	43383	n.d.	Ireland	4914	n.d.	Myanmar	1851	16115	SouthAfrica	1386	105326
Argentina	25557	453381	Cyprus	563	n.d.	Island	202	n.d.	Netherlands	9168	n.d.	Swaziland	3530	n.d.
Armenia	978	n.d.	Czech	7175	n.d.	Israel	5561	n.d.	NZL	854	n.d.	Sweden	3887	n.d.
Australia	3315	n.d.	Denmark	2413	n.d.	Italy	169174	n.d.	Nicaragua	27533	2053	Switzerland	4199	n.d.
Austria	10185	n.d.	Dominican	18595	n.d.	Jamaica	12096	1,250	Norway	3338	n.d.	Syria	5881	n.d.
Bahrain	5245	n.d.	Ecuador	16236	8761	Japan	42151	n.d.	Pakistan	4037	n.d.	Thailand	5986	19240
Bangladesh	1307	n.d.	Egypt	4160	n.d.	Jordan	1275	n.d.	Panama	6337	15004	TrinidadT	5684	n.d.
Barbados	1433	n.d.	ElSalvador	n.d.	1491	Kenya	1552	42130	Peru	40973	5424	Turkey	4092	n.d.
Belgium	3156	n.d.	Estonia	648	n.d.	Kuwait	261	n.d.	Philippines	39879	24063	Uganda	14,706	n.d.
Belize	1042	n.d.	Finland	1645	n.d.	Laos	3380	n.d.	Poland	31588	n.d.	UK	65851	n.d.
Bolivia	68533	5649	France	15466	n.d.	Latvia	1954	n.d.	Portugal	102837	n.d.	Ukraine	5237	n.d.
Brasil	24360	171612	Germany	74043	n.d.	Lesotho	15791	n.d.	PuertoRico		5766	Uruguay	41645	28551
Bulgaria	973	n.d.	Ghana	1147	n.d.	Liberia	446	n.d.	Paraguay	107180	n.d.	USA	38195	808279
Cambodia	1808	10571	Greece	13472	n.d.	Libya	289	n.d.	Romania	4491	n.d.	Venezuela	7,465	286159
Cameroon	286	n.d.	Guatemala	13593	n.d.	Lithuania	2710	n.d.	Russia	145	n.d.	Yemen	307	n.d.
Canada	56040	n.d.	Guayana	4487	n.d.	Malaysia	866	n.d.	Rwanda	131	n.d.	Zambia	2679	n.d.
Chile	92,697	24986	Haiti	7485	n.d.	Malawi	2334	n.d.	SaudiArabia	1318	n.d.			
China	58266	n.d.	HongKong	4468	n.d.	Malta	407	n.d.	SierraLeone	293	n.d.			
Colombia	178218	8076	Honduras	7106	n.d.	Mauritius	518	n.d.	Singapore	1786	n.d.			
Congo	489	n.d.	Hungary	10056	n.d.	Mexico	163648	43448	Spain	128297	n.d.			
Croatia	323	n.d.	Indonesia	11342	n.d.	Morocco	1409	n.d.	Sri Lanka	556	n.d.			

Notes: Number of cases for selected countries. Data on migrant selection descriptively assembled by Monschauer (2013) based on Ruggles et al. (2010).

Table 2: Captured Immigration and Emigration Patterns by Country

3.3 Data Analysis

3.3.1 Baseline Model

In order to test the predictions raised in the theoretical section, we proceed in three steps. First, as a baseline framework, I mainly rely on random effects and fixed effects models with robust standard errors, respectively. Second, we account for partial adjustments in migrant selection by means of dynamic panel models. Third, we disentangle the impact of resource booms on income inequality and migrant selectivity in the course of a structural equation model.

As part of the baseline setup, I start out with a Hausman test in order to check whether the error components model is more efficient compared to the deviations-from-means estimator. In contrast to the fixed effects estimator, the random effects estimator treats fixed effects as part of a composite error term, $\alpha_{ij} + \epsilon_{ijt} = \eta_{ijt}$. Both, fixed and random effects estimators impose strict exogeneity[7],

$$E(\epsilon_{ijt}|X_{ijt}, RESOURCES_{ijt}, \alpha_{ij}) = 0 \tag{31}$$

for $t = 1, ..., T$, but the random effects estimator additionally hinges on

$$E(\alpha_{ij}|X_{ijt}, RESOURCES_{ijt}) = 0 \tag{32}$$

As the null of the Hausman test is rejected, we mainly rely on the fixed effects estimator. However, we display the results of a random effects estimator as well.

The results of the baseline regressions following the econometric specification from the previous section are displayed in table 3 below. The results are mainly in accordance with our theoretical conjectures. Apparently, total oil income per capita - our main variable of interest - appears to be positively related to the selectivity of emigrating individuals. In other words, resource abundant countries are on average more susceptible to brain drain effects, captured by the years of schooling of emigrants compared to the average of schooling years in the source country. This association appears to be qualitatively consistent in all model specifications. However, whether brain drain effects are mediated through inequality shifts - as our theory suggests - is not clear cut. In order to account for mediation effects through income inequality, we have to rely on a structural equation

[7] We abstract from time-fixed effects in a first step.

model below.

In line with our theoretical predictions, the quantity as well as the selectivity of migration are negatively related. The larger the number of individuals who migrated previously from the same source country to the destination country, the lower the selectivity of emigration. This inverse relationship suggests that for low skilled individuals existing communities and networks are much more important while high skilled individuals appear to be more adaptable. In other words, the results suggest a quantity-selectivity-trade-off in migration. The larger the existing community, the lower the costs of migration. Physical costs of migration are captured by distances between source and destination countries and are positively related to the selectivity of emigrating individuals. Like before, migration costs are more easily borne by high-skilled individuals. Hence, the results are consistent with our theoretical predictions.

Moreover, the GDP in the source country seems to depress brain drain effects. Hence, it appears that more developed countries are not prone to this dimension of a resource curse. In order to elaborate further on the role of economic development on the resource curse, in column (7) and (8) high income economies are excluded. High income countries are often able to ease the natural resource curse or even turn it into a blessing due to institutional quality (Van der Ploeg (2011)). "Norway is the world's third largest petroleum exporter after Saudi Arabia and Russia, but is one of the least corrupt countries in the world and enjoys well developed institutions, far sighted management and market friendly policies." (Van der Ploeg (2011), p. 368). Therefore, even though the quality of institutions is not exogenous but depends on natural resource wealth (Isham et al. (2005)), countries lacking in institutional quality and wealth may hardly turn the curse of natural resources into a blessing. This presumption is consistent with Sala-i-Martin and Subramanian (2003) who hypothesized that corruption and the transfer of money to elites is the main reason for the contraction of Nigeria's economy in the course of resource findings. Even though we control for institutional quality, these variables only capture specific aspects. The results depicted in columns 7 and 8 indicate an insignificant effect of relative oil abundance on migrant selectivity if we exclude high-income countries which is in line with our presumption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pooled OLS	Pooled OLS	RE	RE	FE	FE	FE	FE
Country Pair Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects?	No	Yes	No	Yes	No	Yes	No	Yes
High Income Countries?	Yes	Yes	Yes	Yes	Yes	Yes	No	No
GDP_{t-1}	-1.123*	-0.973*	-1.903*	-0.685*	-2.098*	-0.217	-2.421*	0.586
	(0.137)	(0.126)	(0.230)	(0.232)	(0.291)	(0.381)	(0.377)	(0.523)
$GDP_{t-1} \times$ Distance	-2.26e-09	8.18e-10	-1.04e-09	1.49e-10	-1.18e-09	-8.62e-10	-1.18e-08	-1.86e-08
	(1.98e-09)	(1.63e-09)	(2.94e-09)	(2.52e-09)	(3.45e-09)	(3.56e-09)	(1.62e-08)	(1.28e-08)
Distance	0.545*	0.437*	0.465**	0.348***				
	(0.105)	(0.101)	(0.183)	(0.184)				
Common Language	0.295	0.392**	0.400	0.495				
	(0.195)	(0.190)	(0.366)	(0.363)				
Colonial Tie	0.309	0.199	0.511	0.176				
	(0.283)	(0.270)	(0.621)	(0.577)				
Democracy (source-host)	-0.00717	-0.0460**	0.0628***	-0.0862**				
	(0.0198)	(0.0203)	(0.0350)	(0.0393)				
Civil War (source-host)	1.002*	1.068*	0.310*	0.300*	0.211***	0.181**	0.106	0.0610
	(0.219)	(0.211)	(0.117)	(0.0884)	(0.110)	(0.0849)	(0.130)	(0.101)
Quantity Migration	-0.473*	-0.527*	-0.144	-0.251*	-0.0499	-0.133	0.240	0.0438
	(0.0513)	(0.0492)	(0.0885)	(0.0790)	(0.115)	(0.0949)	(0.149)	(0.133)
Oil Income (source-host)	0.244**	0.223***	0.216**	0.177**	0.122*	0.125**	0.0333	-0.133
	(0.121)	(0.122)	(0.0883)	(0.0777)	(0.0377)	(0.0533)	(0.194)	(0.209)
Constant	11.02*	8.855*	16.27*	7.024*	21.53*	6.124**	22.22*	0.546
	(1.614)	(1.473)	(2.743)	(2.645)	(2.452)	(3.017)	(2.798)	(3.713)
N	1147	1147	1147	1147	1187	1187	599	599
R^2	0.235	0.289	0.1818	0.2483	0.378	0.534	0.369	0.564

Notes: Migrant Selection regressed on the difference of oil income per capita between source and host countries in a static framework. Time Span: 1910-2009. Columns (1) and (2) display Pooled OLS estimates, Columns (3) and (4) depict Random Effects estimates and Columns (5)-(8) Fixed Effects estimates. Democracy and the number of civil wars along with the oil Income per capita are considered as the difference between source and host countries. Additionally, ethnic fractionalizations between the source and host countries are controlled for in models (1)-(4). GDP and distances between source and host countries are log-linearized. The data set is aggregated for source-destination country pairs and decades. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Baseline Panel Regressions

In the next step we provide a dynamic panel model in order to account for partial adjustments in the selectivity of migration.

3.3.2 Dynamic Panel Model

A dynamic panel model of migrant selectivity is set out as follows.

$$SELECTIVITY_{ijt} = \alpha_{ij} + \chi_t + \beta SELECTIVITY_{ijt-1} + \gamma RESOURCES_{ijt} + \boldsymbol{X}'_{ijt}\delta + \epsilon_{ijt} \quad (33)$$

Again, the consistency of the fixed effects estimator depends on the strict exogeneity assumption implying that idiosyncratic error terms and covariates are uncorrelated in each period. Formally,

$$E[\epsilon_{ijt}|x_{ijt}, RESOURCES_{ijt}, \alpha_{ij}] = 0 \quad (34)$$

for $t = 1, ..., T$.[8] Conversely, estimators based on the within or first difference transformation necessarily give rise to correlations between ϵ_{ijt} and $SELECTIVITY_{ijt-1}$ in dynamic panel models. In turn, these correlations lead to inconsistent estimates for N tending to infinity and T fixed (Nickell (1981)).

In essence, there are three potential remedies. Anderson and Hsiao (1981) suggested to build first differences in order to remove fixed effects and to instrument the endogenous regressor, $\Delta SELECTIVITY_{i,t-1}$, with an additional exogenous lag in levels or differences. In contrast, Arellano and Bond (1991) make use of all available lags of the endogenous variable in a generalized method of moments (system GMM) approach to instrument lagged differences while improving efficiency. Instruments in levels are reasonably weak for variables in differences if the variable of interest follows a random walk. Therefore, Blundell and Bond (1998) propose a different estimator which makes use of a combination of lagged differences and levels while instrumenting the lagged dependent variable (difference GMM). Table 4 below displays results of both procedures, system GMM and difference GMM. Additionally, Hansen-J-test statistics are provided in order to test for the exogeneity of instruments through overidentifying restrictions.

[8] We abstract from time-fixed effects in a first step.

	(1) Arellano-Bond System GMM	(2) Arellano-Bond System GMM	(3) Arellano-Bond System GMM	(4) Arellano-Bond System GMM	(5) Blundell-Bond Difference GMM	(6) Blundell-Bond Difference GMM	(7) Blundell-Bond Difference GMM	(8) Blundell-Bond Difference GMM
Country-Pair Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects?	No	No	Yes	Yes	No	No	Yes	Yes
High Income Countries?	Yes	Yes	No	No	Yes	Yes	No	No
Selectivity$_{t-1}$	0.904***	0.921***	0.915***	0.928***	0.841***	0.861***	0.860***	0.915***
	(0.0424)	(0.0508)	(0.0634)	(0.0681)	(0.0490)	(0.0648)	(0.0664)	(0.0741)
log(GDP)$_{t-1}$	-0.353***	-0.314***	-0.140**	-0.142**	-0.390***	-0.311***	-0.187***	-0.123**
	(0.0667)	(0.0820)	(0.0664)	(0.0672)	(0.0717)	(0.0822)	(0.0688)	(0.0603)
log(Distance)	0.0191	-0.0328	-0.00547	-0.0234	0.0522	-0.00249	0.0232	-0.0173
	(0.0513)	(0.0649)	(0.0539)	(0.0703)	(0.0506)	(0.0644)	(0.0513)	(0.0679)
Common Language	-0.154*	-0.147	-0.0785	-0.139	-0.125	-0.124	-0.0516	-0.136
	(0.0858)	(0.131)	(0.0828)	(0.120)	(0.0901)	(0.136)	(0.0821)	(0.119)
Colonial Tie	0.268**		0.0913		0.273**		0.101	
	(0.116)		(0.106)		(0.133)		(0.117)	
Democracy (source-host)	0.0524***	0.0418***	0.0255***	0.0325***	0.0469***	0.0359***	0.0218***	0.0305***
	(0.00816)	(0.0124)	(0.00873)	(0.0115)	(0.00845)	(0.0129)	(0.00813)	(0.0112)
Civil War (source-host)	-0.0873	-0.152	-0.0764	-0.106	0.0350	-0.000740	0.0373	-0.0453
	(0.0921)	(0.131)	(0.0940)	(0.129)	(0.108)	(0.165)	(0.118)	(0.174)
log(Quantity Migration)	0.0237	-0.00140	-0.0227	-0.00504	0.0119	-0.0302	-0.0378	-0.00999
	(0.0297)	(0.0460)	(0.0382)	(0.0536)	(0.0359)	(0.0554)	(0.0424)	(0.0601)
Oil Income (source-host)	0.0784*	0.135**	0.0722*	0.116*	0.111***	0.138**	0.0998**	0.119**
	(0.0408)	(0.0654)	(0.0393)	(0.0600)	(0.0382)	(0.0630)	(0.0410)	(0.0597)
Constant	2.599***	2.677***	2.068***	1.906**	2.949***	2.839***	2.274***	1.660**
	(0.712)	(0.942)	(0.645)	(0.753)	(0.797)	(0.973)	(0.676)	(0.718)
N	1147	573	1147	573	1147	573	1147	573
Number Instruments	38	35	46	43	31	28	39	36
Hansen J	42.29	24.26	34.47	15.67	28.02	20.93	13.31	6.69

Notes: Migrant Selection regressed on the difference of oil income per capita between source and host countries in a dynamic framework. Time span: 1908-2010. Columns (1) - (4) display System-GMM estimates, columns (5)-(8) Difference-GMM estimates. Democracy and the number of civil wars along with the oil Income per capita are considered as the difference between source and host countries. GDP and distances between source and host countries are log-linearized. Additionally, ethnic fractionalizations between the source and host countries are controlled for in all specifications. The data set is aggregated for source-destination country pairs and decades. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Dynamic Panel GMM estimates

The results of the dynamic panel depicted above are mainly in line with our previous findings with respect to our main coefficient of interest, γ, and robust through all specifications. Oil abundance between source and destination countries is positively related to the selectivity of emigration. Resource abundant country seem to strengthen brain drain effects. Again, GDP and emigrant selection are negatively associated but excluding high income countries does not impinge on the significance of the resource coefficient. Finally, the results indicate a strong persistency of migrant selection over time which might reflect the insignificant coefficient of the quantity of migration as well.

By now, we exclusively focused on the direct effect of resource abundance on migrant selectivity. However, in the theoretical section 2, inequality effects served as an intermediary between resource booms and brain drain effects. In order to verify (or falsify) the theoretical predictions, we disentangle the effects of resource booms and inequality on the one hand and the relationship between income inequality and migrant selectivity on the other hand by means of a structural equation model. The framework is at the center of the follow section.

3.3.3 Structural Equation Model

In order to verify whether brain drain effects are mediated through inequality effects, we construct a structural equation model (SEM). This model treats income inequality and migrant selectivity as endogenous while applying a three-stage-least squares (3SLS) procedure in order to estimate two equations simultanously. While the first equation relates resource abundance and inequality, the second equation relates inequality effects and migrant selectivity. Formally, I construct the following simultaneous equation system:

$$GINI_{ijt} = \gamma_{ij} + RESOURCES_{ijt}\zeta + \boldsymbol{Z}'_{ijt}\alpha + u_{ijt} \tag{35}$$

$$SELECTIVITY_{ijt} = \theta_{ij} + GINI_{ijt}\beta + \boldsymbol{X}'_{ijt}\gamma + \eta_{ijt} \tag{36}$$

which can be written more compactly as

$$\boldsymbol{Y} = \boldsymbol{Z}'\xi + \epsilon \tag{37}$$

Consistently with the previous sections, the dependent variable, SELECTIVITY, is defined as the difference between the years of schooling of emigrants and the average years of schooling in the source country while the variable RESOURCES is specified as the oil income generated relative to population size in constant prices of 2007. The variable GINI captures GINI coefficients as long as they are available for respective time periods and countries. Complementarily, we rely on inequality measures based on height data (height GINI) which we draw from Baten and Mumme (2010) for those countries for which GINI coefficients are not available. The use of height data is based on the assumption that income inequality and human height variance are correlated. The main variables of interest are accompanied by a set of additional covariates, indicated by $\boldsymbol{Z}_{it}$ (equation 36) and $\boldsymbol{X}_{it}$ (equation 37), which might impinge on income inequality and migrant selectivity, respectively. In the equation explaining migrant selectivity these variables coincide with the baseline setup as long as they are not time invariant and swept out by first differences. In the equation explaining income inequality covariates are selected based on previous studies. Essentially, we refer to Roine et al. (2009) in selecting appropriate covariates. Variables which were shown to be relevant comprise the share of exports as part of the gross domestic product along with the share of manufacturing goods relative to the total amount of exports. Whilst the former captures quantity of market integration the latter accounts for the quality of market integration. Further, we control for the share of people living in urban areas and the inflation rate which gives rise to distributional effects. Additionally, we control for extreme events like civil wars. Finally, we include a variable which captures educational inequality which might translate into income inequality subsequently. Again, in order to account for push and pull factors, we include the difference of the determinants between source and destination countries.

In and effort to estimate the structural equation model above, we proceed in two steps. First, we build first differences of equation 35 and 36 in order to expunge the fixed effects γ_i and θ_i, respectively. Thereby, time-invariant covariates are swept out. Second, we rely on a three-stage-least-squares approach which combines a 2SLS estimator with a generalized-least-squares estimator. Namely, the 2SLS estimator can be specified as follows in the light of the notation above:

$$\hat{\xi}_{2SLS} = \left(\hat{Z}'\hat{Z}\right)^{-1}\hat{Z}y \tag{38}$$

In contrast to the 2SLS estimator, the 3SLS is based on the estimated residuals $E(\hat{\sigma}'\hat{\sigma}) = \hat{\Sigma} \otimes I$:

$$\hat{\xi}_{3SLS} = \left(\hat{Z}'[\hat{\Sigma} \otimes I]\hat{Z}\right)^{-1}\hat{Z}'[\hat{\Sigma} \otimes I]y \tag{39}$$

where I is the identity matrix.

The following table shows results of the structural equation model based on three-stage-least squares estimates described above. The results of the simultaneous equation model depicted above are only partially consistent with our baseline regressions and therefore provide only partial support in favor of our theoretical considerations in section 2.

	(1) Selectivity	(2) Selectivity
Selectivity		
Gini (source-host)	0.0675***	0.0922**
	(0.0374)	(0.0405)
GDP_{t-1}	-0.165	0.0966
	(0.771)	(0.791)
$GDP_{t-1} \times$ Distance	3.59e-09	-3.46e-09
	(7.95e-09)	(7.62e-09)
Civil War (source-host)	0.401**	0.401**
	(0.191)	(0.185)
Quantity Migration	-0.241	-0.319
	(0.295)	(0.302)
Constant	-0.777*	-0.806*
	(0.272)	(0.293)
Gini (source-host)		
GDP_{t-1} (source-host)	-2.216	-2.376***
	(1.403)	(1.364)
Oil Income (source-host)	-0.00289***	
	(0.00165)	(0.00162)
Educational Inequality (source-host)	-0.246	-0.142
	(0.224)	(0.214)
Urbanization (source-host)	0.295*	0.298*
	(0.0700)	(0.0704)
Export (source-host)	-0.130	-0.0407
	(0.124)	(0.109)
Inflation (source-host)	-0.0173	
	(0.0573)	
Manufacturing (source-host)	0.0702	0.0819
	(0.102)	(0.0970)
Civil War	-2.065***	-1.656
	(1.168)	(1.076)
Constant	2.328**	1.847***
	(1.098)	(1.059)
N	59	65
R^2	0.2869	0.2458

Standard errors in parentheses
*** $p < 0.1$, ** $p < 0.05$, * $p < 0.01$

Notes: Migrant Selection regressed on the GINI coefficients between source and host countries and GINI coefficients regressed on oil Income per capita. Columns (1) and (2) are estimated based on a 3 SLS procedure. On the first stage, instruments are obtained by regressing endogenous variables on all exogenous variables which gives us fitted values. On the second stage, an estimate for the covariance matrix is derived and finally the GLS procedure is applied. GDP and distances between source and host countries are log-linearized. All bilateral variables besides of GDP are accounted for as the difference between source and host countries. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Structural Equation Model

In accordance with our theoretical conjectures, increasing oil revenues lead to less dispersed income distributions. Inequality effects depend mainly on the assumption that the share of low-skilled labor in the service sector offsets the share of low-skilled labor in the manufacturing sector. As mentioned previously, services solely capture non-tradable services, while sophisticated business services are part of the tradable sector. Hence, this assumption is mainly satisfied by definition. In contradiction to Borjas (1987), relative income dispersions do not translate into brain drain effects. However, GINI coefficients and covariates are available primarily for high income countries which might be able to turn the curse into a blessing, as suggested previously. The possibility of sample selection biases are discussed in the next section as well.

3.3.4 Further Robustness Checks

In order to confirm the robustness of our results for different model specifications, we have to perform several additional checks. First, we have to check whether our results are just limited to oil abundant countries or whether the results can be generalized to different kind of resources as the title of the paper suggests. In the regression table 5 depicted below we relate the selectivity of migration and an aggregate resource measure based on Haber and Menaldo (2011). Namely, the variable comprises income generated by oil, natural gas, coal, precious metal, and industrial metal industries. Based on aggregate resource income, the results are still in line with our baseline regression. Aggregate resource abundance still gives rise to brain drain effects. The resources accounted for are all point-source natural resources as the theoretical predictions we explicitly derived under the assumptions of a point-source nature. Namely, the manufacturing and service sector was not explicitly accompanied by a resource sector. Rather, resource income was considered in the budget constraint of local residents.

	Arellano-Bond System GMM	Arellano-Bond System GMM	Arellano-Bond System GMM	Arellano-Bond System GMM	Blundell-Bond Difference GMM	Blundell-Bond Difference GMM	Blundell-Bond Difference GMM	Blundell-Bond Difference GMM
Country-Pair Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects?	No	No	Yes	Yes	No	No	Yes	Yes
High Income Countries?	Yes	Yes	No	No	Yes	Yes	No	No
Selectivity								Selectivity
Selectivity$_{t-1}$	0.960*	0.955*	0.970*	1.042*	0.961*	0.961*	0.963*	0.972*
	(0.0351)	(0.0351)	(0.0427)	(0.0582)	(0.0341)	(0.0341)	(0.0409)	(0.0389)
Selectivity$_{t-2}$				-0.135*				-0.0774**
				(0.0424)				(0.0330)
GDP$_{t-1}$	1.016	-0.301*	-0.100***	-0.187*	-0.280*	-0.280*	-0.104**	-0.178*
	(0.668)	(0.0579)	(0.0521)	(0.0625)	(0.0578)	(0.0578)	(0.0505)	(0.0477)
GDP$_t - 1 \times$ Distance	-0.151**							
	(0.0760)							
Distance	1.220***	-0.00605	-0.0323	0.00913	-0.00841	-0.00841	-0.0278	0.0112
	(0.634)	(0.0496)	(0.0480)	(0.0636)	(0.0496)	(0.0496)	(0.0470)	(0.0446)
Common Language (source-host)	-0.236*	-0.190**	-0.114	-0.0596	-0.196**	-0.196**	-0.113	-0.0667
	(0.0895)	(0.0825)	(0.0783)	(0.116)	(0.0824)	(0.0824)	(0.0774)	(0.0775)
Colonial Tie	0.318*	0.274**	0.0940		0.275**	0.275**	0.0973	0.145
	(0.114)	(0.110)	(0.104)		(0.110)	(0.110)	(0.105)	(0.112)
Democracy (source-host)	0.0548*	0.0534*	0.0294*	0.0262**	0.0527*	0.0527*	0.0288*	0.0219*
	(0.00827)	(0.00810)	(0.00747)	(0.0113)	(0.00799)	(0.00799)	(0.00710)	(0.00764)
Civil War (source-host)	-0.128	-0.132	-0.133	-0.184	-0.103	-0.103	-0.0888	0.00291
	(0.0940)	(0.0941)	(0.0953)	(0.147)	(0.105)	(0.105)	(0.0993)	(0.0992)
Quantity Migration	0.0572**	0.0614**	0.00993	-0.00463	0.0791*	0.0791*	0.0203	-0.0237
	(0.0255)	(0.0258)	(0.0282)	(0.0403)	(0.0268)	(0.0268)	(0.0293)	(0.0267)
Resource Income (source-host)	0.117**	0.108**	0.0734**	0.0962	0.118*	0.118*	0.0914*	0.0681***
	(0.0572)	(0.0478)	(0.0355)	(0.0853)	(0.0359)	(0.0359)	(0.0325)	(0.0352)
Constant	-8.717	1.988*	0.548	1.712**	1.714*	1.714*	0.515	2.693*
	(5.575)	(0.660)	(0.617)	(0.785)	(0.665)	(0.665)	(0.615)	(0.623)
N	1147	1147	1147	478	1147	1147	1147	981

Notes: Migrant Selection regressed on the difference of oil income per capita between source and host countries in a dynamic framework. Time Span: 1908-2009. Column (1) -(4) display System-GMM estimates, column (5)- (8) display Difference-GMM estimates. GDP and distances between source and host countries are log-linearized. All bilateral variables besides of GDP are accounted for as the difference between source and host countries. Additionally, ethnic fractionalizations between the source and host countries are controlled for in the model explaining inequality. Robust standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Dynamic Panel GMM estimates

Second we have to encounter two potential selectivity issues, sample selection biases as well as self-selection biases. Introductorily, we already touched on the latter, self-selection biases, suggesting that bilateral migration streams are not exogenous. Instead, individuals self-select themselves into destination countries based on relative skill premia in source and all potential destination countries under consideration of migration costs. This problem is particularly relevant for investigating the effects on the quantity of migration and could be tackled with a conditional logit framework. But since we directly refer to the selectivity of migration, we explicitly allow and account for sample selection with respect to the schooling of migrants. Therefore, this problem is negligible in out setup as long as the correlation between the quantity and the selectivity of migration is sufficiently low.

The former, sample selection biases, are addressed by randomly selecting individuals and countries. Since we exclusively focus on representative survey data, we do not face any sample selection issues at first sight. But since our data are mainly based on bilateral migration patterns between a selection of countries and not based on all potential source and destination countries, we have to check whether the country selection facilitates external validity. Therefore, we exemplarily compare GDP for the set of source countries, the set of destination countries and for all countries available in the World Bank development indicators dataset by decades 1960-2000.

Decade	Source Countries	Destination Countries	All countries
1960	690.3153	652.4576	516.2651
1970	981.3153	1001.26	873.5599
1980	2916.806	2974.765	2716.802
1990	5121.846	5038.228	4325.012
2000	8043.441	8113.205	7435.319

Notes: Mean GDP per capita in current USD for different samples. All countries comprise countries for which World Bank (2015) data are available.

Table 7: Mean GDP for different samples

According to the table above, the sample of source and destination countries is not fully representative, but differences are not large enough to totally undermine external validity.

4 Conclusion

The general question whether the abundance of natural resources is a curse or a blessing has been investigated for more than three decades. While most of the papers focus on the relationship between resource booms and economic development, we illuminate the relationship between resource booms and the selectivity of migration. The main contribution of this paper is to derive theoretical predictions regarding the relationship between resource shocks and migrant selectivity, and to test our theoretical predictions based on panel data. Namely, we aimed at answering the following research questions: Does resource abundance impinge on the selectivity of emigration? Is the impact of resource abundance on migrant selectivity mediated through income inequality, as Borjas (1987) suggests? Do the effects differ with respect to specific country characteristics?

Theoretically, income inequality served as an intermediary between dutch disease effects and selectivity effects. We proved that point-source resource booms lead to brain drain effects as long as the share of low skilled labor in the not-tradable sector outweighs the share of low-skilled labor in the tradable sector and the correlation of income across countries is sufficiently high. Specifically, a resource boom elicits a dutch disease which translates into a contraction of the income distribution in real terms. Everything else being equal, reduced skill premia in the source country lay the ground for brain drain effects through the lens of the Borjas model.

Empirically, we relied on panel data models which account for migrant selectivity between 113 source countries and 26 destination countries between 1910 and 2009 in order to verify or falsify out theoretical predictions. Specifically, we pursued fixed and random effects panel estimates as a baseline setup and carried the empirical analysis forward to dynamic panel estimates and to a structural equation model. The former accounts for partial adjustments in migrant selectivity while the latter disentangles the impact of resource booms on income inequality and migrant selectivity. The results are only partially in line with our theoretical predictions. Consistently through all models, the results show that resource booms foster brain drain effects. Whether brain drain effects are mediated through income inequality, however, is not clear cut.

Introductorily we referred to Gylfason et al. (1999) raising the question whether there is an inverse relationship between natural capital and human capital. According to our results, adverse effects of resource windfalls on human capital are not limited to local residents. Rather, resource booms might even crowd out human capital through migration.

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