Resource Booms, Selective Mobility and Human Capital

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Vorgelegt von

Daniel Steinberg
aus Kassel

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Dekan: Prof. Dr. rer. soc. Josef Schmid

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For my parents.

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INTRODUCTION

"(...) Self-selection plays a dominant role in determining the size and composition of immigrant flows."

– Borjas (1987), p. 1.

Natural resource abundance is generally considered to be a curse rather than a blessing for economic development. This dissertation examines selective mobility patterns and changes in educational investments among local residents in response to natural resource booms. Before I proceed with an overview of the theoretical and empirical linkages between resource shocks, selective mobility and educational investments, I provide a brief introduction into each strand of the literature separately.

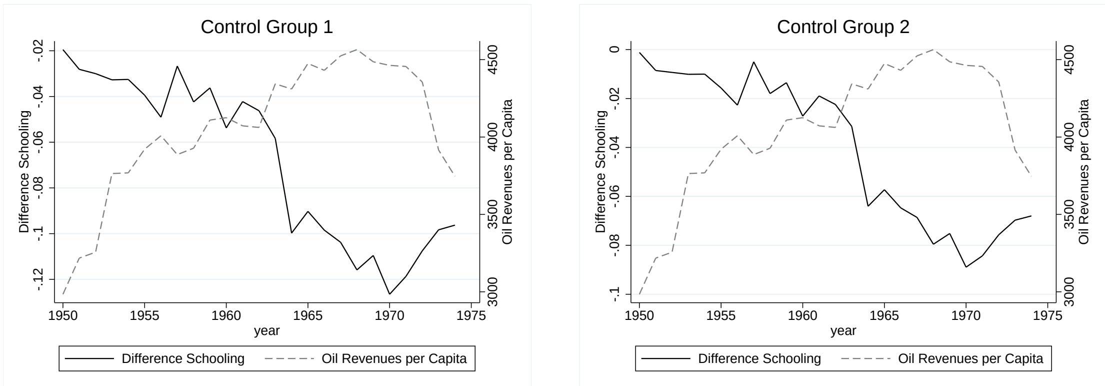
1.1 Natural Resource Economics

Since the seminal contribution of Sachs and Warner (1995), a whole body of literature was devoted to the effect of natural resource abundance on measures of economic performance. According to the findings of Sachs and Warner (1995), resource abundance serves as an impediment rather than a propeller for economic prosperity based on a cross-country panel of 97 countries. For instance, "oil revenues per capita in Nigeria increased from USD 33 in 1965 to USD 325 in 2000, but income per capita has stagnated at around USD 1,100 in PPP." (Van der Ploeg (2011), p. 367) Similarly, Iran, Venezuela, Libya and Kuwait deteriorated economically in the course of the oil boom. Even OPEC as a whole saw a decline in GDP per capita by 1.3 percent, while the developing world grew on average by 2.2 percent annually (Van der Ploeg (2011)). Though challenged by recent findings of Alexeev and Conrad (2009), the conventional wisdom of a negative association between resource abundance and economic prosperity even holds in historical contexts. "In the seventeenth century, resource-poor Netherlands eclipsed Spain besides the overflow of gold and silver from Spanish Colonies in the New

World." (Sachs and Warner (1995), p. 2) Consistently, Auty (1993) and Gelb (1988) have shown that natural resource abundance has a significant but negative impact on economic prosperity. The inverse relationship between economic and natural wealth might be mediated through a Dutch disease (Corden and Neary (1982), Corden (1984), Torvik (2001), Ismail (2010)), through civil conflicts, corruption and public rent seeking activities (Auty (2001)) or through adverse effects on educational investments (Gylfason (2001), Stijns (2006)).

With respect to a Dutch disease, a resource boom lays the ground for a real appreciation of the exchange rate (spending effect) which translates into a boom of the non-tradable sector and a bust of the tradable sector. The Dutch disease also goes along with intersectoral factor movements from the tradable sector towards the resource sector and the non-tradable sector (resource movement effects). The deindustrialisation as a consequence of the Dutch disease might retard economic prosperity in the short run and undermine the competitiveness of the whole economy in the long run. While the first formal Dutch disease models were set out by Corden and Neary (1982) along with Corden (1984) and extended by Wijnbergen (1984a) and Krugman (1987), the term "Dutch disease" goes back to the Economist in 1977, referring to an economic downturn emerging in the Netherlands as a consequence of gas fields discovered in the North Sea in 1959. Empirical studies testing the implications of Dutch disease models are mostly in line with the theoretical predictions for developing countries. While Elbadawi and Soto (1997) as well as Fardmanesh (1990) confirm Dutch disease effects in several developing countries, Bjornland (1998) can find "only weak evidence of a Dutch disease in the UK, whereas manufacturing output in Norway has actually benefited from energy discoveries and higher oil prices." (p. 553)

With respect to educational investments, Gylfason (2001) shows that resource booms might lead to a crowding out of human capital. This consistently holds in terms of years of schooling on the demand side as well as in terms of educational expenditures on the supply side. While Gylfason (2001) refers to cross-country correlations, the crowding out of human capital materializes even on a US state level. In figure 1.1, I report correlations between oil revenues per capita and the difference in years of schooling between oil abundant states and a control group composed of states which have not engaged in oil drilling throughout the 20th century.[1] The control groups serve as a reference in order to account for a counterfactual which is of particular importance due to the path dependencies and unit roots in educational investments. In particular, the panel on the left-hand side is based on a control group composed of all US states which have not not engaged in any oil drilling according to Hamilton (2011) (control group 1) and the panel on the right hand side is based on a large control group made up of US states which have not not engaged in significant oil drilling (control group 2), respectively. With respect to the latter, seven states with the highest oil revenues per capita are excluded.[2]



Notes: Correlation between oil revenues per capita and the difference in educational investments between oil abundant US states and a control group. Control group 1 is composed of all US states besides of Alaska, Texas, Louisiana, California, Oklahoma, Ohio, Wyoming, West Virginia, Pennsylvania, New York, Illinois, Indiana, Kansas, North Dakota, Montana, Colorado, Utah. Control group 2 is composed of all US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Data sources: Hamilton (2011), Ruggles et al. (2010).

Figure 1.1: Correlations: Oil Revenues - Schooling

[1] Oil production data originate from Hamilton (2011), while the years of schooling are derived from Ruggles et al. (2010).

[2] Control group 1 is composed of all US states besides of Alaska, Texas, Louisiana, California, Oklahoma, Ohio, Wyoming, West Virginia, Pennsylvania, New York, Illinois, Indiana, Kansas, North Dakota, Montana, Colorado, Utah. Control group 2 is composed of all US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming.

Conspicuously, until the first oil crisis, oil windfall gains corresponded with a shortfall in relative educational investments measured in the years of schooling by graduation year which is consistent with the simple correlations reported in table 1.1. Again, the outcome variable is defined as the difference in the years of schooling in oil abundant states and the average years of schooling in control group 1 (columns (1) - (3)) and control group 2 (columns (4) - (6)), respectively. Consistently, the panel estimates point at a negative correlation between the relative years of schooling and oil revenues per capita. In fact, both the table and the figure report correlations without any necessary causal implications. I will further elaborate on the causal link between natural and human capital formation in Chapter 4 of the dissertation.

	(1)	(2)	(3)	(4)	(5)	(6)
	Schooling	Schooling	Schooling	Schooling	Schooling	Schooling
Time Period?	1955-1973	1955-1973	1960-1973	1955-1973	1955-1973	1960-1973
Control Group?	1	1	1	2	2	2
Trend?	No	Yes	No	No	Yes	No
Oil Revenues per Capita	-0.244***	-0.118**	-0.352***	-0.213***	-0.105**	-0.306***
	(0.0378)	(0.0491)	(0.0659)	(0.0375)	(0.0494)	(0.0644)
Constant	0.498***	8.633***	0.515***	0.516***	7.498***	0.530***
	(0.0235)	(1.872)	(0.0333)	(0.0228)	(1.864)	(0.0322)
N	190	190	120	190	190	120
R^2	0.971	0.975	0.978	0.973	0.976	0.980

Notes: Relative educational investments regressed on oil revenues per capita. Relative educational investments are defined as the difference in the years of schooling in oil abundant states relative to the years of schooling in states not engaging in oil drilling. Control Group 1 is composed of all US states besides of Alaska, Texas, Louisiana, California, Oklahoma, Ohio, Wyoming, West Virginia, Pennsylvania, New York, Illinois, Indiana, Kansas, North Dakota, Montana, Colorado, Utah. Control group 2 is composed of all US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered. * $p < .1$, ** $p < .05$, *** $p < .01$.

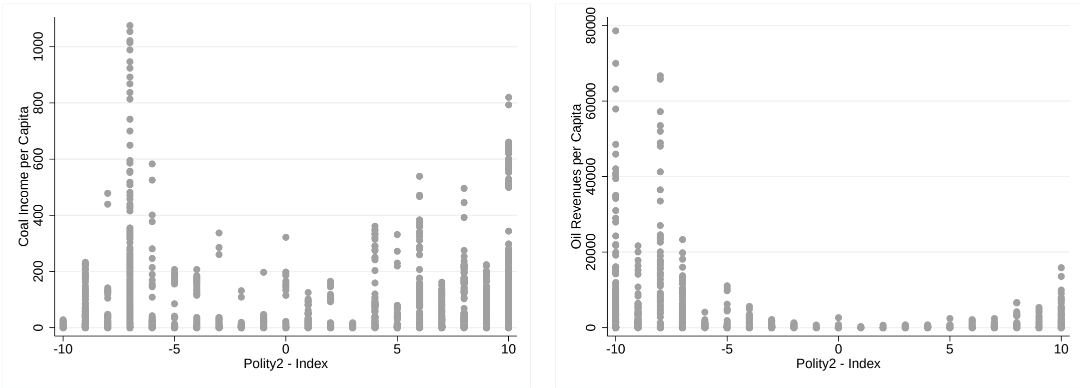
Table 1.1: Correlations Oil Abundance and the Relative Years of Schooling

In general, the adverse effects emerging out of resource booms are often referred to as “resource curse”, a term originally coined by Auty (1993). However, even though highly developed countries are not totally sheltered from a resource curse, it is well established that resource booms primarily dampen economic prosperity in countries with inferior political institutions and do less harm or might even be conducive to economic development in countries with superior political institutions. “The interaction of rich resources and fairly growth-promoting institutions seems to be rather a blessing (...)” (Baten (2016), p. 159) From this point of view, good political institutions might turn the resource curse into a blessing (Van der Ploeg (2011)). However, institutional quality itself is not exogenous. According to Acemoglu and Robinson (2006), resource rich countries often prevent institutional reforms in order to secure their political power and in order to extend the size of the public sector (Robinson et al. (2006)). In addition, resource windfalls might foster rent seeking activities which “lower returns to (...) entrepreneurship with possibly large marginal effects on production.” (Van der Ploeg (2011), p. 22) Finally, Collier and Hoeffler (2005) point out that resource abundance increases the likelihood of civil conflicts, as different groups are competing for resource windfall gains. The following figure depicts correlations between the institutional quality and oil revenues per capita (panel on the right hand side) as well as coal revenues per capita (panel on the left hand side), respectively, in a cross country panel spanning the years from 1800-2008.[3] Clearly, with respect to oil revenues per capita, the panel depicts a concentration of oil abundant states for negative polity2-indexes, while the relationship is almost U-shaped with respect to coal revenues per capita. Hence, the relationship between institutional quality and resource revenues appears to be sensitive to the specific kind of resources.

[3]The respective data are drawn from Haber and Menaldo (2011).

(a) Correlations: Coal Income - Polity2-Index

(b) Correlations: Oil Income - Polity2-Index



Notes: The figures depict correlations between a polity2 - index and a coal revenues per capita (panel on the left hand side) and oil revenues per capita (panel on the right hand side), respectively. Data source: Haber and Menaldo (2011).

Figure 1.2: Correlations: Resource Revenues - Polity2 - Index

While natural capital seems to be detrimental to economic prosperity, human capital is generally considered to be conducive to economic growth. The skill composition of a society is affected by selective mobility patterns as well which are introduced in the next subsection.

1.2 Selective Migration

This dissertation is particularly devoted to the human capital acquired by migrants relative to a specific reference group. The observation that migrants are not a random sample of the original population dates back to the seminal contribution of Borjas (1987) who draws from earlier work on self-selection by Roy (1951). According to the Roy-Borjas model, a positive selection of migrants is attracted from the country of origin if the returns to skills in the destination country exceed the returns to skills in the source country and returns to skills are sufficiently correlated across countries.

Studies relating relative skill premia to the selectivity of migration are only partially in line with the Borjas model. For instance, in international migration contexts, Abramitzky et al. (2012) studies migration patterns between Norway and the US during the era of mass migration and finds that the "return to migration was relatively low (70 percent) and that migrants from urban areas were negatively selected from the sending population." (p. 1832) Stolz and Baten (2012) refer to the era of mass migration as well and conclude that relative returns to skills in fact determined the selectivity of migration based on cross-country data. Additional studies mainly focus on bilateral migration patterns between Mexico and the US. In particular, Borjas (1987) and Moraga (2011) find that Mexican immigrants moving to the US are less skilled compared to the average Mexican resident due to relative returns to skills. In contrast, according to Chiquiar and Hanson (2005), migrants moving from Mexico to the US are better educated compared to the individuals left behind. However, as pointed out by Moraga (2011), Chiquiar and Hanson (2005) do not rely on representative samples. Rather, "U.S.-bound Mexican emigrants from 2000 to 2004 earn lower wages and have less (more for females) schooling than non-migrant Mexicans (...)" (p. 72).

Beyond the selectivity of migration, several studies focus on the impact of migration on the source and destination countries more generally. With respect to the source country, Beine et al. (2008) point out that the perspective of potential migration into more developed countries might be conducive to educational investments, fostering economic development in the source country. Moreover, there might be feedback and spillover effects on the source country through remittances and return migration as well as the transfer of values and norms (e.g. Docquier et al. (2016)).

With respect to the destination country, it has become consensus in the literature that native workers with complementary skills are better off while workers with substitutable skills are worse off in the course of migration (e.g. Dustmann et al. (2005)). In order to verify these theoretical predictions, Card (1990) made use of an influential natural experiment arising from the Mariel Boatlift in 1980 which led to a fierce influx of migrants increasing the workforce in Miami by 7 percent. Apparently, the influx neither affected unemployment nor wages of native workers in Miami. However, according to a recent paper of Borjas (2015), these results are sensitive to the definition of low-skilled workers. Namely, by focussing on high-school dropouts, Borjas (2015) shows that natives earned lower wages post of the boatlift. Complementarily, Glitz (2012) made use of the fall of the iron curtain which allowed ethnic Germans from eastern Europe to settle in Germany. In order to foster integration and assimilation, migrants were distributed exogenously throughout German regions. While exploiting the exogenous settlement of migrants, the authors find "a displacement effect of 3.1 unemployed workers for every 10 immigrants that find a job, but no effect on relative wages." (p. 175)

The exogenous distribution is inevitable, in order to isolate the effect of migration, as migrants are often attracted by peers (Bartel (1989), McKenzie and Rapoport (2007)). However, the relevance of peer-group and network effects in migration differ throughout the skill distribution. Low-skilled labor is much more dependent on communities in order to overcome language barriers and to find jobs. Conversely, high-skilled labor is generally more adaptable and is more likely to succeed even in the absence of network effects. However, in the course of integration and assimilation, communities might become less important. Abramitzky et al. (2013) examine the assimilation of European migrants moving to the US during the era of mass migration and find that "the average immigrant did not face a substantial occupation-based earnings penalty upon first arrival and experienced occupational advancement at the same rate as natives." (p. 467)

1.3 Human Capital Development

Besides of selective migration patterns, human capital of local residents is of particular importance for economic development. The role of educational attainment has been particularly highlighted since the seminal contributions of Schultz (1961) and Becker

(1962). The former took a stand for considering human capital as a complement for non-human capital in promoting economic growth, even though "treating human beings as wealth which can be augmented through investment runs counter to deeply held values." (Schultz (1961), p. 2) Schultz (1961) provided the first theoretical setup of human capital formation, according to which individuals (or their parents) contrast returns to skills in the future with opportunity costs at the present, in order to determine the optimal level of educational investments. Empirically, Mincer (1974) contributed to the literature in disentangling the effect of education and experience on earnings based on his famous Mincer-equation. Most of the studies focus on determinants of educational investments which are approximated by years of schooling or student test scores (e.g. Hanushek and Woessmann (2009)). However, "this emphasis has also become controversial because the expansion of school attainment has not guaranteed improved economic conditions." (Hanushek (2013), p. 204)

On a macro level, the first empirical studies relating educational investments to economic prosperity were conducted by Barro (1991) in a cross-country context. The seminal paper of Barro (1991) spawned a whole line of research verifying the role of human capital as a propeller for economic prosperity. These empirical studies were preceded by several theoretical attempts to incorporate human capital into growth models. Unlike in neoclassical growth models (Solow (1956)) in which technological progress serves as an exogenous determinant of economic growth, endogenous growth models proposed by Romer (1986), Lucas (1988) as well as Rebelo (1990) highlight the causes of technological progress. In this regard, educational attainment serves as an important determinant of technological progress and economic prosperity. Historically, however, endogenous growth models are not suitable to explain economic development prior to the industrial revolution. As a remedy, Galor and Weil (1999), Galor and Weil (2000) as well as Galor (2011) proposed a unified growth theory, according to which human capital plays a major role in explaining economic prosperity since the demographic transition. In particular, the unified growth theory postulates three major epochs. On an early stage of development, incomes stagnate on a low level with slow technological progress. However, with technological advancements, returns to skills increase, and hence educational investments. The rise in income spills into further technological progress and population growth as part of the Malthusian trap. At some point, the Malthusian trap is replaced by a demographic transition which is characterized by a decline in population growth corresponding with an increase in educational investments and sustained economic prosperity.[4]

While educational investments are usually measured in years of schooling and educational attainment in terms of test scores nowadays, historically, researchers might draw upon an ABCC index which measures numerical skills in terms of age heaping (A'Hearn et al. (2009)). In particular, the ABCC index is based on the share of people who state their age correctly rather than providing a rounded age. According to Crayen and Baten (2010), these measures are highly correlated with other common measures of human capital like years of schooling and literacy. Based on these measures, historical studies of human capital development have consistently pointed at land inequality as a major determinant for human capital (e.g. Baten and Juif (2014)).

On a micro level, several studies focused on individual determinants of human capital. Regarding these determinants, researchers pointed at educational attainment of parents, the number of siblings along with the family income. In particular, Solon (1992) as well as Behrman and Taubman (1990) along with Behrman (2010) find an intergenerational earnings coefficient between two consecutive generations of 0.80, 0.41 and 0.54, respectively. These correlation coefficients indicate that educational investments are partially inherited. Intergenerational transmissions might even be mediated through family income which serves as a means to bear educational costs (Teachman (1987), Blanden and Gregg (2004)). In addition, the number of siblings accounts for the

[4]Apart from the level of income, the distribution is affected by educational investments as well. In a recent influential contribution, Goldin and Katz (2007) show that "secular growth in the relative demand for more educated workers combined with fluctuations in the growth of relative skill supplies go far to explain the long-run evolution of U.S. educational wage differentials." (p. 1)

time constraints parents are facing which becomes even more binding with an increasing number of siblings (e.g. Blake (1985), Downey (2001), Ermisch and Francesconi (2001), Teachman (1987)). However, the number of children is not exogenous with respect to educational attainment and income (e.g. Becker et al. (1990)), which induces complex feedback effects between income, the number of children and the intergenerational transmission of educational attainment.

In the next subsection, I describe the linkages between resource booms, selective migration and education.

1.4 Structure

This dissertation sheds light on the relationship between natural resource abundance and the selectivity of international, intersectoral and interregional migration on the one hand and changes in human capital development among local residents on the other hand. In particular, as part of the dissertation, I raise the following questions: Do resource booms spill into brain drain or brain gain effects? Do internal and international migration patterns materialize consistently as a consequence of resource booms? What are the mediating factors relating resource booms to the selectivity of migration? Which role do migration networks play in migration decisions and do the network effects translate into the selectivity of migration? How can the multilateral character of migration decisions be internalized? How do educational investments among local residents respond to income windfalls? Are quasi-experimental setups an appropriate framework in order to analyze selective migration and shifts in educational investments in response to resource windfalls?

In order to tackle these questions, I divide the dissertation into 3 essays, each combining theoretical models with empirical investigations. Theoretically, the setups range from trade models in order to analyze selective migration patterns arising as a consequence of a Dutch disease, multinomial choice models in order to analyze selective regional mobility patterns and dynamic models of educational investments in order to examine the response of schooling to income windfalls. Empirically, I rely on modern econometric technics ranging from gravity equations and static as well as dynamic panel models to quasi-experimental research designs based on difference-in-differences models in order to derive average treatment effects and changes-in-changes setups in order to determine quantile treatment effects. Finally, I make use of non-parametric methods in order to take into account the multilateral character of migration decisions. These approaches are inevitable as migrants make multilateral decisions, prospectively, even though migration materializes as bilateral patterns, retrospectively.

In particular, in **Chapter 2**, I shed light on the effect of resource booms on the selectivity of international migration patterns both theoretically as well as empirically. Theoretically, I make use of a Dutch disease model, according to which a resource windfall leads to a real appreciation of the exchange rate (spending effect), corresponding with intersectoral factor movements from the tradable sector towards the non-tradable sector (resource movement effect). As long as the tradable (non-tradable) sector is skilled (unskilled) labor intensive, the boom of the non-tradable sector and the squeeze of the tradable sector makes skilled labor particularly worth off, setting the stage for brain drain effects. However, in order to translate into brain drain effects, the subsequent decline in skilled labor income has to outweigh initial resource transfers in absolute value. Throughout different regimes, from democratic to autocratic societies, this sufficient condition is satisfied. In a democratic society, the incumbent maximizes the probability of reelection for which the median voter is decisive under a majority rule. Hence, the incumbent has an incentive to exclusively please the median voter with respect to resource transfers. In an autocratic society, however, the political elite maximizes income and appropriates the entire share of resource revenues.

Therefore, from a strictly theoretical point of view, in an autocratic society resource windfall gains are neither forwarded to unskilled labor nor skilled labor, while in a democratic society resource transfers are exclusively devoted to unskilled labor if the median voter is decisive. In total, a resource boom leads to a net decline in income of skilled labor, setting the stage for brain drain effects. However, the net decline in income does not necessarily correspond with a contraction in total income inequality. Empirically, the analysis rests on census data capturing migration patterns between 116 source and 23 destination countries, spanning the period from 1910 to 2009. The econometric analysis is based on static and dynamic panel models along with a simultaneous equation model in order to decompose the relationship between resource booms, income inequality and migrant selectivity in the long run. Consistently, the results are in line with the theoretical conjectures, i.e. resource booms foster brain drain effects. Further, the results indicate that brain drain effects might be mediated through distributional effects. However, unlike the theoretical predictions which refer to labor income inequality, the empirical section refers to total income inequality.[5]

While Chapter 2 investigates the selectivity of international migration patterns in response to resource booms, **Chapter 3** examines whether resource abundance impinges on the skill composition of inter-state migration patterns within the US. Theoretically, I rely on a multinomial choice model, according to which individuals sort themselves into the destination state which offers the highest indirect utility under consideration of migration costs. If low-skilled labor derives a stronger utility gain from resource transfers, a resource boom lowers the relative educational background of prospective immigrants. Empirically, I rely on US decennial census data between 1940 and 2000, in order to relate oil revenues to the selectivity of interstate immigration based on static and dynamic panel setups. Retrospectively, migration patterns materialize as bilateral decisions, while prospectively, migration decisions are based on multilateral and multidimensional comparisons between the source and all potential destination states. In order to take into account multilateral comparisons of multidimensional push and pull

[5]The intuition of an increase of income inequality in the course of resource windfalls originates from the impression that a political elite appropriates the main share of resource windfall gains.

factors, I complement the static and dynamic panel model with a nonparametric approach which accounts for relative net migration in order to build an ordinal ranking of potential destination states, as pointed out above. In particular, if individuals vote with their feet in the sense of Tiebout (1956), the relative amount of net migration reflects the relative standard of living (Douglas and Wall (1993) and Wall (2001)). Consistently with the theoretical predictions, the results indicate that, on average, resource abundance lowers the relative educational background of prospective immigrants and unfolds ambiguous effects on the selectivity of emigration.

In contrast to Chapters 2 and 3 which refer to the educational background of migrants, **Chapter 4** investigates educational investments in response to income windfalls among local residents. Theoretically, I show that resource windfall gains which ease the household budget constraint through unconditional resource transfers might lower labor supply and returns to skills in the future. In light of lower returns to skills in the future, individuals might invest less in human capital at the present. According to Chapter 2, a real appreciation leads to a further decline in the returns to skills due to the deindustrialisation, setting the stage for an additional decay in human capital investments. In contrast, cutting progressive taxes or investing resource windfall gains into the quality of the school system in the course of a resource windfall might be conducive to human capital investments. However, the depletion of proportional labor income taxes is neutral regarding human capital investments as the costs and benefits of human capital investments are equally affected. Empirically, I make use of a unique oil boom in Alaska in 1968, in order to verify or falsify theoretical predictions. Elevating fiscal capacity, the oil boom sets the stage for the Alaska Permanent Fund in 1977 along with the depletion of all state income taxes in 1980. I rely on a difference-in-differences setup contrasting educational trends of local residents in Alaska with educational trends in a control group composed of several US states which were not exposed to resource booms. The results indicate a shortfall of educational investments compared to the control group as a consequence of the income windfall.

I proceed with Chapter 2 of this dissertation, which is devoted to the relationship between resource booms and the selectivity of international migration.

2

RESOURCE SHOCKS AND HUMAN CAPITAL STOCKS - BRAIN DRAIN OR BRAIN GAIN?

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 chapter sheds light on the relationship between resource abundance and the selectivity of migration. Theoretically, I combine a Dutch disease model with a Roy-Borjas model in order to elaborate on the relationship between resource shocks and migrant selectivity. In this regard, I predict that skilled labor is relatively worse off in the course of a deindustrialization as part of a Dutch disease, incentivizing brain drain effects. Empirically, I provide evidence for the effect of resource shocks on migrant selectivity based on a simultaneous equation model in order to disentangle effects on income inequality and migrant selectivity. The results show that resource shocks, especially oil booms, foster brain drain effects in a sample with 116 source and 23 destination countries between 1910 and 2009.[1]

[1]This chapter is single-authored and a version of this chapter has been published as: Steinberg, D. (2017), Resource Shocks and Human Capital Stocks - Brain Drain or Brain Gain? *Journal of Development Economics* 127, p. 250-268.

2.1 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 resource abundance is a curse or a blessing for economic development has been subject to several studies. In their pioneering paper, Sachs and Warner (1995) delivered evidence that the exploration and exploitation of natural resources serves as 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 and Zoega (2003)). 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 lead to distributional effects (Leamer et al. (1999), Goderis and Malone (2011), Gylfason and Zoega (2003)), while the effects depend 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, in this chapter, I relate resource shocks to the selectivity of migrants. Specifically, the chapter raises the following questions: What can be theoretically expected for the effect of resource shocks on the selectivity of migration? Are the selectivity effects mediated through distributional effects, as Borjas (1987) suggests? Do the effects differ with respect to specific country characteristics? In order to address these questions, I complement a theoretical analysis with an empirical investigation.

Theoretically, I rely on classical Dutch disease models (Corden and Neary (1982), Corden (1984), Torvik (2001), Ismail (2010)), according to which a resource boom corresponds with income windfalls which eventually lead to a real appreciation of the exchange rate.[2] The real appreciation translates into a crowding out of the tradable sector and a crowding in of the non-tradable sector (Corden and Neary (1982)).[3] Postulating a relatively skill intensive tradable sector, skilled labor is relatively worse off in the course of a Dutch disease. The latter holds in nominal as well as in real terms due to the Stolper-Samuelson theorem (Stolper and Samuelson (1941)). However, in order to account for net income effects, subsequent labor income effects across the skill distribution have to be contrasted with the initial distribution of resource windfall gains (Goderis and Malone (2011)). Finally, I complement the Dutch disease with a Roy-Borjas model (Roy (1951), Borjas (1987)), according to which selective migration is explained by the relative returns to skills as long as incomes are sufficiently correlated across states. As skilled labor encounters a decline in the returns to skills in the course of a Dutch disease, the probability of skilled emigration increases as a consequence of resource booms.[4]

[2]Additional Dutch disease models are provided by Alexeev and Conrad (2009), Bjornland (1998), Krugman (1987), Lama and Medina (2012), Wijnbergen (1984a), Wijnbergen (1984b).

[3]The term crowding out is not meant in the sense of macroeconomics.

[4]Parts of the framework are related to Ismail (2010), Goderis and Malone (2011) as well as Bougheas

Empirically, I rely on census data (Ruggles et al. (2010)) capturing migration patterns between 116 source and 23 destination countries between 1910 and 2009. Apparently, (quasi-) experimental research designs are not appropriate in order to relate resource booms to the selectivity of migration. This is due to the fact that migration decisions are multilateral decisions, i.e. the individual might compare several potential destination states, prospectively, even though migration materializes as bilateral patterns, retrospectively. However, even countries which were not affected by migration might still be part of the choice set. Hence, all potential control groups are at least partially treated and not separable such that quasi-experimental setups are inappropriate. Rather, I rely on static and dynamic panel models relating the selectivity of migration to the relative resource abundance between the source and host country. While the selectivity is measured as the difference in the years of schooling of migrants and the average years of schooling in the country of origin, resource abundance is measured as oil revenues per capita. In order to disentangle the relationship between resource booms, inequality and migrant selectivity, I complementarily rely on a simultaneous equation model. The results are basically in line with the theoretical predictions, i.e. a resource boom increase the probability of brain drain effects.

Robustness checks concern the sensitivity of the results with respect to the definition of natural resources in particular and to changes in the data set more generally. In addition, 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 individuals might have 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 test whether migrant restrictions have a serious impact on the results.

and Nelson (2012) but with exogenous income shocks easing the household budget constraint.

This chapter is organized as follows. Section 2.2 sets out a theoretical framework which relates resource shocks, income inequality and migrant selectivity. Section 2.3 implements several econometric models in order to relate resource booms and brain drain effects empirically. Section 2.4 concludes.

2.2 Theory

2.2.1 Assumptions

In order to derive the relationship between resource shocks, especially oil abundance, and migrant selectivity, I proceed in three steps. In a first step, I assume a country which experiences a resource windfall. This shock exclusively induces intersectoral labor movements while international migration is totally restricted. In a second step, I dispense with migration restrictions and allow for migration across countries. Finally, I illuminate the selectivity of international migration patterns in response to oil booms. This trichotomy enables me to isolate the effect of resource shocks on migrant selectivity while taking into account distributional effects as an intermediary. The sequential approach is in line with the optimization problems of individuals facing migrant restrictions in the short run. Allowing for perfect international mobility in the first place would upset or even undermine Dutch disease effects. As the theoretical model does not rely on differential equations, time indexes are omitted for the sake of parsimony.

In general, the resource abundant economy, R, comprises two sectors, manufacturing goods, M, which are tradable as well as services, S, which are non-tradable, $i \in \mathcal{I} = \{M, S\}$. As the economy faces exogenous world prices for the manufacturing good, the country can be characterized as a small open economy. Both sectors employ two sorts of labor, high-skilled labor, H, as well as low-skilled labor, L, $j \in \mathcal{J} = \{H, L\}$, though, the service sector (manufacturing sector) is low-skilled labor (high-skilled labor) intensive. This assumption is particularly relevant for developing countries in which the tertiary sector is not as sophisticated as in developed countries. However, in the framework set out below, services only capture basic services which are non-tradable while tradable and sophisticated business services are part of the tradable sector. In both sectors, I abstract from capital in the production process in line with Goderis and Malone (2011). However, accounting for capital as a production factor would probably even strengthen the results, as discussed below. Meanwhile, I set out the basic framework formally.

On the **supply side**, I assume perfectly competitive markets in both sectors while production in each sector, Y_i, is based on a Cobb-Douglas production technology with constant returns to scale:

$$Y_i = A_i L_i^{\alpha_i} H_i^{1-\alpha_i} \tag{2.1}$$

with $0 < \alpha_i < 1$. A_i is a technology parameter and α_i as well as $(1-\alpha_i)$ represent production elasticities of low-skilled labor, L_i, and high-skilled labor, H_i, in the service as well as the manufacturing sector, respectively. As I assume that the manufacturing sector (service sector) is high-skilled labor (low-skilled labor) intensive, it holds that $\alpha_S > \alpha_M$. Firms in both sectors are striving for maximized profits, π_i:

$$\max_{L_i, H_i} \qquad \pi_i = p_i A_i L_i^{\alpha_i} H_i^{1-\alpha_i} - w_H H_i - w_L L_i \tag{2.2}$$

$$\text{subject to} \qquad L_i \geqslant 0, H_i \geqslant 0 \tag{2.3}$$

where p_i, w_H and w_L indicate output prices and input prices for high-skilled and low-skilled labor, respectively. Firms wind up with the following first-order conditions:

$$w_L = p_i A_i \alpha_i L_i^{\alpha_i - 1} H_i^{1-\alpha_i} \tag{2.4}$$

$$w_H = p_i A_i (1-\alpha_i) L_i^{\alpha_i} H_i^{-\alpha_i} \tag{2.5}$$

Perfect competition precipitates zero profits in both sectors. This implies in the light of the dual approach that prices equal unit cost functions. Formally,

$$p_i = c_i(w_L, w_H, Y_i = 1) = \left[w_L^{\alpha_i} \left(\frac{\alpha_i w_H}{1-\alpha_i} \right)^{(1-\alpha_i)} + w_H^{(1-\alpha_i)} \left(\frac{(1-\alpha_i) w_L}{\alpha_i} \right)^{\alpha_i} \right] \tag{2.6}$$

Further, I assume full employment of low-skilled and high-skilled labor across sectors indicated by the following equations:

$$a_{MH} Y_M + a_{SH} Y_S = H \tag{2.7}$$

$$a_{ML} Y_M + a_{SL} Y_S = L \tag{2.8}$$

where $a_{iH} = \frac{H_i}{Y_i}$ and $a_{iL} = \frac{L_i}{Y_i}$ state the average amount of low-skilled labor and high-skilled labor which is necessary to produce one unit of output, Y_i. According to the full employment conditions, aggregate labor demand and labor supply decisions are totally exogenous. However, sectoral labor demand functions are endogenous and can be derived by a combination of first order and full employment conditions set out above. With respect to low-skilled labor the sectoral demand functions are (with $H = 1$) (e.g. Sayan (2005)):

$$L_M = -\frac{L \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_S}{\alpha_M-\alpha_S}\right)} \left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_S}{\alpha_M-\alpha_S}\right)} - \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M+\alpha_S}{\alpha_M-\alpha_S}\right)} \left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{2-\alpha_M-\alpha_S}{\alpha_M-\alpha_S}\right)} p^{\left(\frac{1}{\alpha_M-\alpha_S}\right)}}{\left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M}{\alpha_M-\alpha_S}\right)} \left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_M}{\alpha_M-\alpha_S}\right)} - \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_S}{\alpha_M-\alpha_S}\right)} \left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_S}{\alpha_M-\alpha_S}\right)}} \tag{2.9}$$

$$L_S = \frac{L \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M}{\alpha_M-\alpha_S}\right)} \left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_M}{\alpha_M-\alpha_S}\right)} - \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M+\alpha_S}{\alpha_M-\alpha_S}\right)} \left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{2-\alpha_M-\alpha_S}{\alpha_M-\alpha_S}\right)} p^{\left(\frac{1}{\alpha_M-\alpha_S}\right)}}{\left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M}{\alpha_M-\alpha_S}\right)} \left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_M}{\alpha_M-\alpha_S}\right)} - \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_S}{\alpha_M-\alpha_S}\right)} \left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_S}{\alpha_M-\alpha_S}\right)}} \tag{2.10}$$

while for high-skilled labor the demand functions are given by:

$$H_M = \frac{\left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_M}{\alpha_M-\alpha_S}\right)} - Lp^{\left(\frac{1}{\alpha_S-\alpha_M}\right)}}{\left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_M}{\alpha_M-\alpha_S}\right)} - \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_S}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_S}{\alpha_M-\alpha_S}\right)}} \tag{2.11}$$

$$H_S = -\frac{\left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_S}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_S}{\alpha_M-\alpha_S}\right)} - Lp^{\left(\frac{1}{\alpha_S-\alpha_M}\right)}}{\left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_M}{1-\alpha_S}\right)^{\left(\frac{1-\alpha_M}{\alpha_M-\alpha_S}\right)} - \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_S}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_M}{1-\alpha_S}\right)^{\left(\frac{1-\alpha_S}{\alpha_M-\alpha_S}\right)}} \tag{2.12}$$

Plugging in the factor demand functions into equations 2.4 and 2.5 yields the respective wages for low-skilled and high-skilled labor.

On the **demand side**, I posit a population composed of low-skilled individuals, L, along with high-skilled individuals, H, introduced above. Further, the population comprises a political elite, E, entailing individuals neither being involved in the provision of services nor in the production of manufacturing goods. Agents, $l \in \mathcal{L} = \{H, L, E\}$, choose consumption of manufacturing goods, M_l, and services, S_l, in order to bring utility, U_l, to a maximum, subject to their respective budget constraint (while manufacturing goods serve as a numeraire, $p = \frac{p_S}{p_M}$):

$$\max_{S_l, M_l} \quad U_l = \beta_l \log M_l + (1-\beta_l)\log S_l \tag{2.13}$$

$$s.t. \quad pS_l + M_l \leq Y_l \tag{2.14}$$

Unlike aggregate incomes, $Y = \sum_{l\in\mathcal{L}} Y_l$, individual incomes, Y_l, differ with respect to labor income, $w_H H = Y_H$ and $w_L L = Y_L$, as well as with respect to the individual share of resource income, $\mu_l \mathcal{R} = \tau_l(\mathcal{R})$ where τ_l represents the resource transfer in favor of l with $\sum_{l\in\mathcal{L}} \mu_l = 1$. Hence, total incomes equal $Y_H = w_H H + \mu_H \mathcal{R}$ for skilled labor, $Y_L = w_L L + \mu_L \mathcal{R}$ for unskilled labor and $Y_E = \mu_E \mathcal{R}$ with respect to the political elite.

This setup is based on the assumption that transportation costs are modest such that resource windfall gains are easing the household budget constraint, consistently with Torvik (2001). This assumption is standard in the literature and discussed in more detail below. The political elite serves as a gatekeeper for the distribution of resource transfers, $(\mu_H + \mu_L)\mathcal{R} = (1 - \mu_E)\mathcal{R}$, such that the shares μ_l are endogenously determined by the political elite. In order to allow for flexibility across different regimes, I do not make any further assumptions with respect to the objective of the political elite. However, in proposition 2 below, I contrast resource transfers in democratic regimes in which candidates compete under a majority rule as well as in autocratic regimes in which incumbents do not encounter any competition. Without loss of generality, in order to derive the market equilibrium, I assume a representative consumer. As usual, the optimal decision equates the marginal rate of substitution and the relative price.

$$\frac{\beta}{1-\beta}\frac{S}{M} = \frac{1}{p} \tag{2.15}$$

In light of the **market clearing** condition for services, $S = Y_S$, I further get for the relative price of services in terms of manufacturing goods:

$$p = (1-\beta)\frac{Y(\mathcal{R})}{Y_S} \tag{2.16}$$

which is a similar expression as in Torvik (2001). While the price of the manufacturing good is exogenously determined on the world market, the price of services is endogenous. Based on the equation above, resource windfalls increase the price of non-tradables in terms of tradables, $\frac{dp}{d\mathcal{R}} > 0$, which can be interpreted as an appreciation of the exchange rate. A real appreciation in the course of resource booms is often referred to as spending effect as part of a Dutch disease (Corden and Neary (1982), Corden (1984)). The real appreciation translates into a crowding out of the tradable sector in favor of the non-tradable sector. The theoretical prediction of a deindustrialisation in the course of a Dutch disease is confirmed by several empirical studies (e.g. Alexeev and Conrad (2009), Bjornland (1998), Krugman (1987), Lama and Medina (2012)). The real appreciation also translates into intersectoral labor movement effects due to the boom of the non-tradable sector and the squeeze of the tradable sector. Labor reallocations directly emerge from the sectoral factor demand functions derived above while taking into account that $\alpha_S > \alpha_M$:

$$\frac{\partial H_M}{\partial p} = \frac{-L\left(\frac{1}{\alpha_S-\alpha_M}\right)p^{\left(\frac{1-\alpha_S+\alpha_M}{\alpha_S-\alpha_M}\right)}}{\left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_M}{\alpha_M-\alpha_S}\right)} - \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_S}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_S}{\alpha_M-\alpha_S}\right)}} < 0 \quad (2.17)$$

$$\frac{\partial L_S}{\partial p} = \frac{-\left(\frac{1}{\alpha_M-\alpha_S}\right)\left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M+\alpha_S}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{2-\alpha_M-\alpha_S}{\alpha_M-\alpha_S}\right)}p^{\left(\frac{1+\alpha_S-\alpha_M}{\alpha_M-\alpha_S}\right)}}{\left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_M}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_M}{\alpha_M-\alpha_S}\right)} - \left(\frac{\alpha_S}{\alpha_M}\right)^{\left(\frac{\alpha_S}{\alpha_M-\alpha_S}\right)}\left(\frac{1-\alpha_S}{1-\alpha_M}\right)^{\left(\frac{1-\alpha_S}{\alpha_M-\alpha_S}\right)}} > 0 \quad (2.18)$$

Due to the real appreciation, demand for high-skilled labor in the manufacturing sector goes down, while demand for low-skilled labor in the service sector goes up. Though sectoral demand functions are endogenous, aggregate demand functions are exogenous in the first place which implies that the real appreciation does not impinge on aggregate labor demand.

However, after the materialization of the Dutch disease, I dispense with full employment conditions, and therefore with international **migration** restrictions. In a scenario with binary skills, individuals sort themselves into the country which provides them the highest income under consideration of migration costs (Sjaastad (1962)). Formally, in a world comprised by two countries, $k \in \{R, S\}$, a resource abundant country introduced above, R, and a resource scarce rest of the world, S, an individual, j, emigrates from R to S if income in S net of migration costs, C_{RS}, offsets income in R. Formally based on an Indicator, I,

$$I_j = \log\left(\frac{Y_S^j(w_j^S)}{Y_R^j(w_j(\mathcal{R}), \tau_j(\mathcal{R})) + C_{RS}}\right) > 0 \quad (2.19)$$

While income in the resource abundant country, Y_R, comprises both, labor income, $w_H H$ and $w_L L$, as well as resource transfers, τ_j, income in S is exclusively made up of exogenous labor income. As the empirical part investigates migrant selection based on continuous rather than binary skills, this case has to be discussed as well. In a world with continuous skills it will prove beneficial to assume a specific income distribution following Borjas (1987) while dispensing with individual indexes for the sake of parsimony subsequently:

$$\hat{Y}_k^j = \mu_k + \epsilon_k^j \tag{2.20}$$

where μ_k is a deterministic component reflecting mean incomes in country k while ϵ_k is a stochastic component reflecting individual specific deviations from the mean. The stochastic components are normally distributed with zero mean and a variance given by σ_k^2. Formally,

$$\epsilon_k^j \sim N(0, \sigma_k^2) \tag{2.21}$$

The correlation coefficient reflecting the transferability of skills across countries k is given by

$$\rho_{RS} = \frac{\sigma_{RS}}{\sigma_R \sigma_S} \tag{2.22}$$

In the specific setting, the probability of emigration can be stated as follows:

$$P_{RS} = P(\epsilon_S - \epsilon_R > -\mu_S + \mu_R + \pi_{RS}) \tag{2.23}$$

or equivalently

$$P_{RS} = 1 - \Phi\left(\frac{-\mu_S + \mu_R + \pi_{RS}}{\sigma_{\epsilon_S - \epsilon_R}}\right) \tag{2.24}$$

where Φ denotes the cumulative distribution function of a normally distributed variable. In line with the general expression above, the probability of migration from country R to S increases (decreases) with mean incomes in country S (in country R). Additionally, migration costs from R to S impinge negatively on the probability of migration, whilst $\pi_{RS} = \frac{C_{RS}}{Y_R}$. Analogous to Borjas (1987), I can compare expected wages if the individual migrates with the counterfactual of expected wages if the same individual would not have been migrated:

$$E(\hat{Y}_S|M_{RS} > 0) = \mu_S + \rho_{S\epsilon_S-\epsilon_R}\sigma_S \left(\frac{\phi(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S-\epsilon_R}})}{\Phi\left(\frac{-\mu_R+\mu_S-\pi_{RS}}{\sigma_{\epsilon_S-\epsilon_R}}\right)} \right) \tag{2.25}$$

$$E(\hat{Y}_R|M_{RS} > 0) = \mu_R + \rho_{R\epsilon_S-\epsilon_R}\sigma_R \left(\frac{\phi(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S-\epsilon_R}})}{1-\Phi\left(\frac{-\mu_R+\mu_S+\pi_{RS}}{\sigma_{\epsilon_S-\epsilon_R}}\right)} \right) \tag{2.26}$$

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

$$E(\hat{Y}_S|M_{RS} > 0) = \mu_S + \frac{\sigma_R\sigma_S}{\sigma_{\epsilon_S-\epsilon_R}} \left(\frac{\sigma_S}{\sigma_R} - \rho \right) \left(\frac{\phi(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S-\epsilon_R}})}{1-\Phi\left(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S-\epsilon_R}}\right)} \right) \tag{2.27}$$

$$E(\hat{Y}_R|M_{RS} > 0) = \mu_R + \frac{\sigma_R\sigma_S}{\sigma_{\epsilon_S-\epsilon_R}} \left(\rho - \frac{\sigma_R}{\sigma_S} \right) \left(\frac{\phi(\frac{-\mu_S+\mu_R+\pi_{RS}}{\sigma_{\epsilon_S-\epsilon_R}})}{1-\Phi\left(\frac{-\mu_R+\mu_S+\pi_{RS}}{\sigma_{\epsilon_S-\epsilon_R}}\right)} \right) \tag{2.28}$$

Under the assumption that $\rho > \frac{\sigma_R}{\sigma_S}$ along with $\sigma_S > \sigma_R$, individuals migrating from R to S are positively selected compared to the average skills in R. According to these inequalities, the attraction of a positive selection is based on two conditions. First, correlations of skill premia across countries are sufficiently high. 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. This condition implies that skills are sufficiently transferable across states and holds particularly for migration patterns between similar countries. Second, skill premia in the resource scarce country have to offset skill premia in the resource abundant country. In contrast, if it holds that $\rho > \frac{\sigma_S}{\sigma_R}$ and $\sigma_R > \sigma_S$, 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 income distribution in S.

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 those of Mexican residents. 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 dispersions are significant only if poverty constraints are considered. Stolz and Baten (2012) test the Borjas model in the era of mass migration and confirm the theoretical predictions.

The following section makes use of the assumptions set out above in order to elaborate on the relationship between resource shocks and the selectivity of migration while taking into account binary skills.

2.2.2 Resource Shocks and Migrant Selectivity

In order to shed light on the effect of resource windfalls on the selectivity of migration, I start out with a lemma showing that brain drain effects are propelled if the resource windfall leads to a decline in high-skilled wages (necessary condition), sufficient enough in order to compensate for the initial resource transfer (sufficient condition). The subsequent proposition 1 shows that the necessary brain drain condition, a decline in skilled labor income in the course of resource booms, is always satisfied as long as the manufacturing sector is relatively high-skilled labor intensive and the production technology has constant returns to scale. In addition, proposition 2 suggests that the sufficient brain drain condition is satisfied in a democracy as well as in an autocracy.

***Lemma**: A resource windfall, $d\mathcal{R} > 0$, leading to a decline in skilled labor income, sufficient enough in order to compensate for initial resource transfers, increases the probability of skilled emigration. A resource windfall, $d\mathcal{R} > 0$, leading to an increase in unskilled labor income reduces the probability of unskilled emigration.*

Proof: Differentiating equation (2.19) with respect to resource revenues yields:

$$\frac{\partial I_H}{\partial \mathcal{R}} = -\left(\frac{w'_H(\mathcal{R})H + \tau'_H(\mathcal{R})}{w_H(\mathcal{R})H + \tau_H(\mathcal{R}) + C_{RS}}\right) > 0 \quad (2.29)$$

$$\frac{\partial I_L}{\partial \mathcal{R}} = -\left(\frac{w'_L(\mathcal{R})L + \tau'_L(\mathcal{R})}{w_L(\mathcal{R})L + \tau_L(\mathcal{R}) + C_{RS}}\right) < 0 \quad (2.30)$$

According to these derivatives, the effect of resource shocks, $d\mathcal{R}$, on the migration indicator depends qualitatively on $w'_j(\mathcal{R})j + \tau'_j(\mathcal{R})$. If the resource boom leads to a decline in skilled labor income, $w'_H(\mathcal{R})H < 0$, which offsets the initial resource transfer in absolute value, $|w'_H(\mathcal{R})H| > \tau'_H(\mathcal{R})$, the *skilled* migration indicator increases, $\frac{\partial I_H}{\partial \mathcal{R}} > 0$. Correspondingly, a rise in *unskilled* labor income, $w'_L(\mathcal{R})L > 0$ is sufficient for a decline in the unskilled migration indicator, $\frac{\partial I_H}{\partial \mathcal{R}} < 0$. Assuming exogenous incomes in S, the migration indicator corresponds with the probability of emigration. ■

The lemma sets out necessary and sufficient conditions for brain drain effects in the light of the theoretical setup described above. A rise in the probability of skilled emigration requires a decline in labor income (necessary condition) which more than compensates the initial resource transfer (sufficient condition). However, a rise in labor income of unskilled labor is sufficient in order to reduce the unskilled emigration probability.[5] The following proposition 1 proves whether the necessary condition is satisfied in the theoretical setup posited above.

Proposition 1: *A resource windfall, $d\mathcal{R} > 0$, leads to a decline in real high-skilled labor incomes and a rise in real low-skilled labor incomes if $\alpha_S > \alpha_M$.*

Proof: Following Feenstra (2016) and Corden (1984), totally differentiating the zero profit conditions in equation 2.6 while taking into account that $\hat{p} = d\ln p = \frac{dp}{p}$, leads to an expression relating output price changes to input price changes:

$$\begin{bmatrix} \hat{p}_M \\ \hat{p}_S \end{bmatrix} = \begin{bmatrix} 1-\alpha_M & \alpha_M \\ 1-\alpha_S & \alpha_S \end{bmatrix} \times \begin{bmatrix} \hat{w}_H \\ \hat{w}_L \end{bmatrix} \tag{2.31}$$

The coefficients can be interpreted as the cost elasticities of factor price changes, implicitly depending on relative labor intensities. Isolating factor prices on the left-hand-side of the equation yields an expression which describes factor prices as a function of output prices.

$$\begin{bmatrix} \hat{w}_H \\ \hat{w}_L \end{bmatrix} = \frac{1}{\mid \lambda \mid} \begin{bmatrix} \alpha_S & -\alpha_M \\ \alpha_S - 1 & 1-\alpha_M \end{bmatrix} \times \begin{bmatrix} \hat{p}_M \\ \hat{p}_S \end{bmatrix} \tag{2.32}$$

with the determinant given by:

$$\mid \lambda \mid = \alpha_S - \alpha_M \begin{cases} > 0 & \text{if } \alpha_S > \alpha_M \\ < 0 & \text{if } \alpha_S < \alpha_M \end{cases} \tag{2.33}$$

Based on the previous expression, I can relate Dutch disease induced 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

[5]It is worth mentioning that these results hold under the assumption that all workers have accumulated sufficient wealth in order to bear C_{RS} prior to the oil boom. If some of the unskilled workers would have encountered fiscal constraints such that they are not able to bear C_{RS} a resource boom might enable these workers to realize their migration decision. However, simultaneously the incentive for emigration is reduced due to the increase in income. As the setup above does not allow for wealth accumulation, these effects are not part of the model.

stated in Feenstra (2016):

$$\hat{w}_H - \hat{w}_L = \underbrace{\frac{\hat{p}_M(\alpha_S - \alpha_M) + (\hat{p}_M - \hat{p}_S)\alpha_M}{(\alpha_S - \alpha_M)}}_{<\hat{p}_M, \alpha_S > \alpha_M} \tag{2.34}$$

$$- \underbrace{\frac{\hat{p}_S((1-\alpha_M) - (1-\alpha_S)) - (\hat{p}_M - \hat{p}_S)(1-\alpha_S)}{(\alpha_S - \alpha_M)}}_{>\hat{p}_S, \alpha_S > \alpha_M} \tag{2.35}$$

$$\hat{w}_H - \hat{w}_L \begin{cases} < 0 & \text{if } \alpha_S > \alpha_M \\ > 0 & \text{if } \alpha_S < \alpha_M \end{cases} \tag{2.36}$$

A Dutch disease, $\hat{p} = \hat{p}_S - \hat{p}_M > 0$, materializes in less dispersed labor income distributions as long as $\alpha_S > \alpha_M$. The contraction of the labor income distribution is due to both, a rise in low skilled labor incomes and a decline in high skilled labor incomes in real as well as in nominal terms. The latter immediately follows from the zero profit condition in equation 2.6. Therefore, $w'_L(\mathcal{R})L > 0$ and $w'_H(\mathcal{R})H < 0$ hold unambiguously in this setup. However, net income effects of resource booms are unambiguously positive for low-skilled labor and ambiguous for high-skilled labor. A resource boom precipitates negative net income effects for skilled labor if $|w'_H H| > \tau'_H(\mathcal{R})$, giving rise to brain drain effects in light of the lemma above. ■

In light of proposition 1, the resource windfall leads to a real appreciation which translates into a boom in the service sector and a squeeze in the manufacturing sector. As the service sector (manufacturing sector) is low- (high-)skilled labor intensive, low-skilled labor is better off, while high-skilled labor is worse off with respect to labor income. Namely, the manufacturing sector intends to set free more high-skilled labor than the service sector is striving for. Hence, the zero profit conditions require lower wages for skilled labor. This is an application of the Stolper-Samuelson theorem, saying that an increase in the output price leads to an increase in the factor price used disproportionately in the respective sector and a decline in the price of the other factor of production. Through magnification effects, subsequent wage effects offset initial price effects translating into real changes in the income distribution. This is in line with Goderis and Malone (2011) who investigate Gini coefficients in resource abundant countries. However, whether brain drain effects are fostered in the course of resource booms depends on net income effects rather than labor income effects. In contrast to labor income, net income effects internalize the initial distribution of resource windfall gains as well. While net incomes of low-skilled labor are raised unambiguously, high-skilled labor faces lower net incomes if $|w'_H(\mathcal{R})H| > \tau'_H(\mathcal{R})$, increasing the probability of brain drain. This is in line with the results of the Borjas model above. A resource boom translating into a less dispersed income distribution gives rise to brain drain effects. However, whether the sufficient brain drain condition, $|w'_H(\mathcal{R})H| > \tau'_H(\mathcal{R})$, is satisfied, has to be discussed separately for democratic and autocratic societies in the course of proposition 2.

Proposition 2*: A resource windfall, $d\mathcal{R} > 0$, satisfies $|w'_H(\mathcal{R})H| > \tau'_H(\mathcal{R})$ in a democratic society under majority rule as well as in an autocratic society.*[6]

Proof: In a **democracy** under majority rule with two candidates, $c = 1, 2$, the median voter is decisive. If candidate 1 splits resource transfers between skilled and unskilled labor, $\mu_{1L} < 1$, $\mu_{1H} > 0$ (μ_{cj} is the share candidate c attributes to individual j), candidate 2 takes a stand for $\mu_{1L} + \epsilon = \mu_{2L}$, $\mu_{1H} - \epsilon = \mu_{2H}$ (with ϵ small) attracting additional voters as long as $L > H$ which holds by definition. If and only if $\mu_{1L} = \mu_{2L} = 1$ and $\mu_{1H} = \mu_{2H} = 0$ neither candidate 1 nor candidate 2 has an incentive to deviate. From the equilibrium transfers and proposition 1 directly follows that $|w'_H(\mathcal{R})H| > \tau'_H(\mathcal{R})$. In an **autocracy**, the incumbent does not encounter any electoral competition and sets $\mu_E = 1$, leading to $|w'_H(\mathcal{R})H| > \tau'_H(\mathcal{R})$ in light of proposition 1 as well. ■

[6] I postulate that voters in a democracy exclusively decide upon the distribution of resource windfall gains. Further, in an autocracy the incumbent is exclusively interested in windfall gains.

In light of proposition 2, resource windfall gains are either forwarded towards low-skilled labor serving as the median voter or towards the political elite. Hence, low-skilled labor is unambiguously better off in the course of resource booms, receiving a higher labor income along with a potential resource transfer. However, high-skilled labor is unambiguously worse off, earning lower labor incomes which are not compensated by resource transfers. This sets the stage for brain drain effects.[7]

The theoretical predictions were based on the assumption that resource windfalls materialize as transfers rather than serving as factors of production in the manufacturing sector which is standard in the literature as transportation costs are modest. Even if some of the resources might spill into the production of the tradable good, as long as exchange rate effects eventually lead to a decline in the manufacturing sector, skilled labor is relatively worse off. The net decline in the tradable sector is supported by several empirical studies testing the theoretical predictions of Dutch disease models (e.g. Elbadawi and Soto (1997) and Fardmanesh (1990)). Moreover, I dispensed with capital in the production technology of manufacturing goods. However, accounting for capital might even strengthen the distributional effects in the course of a deindustrialisation, as capital income is unequally distributed in favor of skilled labor. Hence, not accounting for capital in the production technology rather biases the results towards zero.

Finally, in order to take up the parameters of the Borjas model from the previous section, I confront inequality effects arising out of a Dutch disease with income correlations in light of the Borjas model. As pointed out previously, the correlation of income across countries, ρ, along with relative net returns to skills, denoted as $\frac{Y_{jR}}{Y_{jS}}$, are particularly important in order to predict selectivity effects. In an effort to relate resource booms to the selectivity of migration, I have to differentiate between three

[7]But even in case of positive resource transfers in favor of high skilled labor, on average, individuals migrating from R to S are better selected after the resource boom as long as the decline in the probability of skilled emigration falls short of the decline in the probability of unskilled emigration in absolute value.

different cases.[8]

(1) $\Delta p > 0$, $|w'_H H| > \tau'_H(\mathcal{R})$, $Y_{HR} < Y_{HS}$ and $\rho > \frac{Y_{HR}}{Y_{HS}}$.

Firstly, I posit that the resource boom sets the stage for a real appreciation, translating into a contraction of relative returns to skills. If the contraction of the returns to skills is sufficiently strong in order to fall short of returns to skills in the resource scarce country and the transferability of skills across countries is sufficient as well, the resource boom carries over to brain drain effects.[9]

(2) $\Delta p > 0$, $|w'_H H| > \tau'_H(\mathcal{R})$, $Y_{HR} > Y_{HS}$.

Secondly, I posit that the resource boom sets the stage for a real appreciation, translating into a contraction of relative returns to skills. However, the contraction of the returns to skills is insufficient in order to fall short of the returns to skills in the resource scarce country. In this case resource booms do not promote brain drain effects.

(3) $\Delta p > 0$, $|w'_H H| > \tau'_H(\mathcal{R})$, $Y_{HR} < Y_{HS}$ and $\rho < \frac{Y_{HR}}{Y_{HS}}$.

Thirdly, I posit that the resource boom sets the stage for a real appreciation, translating into sufficient distributional effects in order to promote brain drain effects. However, the correlation of income is insufficient between the resource abundant and the resource scarce country. In this case, the resource boom does not promote brain drain effects of migration.

The parameter constellations exclusively hold in a setup with two countries. In

[8]The conditions exclusively refer to high skilled labor as low skilled labor is unambiguously better off in the course of a resource boom.

[9]This holds under the assumption that migration costs are zero.

a framework with multiple countries, individuals self-select themselves into the most appropriate one as long as migrant restrictions are precluded. Hence, with multiple countries it is more likely that skilled labor encounters various alternatives abroad when experiencing a decline in income at home.

In the following section, I examine the relationship between resource shocks and emigrant selectivity empirically.

2.3 Evidence

2.3.1 Empirical Framework and Data

The empirical framework mainly draws upon longitudinal data based on Ruggles et al. (2010) which capture migration patterns between 116 source and 23 destination countries spanning the period from 1910 to 2009, commonly known as IPUMS (Integrated Public Use Microdata Series).[10] In the baseline regression I posit the following equation of interest which relates the selectivity of emigration to relative oil revenues per capita along with several additional covariates, denoted as $\boldsymbol{X}_{ijt}$.

$$SELECTIVITY_{ijt} = \alpha_{ij} + \chi_t + \phi\,(RESOURCES_{it} - RESOURCES_{jt}) + \xi \boldsymbol{X}'_{ijt} + \epsilon_{ijt} \tag{2.37}$$

In line with Grogger and Hanson (2011) as well as Stolz and Baten (2012), the data set is collapsed for source-destination country pairs, ij, and aggregated by decades.[11] Hence, α_{ij} captures country pair fixed effects while χ_t indicates time fixed effects similar to Egger and Pfaffermayr (2003). 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

[10] Data on migrant selection were descriptively assembled by Monschauer (2013) based on Ruggles et al. (2010).

[11] As the statistical analysis is restricted by the availability of covariates, estimation results rely on a shorter time span than the availability of data on migrant selectivity.

is determined for 2.1 million individuals migrating from 116 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 of migrants relative to the wages of local residents (Borjas (1987), Kaestner and Malamud (2014)) over potential wages of migrants 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, the selectivity measure in this paper is consistent with the latter. 73 censuses are taken into account based on IPUMS from which information on the years of schooling of migrants and their place of birth as well as the country and place of residence are drawn. The data set is complemented by recently collected data from Barro and Lee (2012) providing information on 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, Monschauer (2013) retraces the years of schooling until 1910.

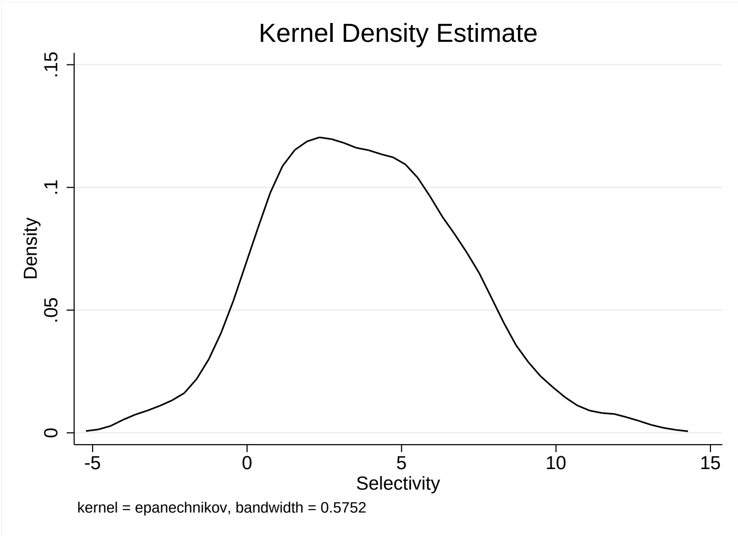
In order to account for the dynamics of migration, the analysis is based on the assumption that the average age of migrants is 25 which is consistent with data from the United Nations which state that modal migration ages are between 23 and 27 years (United Nations (2011)). Most of the individuals migrate 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, migration patterns into high income European countries are not considered (Monschauer (2013)).

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 served 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 the data set. Additionally, illegal migration streams are not captured which are expected to be negatively selected on average, at least in comparison with the destination country. This might induce an upward bias in the migrant selectivity data. In order to account for migrant restrictions and additional unobserved heterogeneity, I control for country pair and time fixed effects.

By means of a Kernel density estimator, I show that migrant selectivity is approximately normally distributed. The density estimation depicted below is based on an Epanechnikov Kernel and a bandwidth given by 0.5752. This is the optimal bandwidth minimizing the mean integrated squared error (MISE) if migrant selectivity follows a Gaussian distribution and the Kernel used is normally distributed as well.[12]

[12] 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 Squared 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 I would



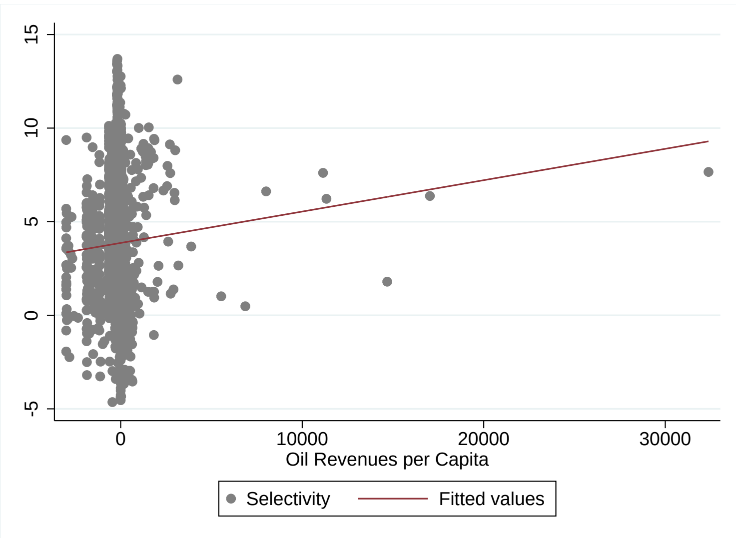
Notes: The figures depicts Kernel Density Estimates for the selectivity of migration in a pooled sample. Data source: Ruggles et al. (2010).

Figure 2.1: Kernel Density Estimate: Migrant Selectivity

The independent variable $RESOURCES_{it} - RESOURCES_{jt}$ captures relative oil revenues generated in the source and destination country based on Haber and Menaldo (2011). More precisely, resource revenues are measured in terms of 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 rather than resource abundance. In the course of further robustness checks I additionally rely on resource income generated by oil, natural gas, coal, precious metal, and industrial metal industries. Since I am interested in the relationship between resource revenues

like to choose a large bandwidth whereas for the bias to be small I 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, in order to find K, I 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.

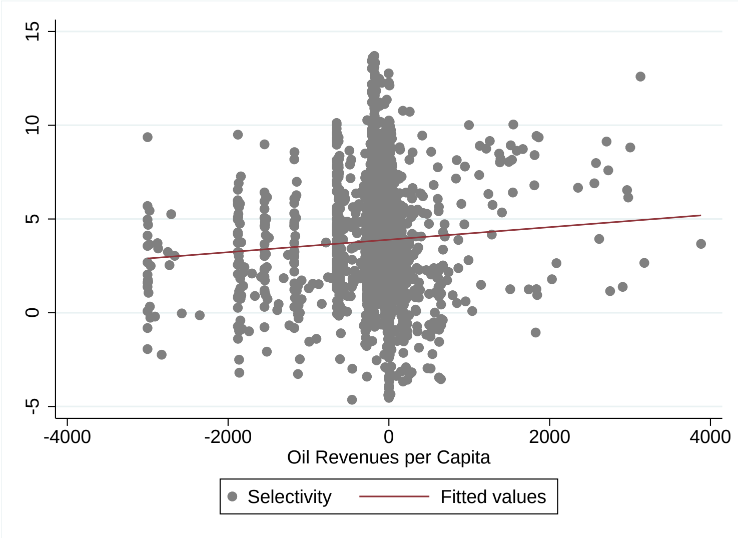
per capita and migrant selectivity, the main coefficient of interest is ϕ. I expect the selectivity of emigrating individuals to be positively related to the abundance of natural resources. Namely, resource windfalls are expected to reduce labor income inequality which gives rise to brain drain effects. However, resource abundance might serve as push and pull factors in migration decisions. Hence, I build differences in resource revenues between source and destination countries. The following figure descriptively associates relative oil revenues per capita and emigrant selectivity, visualizing a positive relationship in line with the theoretical predictions.



Notes: The figures depicts correlations between oil revenues per capita and the selectivity of migration. Data sources: Haber and Menaldo (2011), Ruggles et al. (2010).

Figure 2.2: Scatter Plot: Oil Revenues per Capita - Migrant Selectivity

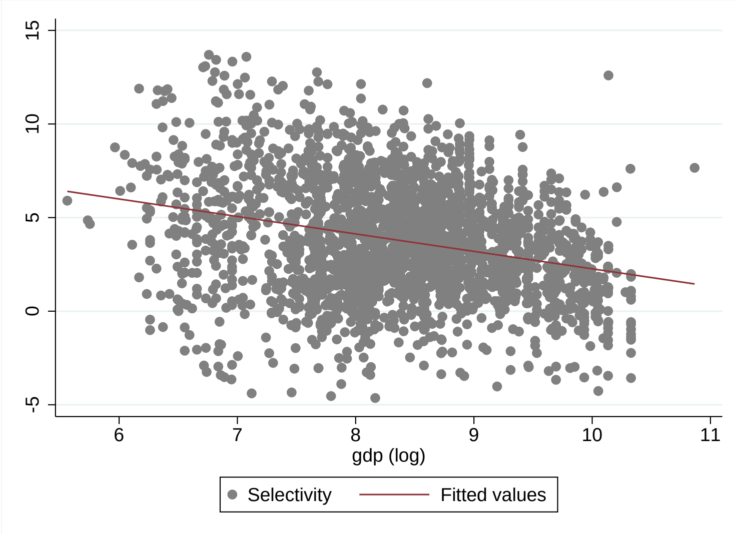
However, as most of the observations are clustered between -4000 and + 4000 USD of oil revenues, I provide an additional scatter plot relating emigrant selectivity to relative oil revenues per capita while excluding observations with oil revenues above 4000 USD per capita, again leading to a positive correlation.



Notes: The figures depicts correlations between oil revenues per capita and the selectivity of migration for oil revenues between 4000 and +4000 USD. Data sources: Haber and Menaldo (2011), Ruggles et al. (2010).

Figure 2.3: Scatter Plot: Oil Revenues per Capita - Migrant Selectivity (Subsample)

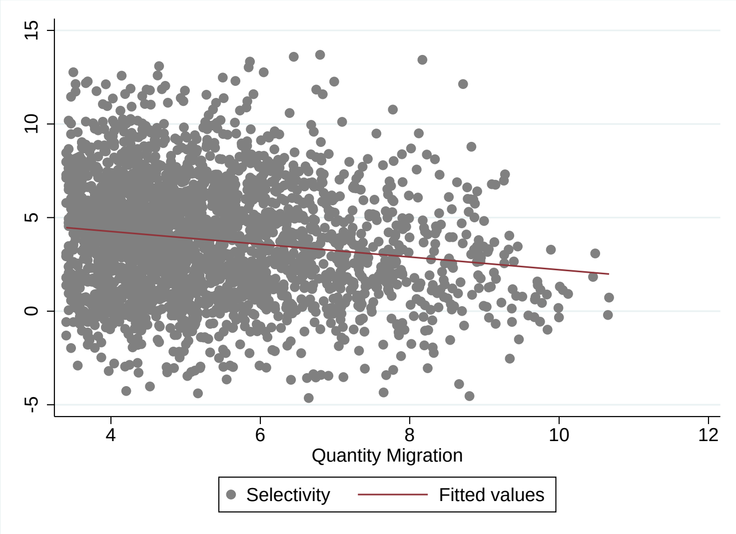
The covariates, $\boldsymbol{X}_{ijt}$, are inspired by Belot and Hatton (2012) along with Stolz and Baten (2012). Similarly to Stolz and Baten (2012), I claim that in order to emigrate, individuals need a certain amount of income. Hence, I control for the gross domestic product per capita in the source country in order account for poverty constraints which might serve as an impediment for emigration. The required income increases with the distance between the source and destination country even though the distance is not exogenous due to self-selection. In particular, I assume that high-skilled individuals can overcome poverty constraints more easily. In order to reduce potential feedback effects, I consider the gross domestic product per capita in the previous period. In general, gross domestic products capture additional resource revenues as well. However, resource income is measured in constant prices whilst GDP is measured in nominal terms before taking the logarithm. Therefore, perfect collinearity is ruled out between these variables. Figure 2.4 visualizes a scatter plot relating GDP per capita and migrant selectivity. Apparently, a rise in income per capita allows even unskilled labor to bear migration costs, incentivizing migration.



Notes: The figures depicts correlations between GDP per Capita and the selectivity of migration. Data sources: Haber and Menaldo (2011), Ruggles et al. (2010).

Figure 2.4: Scatter Plot: GDP per Capita - Migrant Selectivity

Additionally, I 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 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. However, the following figure relating the quality and the log-transformed quantity of migration only shows a slightly negative correlation.



Notes: The figures depicts correlations between the Quantity and the Selectivity of migration. Data source: Ruggles et al. (2010).

Figure 2.5: Scatter Plot: Selectivity-Quantity-Tradeoff in Migration

As community effects can be approximated by measures of cultural proximity, I further take into account a dichotomous variable which is 1 if languages in source and destination countries coincide and 0 otherwise. Consistently, I add a dummy variable for colonial ties between source and host countries which is 1 if source and destination countries have a colonial history and 0 otherwise. I expect both variables, common languages as well as colonial ties, to be negatively related with the selectivity of migration since low-skilled workers are more likely to self-select into countries which are culturally proximal. These sorting effects lead to the endogeneity of bilateral migration patterns, though, I directly account for self-selection with the 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 affecting migration costs, which are more easily borne by high-skilled individuals as well. Hence, I expect the effect of migration costs on migrant selectivity to be positive.

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 conducive to the selectivity of migration, I account for the openness and degree of democratization. By means of a polity2 variable, made available, for instance, by Przeworski et al. (2000), which ranges from -10 (autocracy) to 10 (democracy), I capture these effects. As democracy serves as a push and pull factor, I account for the difference in democratization between source and destination countries.

2.3.2 Descriptive Statistics

Before I proceed with the econometric analysis, I provide a descriptive overview capturing all the variables I make use of below. Specifically, table 2.1 reports 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, I capture 2,572 cases of migrant selection. Migrants are 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 rather a sample for bilateral migration patterns between 116 source and 23 destination countries. Whether the results are externally valid even beyond countries included in the sample is further discussed below. In table 2.2, I display the number of migration patterns for a set of countries included in the data set. Regarding emigration, I rely on a number of patterns ranging from 131 cases in Rwanda to 178,218 cases in Colombia. Conversely, regarding immigration patterns the numbers range from Jamaica with 1,250 cases to the United States with 808,279 cases, respectively.

Variable	N	Mean	SE	Min	Max	Source
GDP	2,453	8271.742	7147.458	260.366	30578.49	Haber and Menaldo (2011)
logGDP	2,365	8.3530	0.91454	5.5621	10.8661	Haber and Menaldo (2011)
Gini	1,092	40.0336	8.6704	15.42	62.8	Baten and Mumme (2010), Zanden et al. (2014)
Migrant Selection	2,572	3.8048	3.0735	-4.6383	13.6974	Ruggles et al. (2010), Monschauer (2013)
Total Oil Income per Capita	2,410	149.0094	1007.145	0	33032.62	Haber and Menaldo (2011)
Total Resource Income per Capita	2,404	251.0896	1044.074	0	33304.23	Haber and Menaldo (2011)
Civil War	2,572	.1431	.3502	0	1	Przeworski et al. (2000)
Polity2	1,404	1.3054	6.6974	-10	10	Przeworski et al. (2000)
Colonial Tie	1,788	.0515	.2210	0	1	Mayer and Zignago (2011)
Distance	1,768	7683.157	4574.862	0	18703.86	Mayer and Zignago (2011)
logDistance	1,764	8.6355	.9572	5.4929	9.8365	Mayer and Zignago (2011)
Share Exports	1,501	22.41491	18.65768	0	171.8862	World Bank (2015)
Share Public Expenditures	1,487	13.86017	5.721131	0	37.82532	World Bank (2015)
Share Urbanization	2,300	52.27299	25.77516	2.077	100	World Bank (2015)
Educational Inequality	2,460	32.71864	16.0626	12.85171	86.62819	World Bank (2015)

Notes: The table reports the raw data, though several specifications account for the difference of covariates between source and destination countries.

Table 2.1: Descriptive Statistics and Data Sources

Country	Em	Im	Country	Em	Im	Country	Em	Im	Country	Em	Im	Country	Em	Im
Afghanistan	686	n.d.	Czech	7,175	n.d.	Japan	42,151	n.d.	Panama	6,337	15,004	UK	65,851	n.d.
Albania	794	n.d.	Denmark	2,413	n.d.	Jordan	1,275	n.d.	Paraguay	107,180	n.d.	Uruguay	41,645	28,551
Argentina	25,557	453,381	Dominican	18,595	n.d.	Kenya	1,552	42,130	Peru	40,973	5,424	Ukraine	5,237	n.d.
Armenia	978	n.d.	Ecuador	16,236	8,761	Kuwait	261	n.d.	Philippines	39,879	24,063	USA	38,195	808,279
Australia	3,315	n.d.	Egypt	4,160	n.d.	Korea	1,320	n.d.	Poland	31,588	n.d.	Venezuela	7,465	286,159
Austria	10,185	n.d.	El Salvador	15,385	1,491	Kongo	617	n.d.	Portugal	102,837	n.d.	Vietnam	26,257	n.d.
Bahrain	5,245	n.d.	Estonia	648	n.d.	Laos	3,380	n.d.	Puerto Rico	n.d.	5,766	Yemen	307	n.d.
Bangladesh	1,307	n.d.	Finland	1,645	n.d.	Latvia	1,954	n.d.	Romania	4,491	n.d	Zambia	2,679	n.d.
Barbados	1,433	n.d.	France	15,466	n.d.	Lesotho	15,791	n.d.	Russia	145	n.d.	Zimbabwe	11,941	n.d.
Belgium	3,156	n.d.	Germany	74,043	n.d.	Liberia	446	n.d.	Rwanda	131	n.d.			
Belize	1,042	n.d.	Ghana	1,147	n.d.	Libya	289	n.d.	Saudi Arabia	1,381	n.d.			
Bolivia	68,533	5,649	Greece	13,472	n.d.	Lithuania	2,710	n.d.	Sierra Leone	293	n.d.			
Botswana	2,050	n.d	Guatemala	13,593	n.d.	Malaysia	866	n.d.	Singapore	1,786	n.d			
Brazil	24,360	171,612	Guayana	4,487	n.d.	Malawi	2,334	n.d.	SouthAfrica	1,386	105,326			
Bulgaria	973	n.d.	Haiti	7,485	n.d.	Mauritius	518	n.d.	Spain	128,297	n.d.			
Cambodia	1,808	10,571	Hong Kong	4,468	n.d.	Mexico	163,648	43,448	Sri Lanka	556	n.d.			
Cameroon	286	n.d.	Honduras	7,106	n.d.	Moldova	171	n.d.	Sudan	2,519	n.d.			
Canada	56,040	n.d.	Hungary	10,056	n.d.	Morocco	1,409	n.d.	Swaziland	3,530	n.d.			
Czech Republic	7,175	n.d.	India	38,578	n.d.	Mozambique	30,923	n.d.	Sweden	3,887	n.d.			
Chile	92,697	24,986	Indonesia	11,342	n.d.	Myanmar	1,851	16,115	Switzerland	4,199	n.d.			
China	58,266	n.d.	Iran	7,899	n.d.	Namibia	4,680	n.d.	Syria	5,881	n.d.			
Colombia	178,218	8,076	Ireland	4,914	n.d.	Nepal	345	n.d.	Tanzania	12,248	n.d.			
Congo	489	n.d.	Iraq	2,068	n.d.	Netherlands	9,168	n.d.	Taiwan	7,987	n.d.			
Croatia	323	n.d.	Iceland	202	n.d.	Nicaragua	27,533	2,053	Thailand	5,986	19,240			
Costa Rica	3,886	28,973	Israel	5,561	n.d.	Norway	3,338	n.d.	TrinidadT	5,684	n.d.			
Cuba	43,383	n.d.	Italy	169,174	n.d.	NZL	854	n.d.	Turkey	4,092	n.d.			
Cyprus	563	n.d.	Jamaica	12,096	1,250	Pakistan	4,037	n.d.	Uganda	14,706	n.d.			

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

Table 2.2: Captured Immigration and Emigration Patterns by Country

2.3.3 Data Analysis

Baseline Model

In order to test the predictions raised in the theoretical section, I 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, I account for partial adjustments in migrant selection by means of dynamic panel models. Third, I disentangle the impact of resource booms on income inequality and migrant selectivity based on a simultaneous equation model.

As part of the baseline setup restated below,

$$SELECTIVITY_{ijt} = \alpha_{ij} + \phi\left(RESOURCES_{it} - RESOURCES_{jt}\right) + \xi \boldsymbol{X}'_{ijt} + \epsilon_{ijt} \tag{2.38}$$

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[13],

$$E(\epsilon_{ijt}|X_{ijt}, RESOURCES_{ijt}, \alpha_{ij}) = 0 \tag{2.39}$$

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

$$E(\alpha_{ij}|X_{ijt}, RESOURCES_{ijt}) = 0 \tag{2.40}$$

As the null hypothesis of the Hausman test is rejected with $\chi^2 = 35.55$ for the baseline model, I henceforth mainly rely on the fixed effects estimator.

[13] I abstract from time-fixed effects in a first step. Further, for the sake of parsimony, I account for differences of oil revenues as $RESOURCES_{ijt} = RESOURCES_{it} - RESOURCES_{jt}$ as well as for other differenced variables.

The results of the baseline setup are reported in table 2.3 below. In particular, three different estimators are considered, a pooled OLS estimator in columns (1) - (4), a random effects estimator in columns (5) - (8) and a fixed effects estimator in columns (9) - (12), even though the results of the fixed effects estimator serve as the main reference in light of the Hausman test. Both the random effects and the fixed effects models rely on country pair fixed effects, while I complementarily control for time fixed effects (columns (3), (4), (7), (8), (11), (12)) following Egger and Pfaffermayr (2003). Moreover, I test for non-linearities in the relationship between migrant selectivity and resource revenues and the relationship between migrant selectivity and the polity2 index (columns (1)-(12)). In addition, I test for pairwise interactions between oil revenues and the polity index (columns (6), (8)), between oil revenues and a civil war dummy (columns (2), (4) (10), (12)) and finally between the polity2 index and the civil war dummy (columns (3), (7)). The results do not refute the theoretical claim that resource booms foster brain drain effects. Apparently, oil revenues per capita, the main variable of interest, appears to be positively and significantly related to the selectivity of emigration (in the absence of civil wars and a polity index equal to 0). In other words, a rise in relative oil abundance corresponds with an increase in brain drain effects, captured by the years of schooling of emigrants compared to the average years of schooling in the source country. This association appears to be qualitatively consistent through all model specifications. Moreover, the results display significant non-linearities in the relationship between relative oil abundance and migrant selectivity. Namely, oil abundance sets the stage for brain drain effects, though this effect is decreasing in the level of oil abundance. I test the robustness of this finding with respect to the dynamic setup in section 2.3.3.2 below. Whether brain drain effects are mediated through distributional effects, as the theory suggests, is not clear-cut. In order to account for mediating effects through income inequality, I have to rely on a simultaneous equation model in section 2.3.3.3.

With respect to covariates, the quantity as well as the selectivity of migration are negatively associated in the pooled OLS model as well as the random effects specifications with time fixed effects. The larger the number of individuals migrating between two countries in one period, the lower the selectivity of emigration in the following period. This inverse relationship indicates 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. However, as opposed to the other specifications, the fixed effects estimates do not display any apparent selectivity-quantity tradeoff. Physical costs of migration are captured by distances between source and destination countries and are positively related to the selectivity of emigrating individuals. Migration costs are more easily borne by high-skilled individuals. Hence, the results are consistent with the theoretical predictions.

Moreover, the average income per capita in the source country seems to dampen brain drain effects which signifies that in developed countries individuals encounter lower poverty constraints of migration. Yet, the relationship is insignificant in several fixed effects specifications, especially while accounting for time fixed effects as well. Another variable indicating development and institutional quality is the polity-index ranging from -10 (autocracy) to 10 (democracy). Apparently, the selectivity of migration and the polity index are not significantly associated while accounting for country pair fixed effects. Likewise, interacting oil revenues with a civil war dummy does not lead to significant estimates in the fixed effects specifications legitimized by the Hausman test either. In general, I expect that more developed countries with good institutions are less prone to a resource curse. Countries with good institutions 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 and Busby (2005)), countries lacking in institutional quality 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. However, with respect to migration, better institutions might correspond with trade openness as well setting the stage for migration opportunities in the course of a Dutch disease. Yet, neither the interaction between oil revenues and the polity2 index nor the relationship between oil revenues and the civil war dummy are significant according to the estimates of the static panel model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity
	Pooled OLS	Pooled OLS	Pooled OLS	Pooled OLS	RE	RE	RE	RE	FE	FE	FE	FE
Country Pair FE?	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE?	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
GDP_{t-1}	-1.205***	-1.195***	-0.981***	-0.948***	-1.682***	-1.674***	-0.433**	-0.432**	-1.788***	-1.791***	0.556	0.555
	(0.131)	(0.133)	(0.135)	(0.136)	(0.176)	(0.178)	(0.212)	(0.214)	(0.220)	(0.220)	(0.367)	(0.367)
Distance	0.408***	0.406***	0.373***	0.362***								
	(0.126)	(0.127)	(0.126)	(0.126)								
Common Language	0.490**	0.488**	0.477**	0.490**								
	(0.229)	(0.230)	(0.225)	(0.228)								
Polity2	-0.0351**	-0.0358**	-0.0580***	-0.0564***	0.00102	0.000539	-0.0223**	-0.0235**	0.00676	0.00643	-0.0131	-0.0134
	(0.0143)	(0.0144)	(0.0151)	(0.0147)	(0.0113)	(0.0112)	(0.0101)	(0.00996)	(0.0126)	(0.0126)	(0.0102)	(0.0102)
Polity2 squared	0.00296***	0.00301***	0.00217*	0.00213*	0.000971	0.00106	-0.000731	-0.000583	0.000706	0.000706	-0.000596	-0.000594
	(0.00112)	(0.00113)	(0.00111)	(0.00111)	(0.000806)	(0.000850)	(0.000704)	(0.000723)	(0.000855)	(0.000852)	(0.000702)	(0.000700)
Civil War	0.621**	0.588**	0.864***	0.673**	0.222	0.222	0.155	0.180	0.217	0.165	0.0339	-0.00852
	(0.260)	(0.262)	(0.292)	(0.263)	(0.197)	(0.197)	(0.155)	(0.143)	(0.207)	(0.223)	(0.144)	(0.159)
Fractionalization	-0.000449***	-0.000454***	-0.000445***	-0.000462***								
	(0.0000908)	(0.0000911)	(0.0000880)	(0.0000881)								
Quantity Migration	-0.509***	-0.508***	-0.533***	-0.534***	0.0275	0.0248	-0.170*	-0.173*	0.107	0.105	-0.0902	-0.0918
	(0.0664)	(0.0664)	(0.0639)	(0.0639)	(0.104)	(0.103)	(0.0996)	(0.0990)	(0.125)	(0.125)	(0.110)	(0.110)
Oil Revenues	0.639***	0.664***	0.746***	0.784***	0.425***	0.408***	0.400***	0.357***	0.238**	0.256**	0.195*	0.210*
	(0.164)	(0.174)	(0.168)	(0.179)	(0.117)	(0.125)	(0.109)	(0.109)	(0.116)	(0.122)	(0.109)	(0.111)
Oil Revenues squared	-0.0554***	-0.0572***	-0.0680***	-0.0704***	-0.0244***	-0.0268***	-0.0249***	-0.0303***	-0.0153**	-0.0164**	-0.0149**	-0.0158**
	(0.0114)	(0.0121)	(0.0118)	(0.0124)	(0.00700)	(0.00909)	(0.00663)	(0.00915)	(0.00731)	(0.00765)	(0.00719)	(0.00729)
Oil Revenues × Civil War		-0.400		-0.716*						-0.156		-0.127
		(0.431)		(0.432)						(0.199)		(0.144)
Oil Revenues × Polity2						-0.00311		-0.00703				
						(0.00720)		(0.00686)				
Polity2 × Civil War			0.0130				-0.00150					
			(0.0123)				(0.00833)					
Constant	12.58***	12.51***	9.048***	8.891***	17.48***	17.43***	7.069***	7.065***	17.82***	17.86***	-0.467	-0.445
	(1.497)	(1.498)	(1.709)	(1.699)	(1.590)	(1.603)	(1.707)	(1.715)	(1.977)	(1.978)	(2.859)	(2.855)
N	642	642	642	642	929	929	929	929	929	929	929	929
R^2	0.328	0.328	0.372	0.372	0.281	0.281	0.5437	0.5452	0.286	0.286	0.560	0.560

Notes: Migrant Selectivity regressed on the difference of oil revenues per capita between source and host countries in a static framework. Time Span: 1910-2009. Migrant selectivity is defined as the difference between the years of schooling of migrants and the average years of schooling in the country of origin. Columns (1) - (4) display Pooled OLS estimates, columns (5) to (8) depict Random Effects estimates and columns (9)-(12) report Fixed Effects estimates. For each model a specification with time fixed effects is provided as well (columns (3), (4), (7), (8), (11), (12)). The specifications further differ with respect to interactions between oil revenues and the polity2 index (columns (6), (8)), between oil revenues and a civil war dummy (columns (2), (4) (10), (12)), between the polity2 index and the civil war dummy (columns (3), (7)) along with a test of non-linear relationships between migrant selectivity and oil revenues along with the polity2 index, respectively (columns (1)-(12)). All bilateral variables besides of civil wars are accounted for as the difference between source and host countries. GDP and distances between source and host countries are log-transformed. 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 2.3: Static Panel Model

In the next section, I set out a dynamic panel model in order to account for partial adjustments in the selectivity of migration.

Dynamic Panel Model

A dynamic panel model of migrant selectivity is specified as follows:

$$\begin{aligned} SELECTIVITY_{ijt} =& \alpha_{ij} + \beta SELECTIVITY_{ijt-1} + \\ & \gamma(RESOURCES_{it} - RESOURCES_{jt}) + \boldsymbol{X}'_{ijt}\delta + \epsilon_{ijt} \end{aligned} \tag{2.41}$$

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,

$$E[\epsilon_{ijt}|x_{ijt}, RESOURCES_{ijt}, \alpha_{ij}] = 0 \tag{2.42}$$

for $t = 1, ..., T$.[14] 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, the remedy proposed by Arellano and Bond (1991) makes use of all available lags of the endogenous variable in a generalized method of moments (difference GMM) approach in order to instrument lagged differences while improving efficiency. However, instruments in levels are reasonably weak for variables in differences if the variable of interest follows a random walk. Therefore, Blundell and Bond (1998)

[14]I abstract from time fixed effects in a first step.

propose a different estimator which makes use of a combination of lagged differences and levels while instrumenting the lagged dependent variable (system GMM). Table 2.4 below displays system GMM estimates of the parameters in equation 2.41 which are more efficient compared to those of the difference GMM approach. Columns (1) - (12) rely on country pair fixed effects while columns (2), (4), (6), (8), (10) complementarily provide time fixed effects. Moreover, the columns differ with respect to the inclusion of interactions between oil revenues and the polity2 index along with a civil war dummy (columns (3)-(12)), respectively, test for non-linearities in the relationship between oil revenues and emigrant selectivity (columns (1)-(2), (5)-(12)), and account for a second lag in the outcome variable (columns (9)-(12)). Additionally, Hansen-J-test statistics are provided in order to test for the exogeneity of instruments through overidentifying restrictions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity
	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell
Country Pair Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects?	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Selectivity$_{t-1}$	0.863***	0.978***	0.868***	0.971***	0.875***	0.975***	0.867***	0.976***	1.081***	1.010***	1.084***	1.010***
	(0.0291)	(0.0388)	(0.0298)	(0.0380)	(0.0292)	(0.0386)	(0.0298)	(0.0386)	(0.0435)	(0.0422)	(0.0440)	(0.0424)
Selectivity$_{t-2}$									-0.277***	-0.117***	-0.278***	-0.118***
									(0.0394)	(0.0397)	(0.0392)	(0.0397)
GDP$_{t-1}$	-0.370***	0.0146	-0.373***	0.00340	-0.337***	0.00798	-0.367***	0.00989	-0.318***	-0.102	-0.325***	-0.101
	(0.0661)	(0.0630)	(0.0662)	(0.0627)	(0.0650)	(0.0633)	(0.0661)	(0.0626)	(0.0679)	(0.0645)	(0.0644)	(0.0643)
Civil War	-0.154	-0.116	-0.167	-0.124	-0.214**	-0.134	-0.225**	-0.134	0.00594	0.0109	-0.0296	0.00993
	(0.0960)	(0.0901)	(0.107)	(0.0965)	(0.102)	(0.0965)	(0.108)	(0.0973)	(0.102)	(0.0936)	(0.105)	(0.0937)
Quantity Migration	-0.0297	-0.0272	-0.0283	-0.0262	-0.00698	-0.0251	-0.0302	-0.0252	-0.0277	-0.0426**	-0.0401	-0.0427**
	(0.0265)	(0.0267)	(0.0267)	(0.0259)	(0.0257)	(0.0263)	(0.0265)	(0.0262)	(0.0257)	(0.0215)	(0.0260)	(0.0214)
Polity2	0.00968**	0.00873*	0.0138***	0.00952**	0.00947**	0.00934*	0.00934*	0.0103**	-0.00144	0.00438	-0.00130	0.00505
	(0.00480)	(0.00506)	(0.00467)	(0.00460)	(0.00464)	(0.00487)	(0.00482)	(0.00488)	(0.00471)	(0.00474)	(0.00497)	(0.00491)
Oil Revenues	0.248***	0.123**	0.213***	0.189***	0.261***	0.191***	0.276***	0.186***	0.302***	0.267***	0.308***	0.264***
	(0.0567)	(0.0515)	(0.0519)	(0.0473)	(0.0500)	(0.0519)	(0.0566)	(0.0510)	(0.0652)	(0.0597)	(0.0766)	(0.0599)
Oil Revenues sqrd	-0.0190***	-0.0104**			-0.0207***	-0.00234	-0.0232***	-0.00301	-0.0154***	-0.00194	-0.0142**	-0.00243
	(0.00437)	(0.00425)			(0.00542)	(0.00575)	(0.00632)	(0.00589)	(0.00567)	(0.00545)	(0.00595)	(0.00547)
Oil Revenues × Polity2			0.0100***	0.0115***	-0.000888	0.0102***	-0.00205	0.00958***	0.00639	0.0145***	0.00739	0.0141***
			(0.00371)	(0.00256)	(0.00342)	(0.00335)	(0.00357)	(0.00336)	(0.00571)	(0.00509)	(0.00609)	(0.00510)
Oil Revenues × Civil War			-0.0856	-0.108	-0.215*	-0.128	-0.248**	-0.135	-0.134	-0.0873	-0.168*	-0.0933
			(0.101)	(0.0997)	(0.111)	(0.101)	(0.111)	(0.102)	(0.109)	(0.101)	(0.0950)	(0.102)
Polity2 squared							0.0000558	0.000262			0.0000540	0.000173
							(0.000348)	(0.000367)			(0.000323)	(0.000313)
Constant	3.447***	0.821	3.404***	0.938	3.001***	0.884	3.409***	0.844	3.220***	1.978***	3.334***	1.956***
	(0.699)	(0.700)	(0.702)	(0.695)	(0.698)	(0.704)	(0.699)	(0.690)	(0.699)	(0.654)	(0.665)	(0.649)
N	929	929	929	929	929	929	929	929	774	774	774	774
Number of Instruments	51	59	52	60	53	61	54	62	65	72	66	73
Hansen J	81.52	62.63	82.53	60.82	82.25	61.53	82.83	61.94	75.82	66.20	75.68	66.44

Notes: Migrant Selectivity regressed on the difference of oil revenues per capita between source and host countries in a dynamic framework. Time Span: 1910-2009. Migrant selectivity is defined as the difference between the years of schooling of emigrants and the average years of schooling in the country of origin. Columns (1) - (12) display system GMM estimates controlling for country pair fixed effects, while the specifications in columns (2), (4), (6), (8), (10), (12) complementarily control for time fixed effects. The columns differ with respect to interactions between oil revenues and the polity2 index as well as between oil revenues and a civil war dummy (columns (3)-(12)), non-linear relationships between migrant selectivity and resource revenues (columns (1)-(2), (5)-(12)) and the polity index (columns (7), (8)), respectively, as well as with respect to the inclusion of a further lag of the outcome variable (columns (9)-(12)). All bilateral variables besides of GDP and civil wars are accounted for as the difference between source and host countries. GDP is log-transformed. 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 2.4: Dynamic Panel Model

The results of the dynamic panel depicted above are mainly consistent with the previous findings according to the main coefficient of interest, γ, and robust through all specifications. Hence, relative oil abundance between source and destination countries is positively related to the selectivity of emigration, and therefore to brain drain effects.[15] However, in contrast to the static panel model above, the specifications do not depict significant non-linearities in this relationship while accounting for country pair and time fixed effects. Interacting oil revenues with the polity2 index leads to a positive and significant coefficient (in the absence of civil wars), at least while controlling for country pair and time fixed effects. However, this might originate from the fact that countries with good political institutions are more open and skilled individuals are more mobile across developed countries. Moreover, in democratic societies the median voter theorem in the previous section pointed at larger resource transfers in favor of unskilled labor, setting the stage for brain drain effects. In addition, interacting the civil war dummy with oil revenues suggests that in case of a civil war even less skilled individuals are forced to emigrate. Again, average incomes per capita and emigrant selection are negatively associated, though the coefficients turn insignificant while controlling for time fixed effects. Finally, the results indicate a strong persistency of migrant selection over time.

Up to now, I exclusively focused on the direct effect of resource abundance on migrant selectivity. However, in the theoretical section 2.2.1, inequality effects served as an intermediary between resource booms and brain drain effects. Hence, I 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 simultaneous equation model. The framework is at the center of the following section.

[15]In specifications with interactions this holds in the absence of civil wars and a polity2 index that equals 0.

Simultaneous Equation Model

In order to verify whether brain drain effects are mediated through inequality effects, I construct a simultaneous 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 simultaneously. While the first equation relates relative resource abundance and inequality, the second equation associates relative income inequality and migrant selectivity. Formally, I construct the following simultaneous equation model:

$$GINI_{it} - GINI_{jt} = \gamma_{ij} + (RESOURCES_{it} - RESOURCES_{jt})\zeta + \boldsymbol{W}'_{ijt}\alpha + u_{ijt} \quad (2.43)$$

$$SELECTIVITY_{ijt} = \theta_{ij} + (GINI_{it-1} - GINI_{jt-1})\beta + \boldsymbol{X}'_{ijt}\pi + \eta_{ijt} \quad (2.44)$$

which can be written more compactly as

$$\boldsymbol{Y} = \boldsymbol{Z}'\xi + \epsilon \quad (2.45)$$

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 $RESOURCES_{it} - RESOURCES_{jt}$ is specified as the difference in oil revenues per capita in constant prices of 2007 between the source and the destination country. The variable GINI captures Gini coefficients as long as they are available for respective time periods and countries and is differenced between source and destination countries as well. Complementarily, I rely on inequality measures based on height data (height GINI) which I draw from Zanden et al. (2014) and 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 the variation in human height are correlated.[16] The main variables of interest are accompanied by a set of additional covariates, indicated by $\boldsymbol{W}_{ijt}$ (equation 2.43) and

[16] Moradi and Baten (2005) relate income inequality and the coefficient of variation of human height based on the following formula, $Gini_{it} = -33.5 + 20.5CV_{it}$.

$\boldsymbol{X}_{ijt}$ (equation 2.44), which might impinge on income inequality and migrant selectivity, respectively. In the equation explaining migrant selectivity these variables mainly coincide with those of 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 the literature. Essentially, I 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 capturing the quantity of market integration. Further, I control for the share of people living in urban areas and the polity2 index which might impinge on the income distribution as well. Moreover, I account for public expenditures as a share of gross domestic product as well as educational inequality. Again, in order to account for push and pull factors, I include the difference of bilateral covariates between source and destination countries.

In an effort to estimate the simultaneous equation model above, I proceed in two steps. First, I build first differences of equation (2.43) and (2.44) in order to expunge fixed effects γ_{ij} and θ_{ij}, respectively, sweeping out time-invariant covariates. Second, I 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 light of the notation above:

$$\hat{\xi}_{2SLS} = \left(\hat{Z}'\hat{Z}\right)^{-1}\hat{Z}y \tag{2.46}$$

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

$$\hat{\xi}_{3SLS} = \left(\hat{Z}'[\hat{\Sigma} \otimes I]\hat{Z}\right)^{-1}\hat{Z}'[\hat{\Sigma} \otimes I]y \tag{2.47}$$

where I is the identity matrix.

The following table shows estimates of the structural equation model based on three-stage-least squares estimates described above. In columns (1) to (10) of table 2.5

below I account for different combinations of covariates in order to test the sensitivity of the results through various specifications based on a 3SLS procedure while controlling for country pair fixed effects. Complementarily, the specifications in columns (6) to (10) account for time fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity
	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS
Country Pair FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE?	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes
$Gini_{t-1}$	-0.0182*	-0.0195**	-0.0190*	-0.0193**	-0.0196**	-0.0185*	-0.0198**	-0.0194**	-0.0197**	-0.0199**
	(0.00991)	(0.00979)	(0.00989)	(0.00970)	(0.00963)	(0.00983)	(0.00971)	(0.00980)	(0.00960)	(0.00952)
Quantity Migration	-0.00295	0.106	0.105	0.0529	0.0132	-0.0371	0.0682	0.0677	0.00692	-0.0375
	(0.134)	(0.138)	(0.138)	(0.137)	(0.144)	(0.145)	(0.146)	(0.146)	(0.145)	(0.151)
Polity2	-0.00722				-0.0146**	-0.00724				-0.0148**
	(0.00571)				(0.00620)	(0.00566)				(0.00613)
Educational Inequality		0.0309**	0.0308**	0.0244*	0.0189		0.0323**	0.0323**	0.0258**	0.0202
		(0.0130)	(0.0130)	(0.0130)	(0.0130)		(0.0129)	(0.0129)	(0.0129)	(0.0128)
Export Share			0.00255	0.00609	0.00429			0.00199	0.00561	0.00386
			(0.00807)	(0.00805)	(0.00800)			(0.00800)	(0.00797)	(0.00791)
Share Public Expenditure				-0.0421**	-0.0619***				-0.0430**	-0.0634***
				(0.0170)	(0.0185)				(0.0168)	(0.0183)
GDP_{t-1}					0.147					0.191
					(0.494)					(0.489)
Constant	-0.936***	-0.920***	-0.924***	-0.923***	-0.951***	-0.764***	-0.723***	-0.726***	-0.695***	-0.701***
	(0.0758)	(0.0750)	(0.0758)	(0.0744)	(0.140)	(0.230)	(0.227)	(0.228)	(0.223)	(0.244)
Gini										
Oil Revenues per Capita	-0.00284***	-0.00286***	-0.00286***	-0.00286***	-0.00286***	-0.00298***	-0.00302***	-0.00302***	-0.00301***	-0.00301***
	(0.000936)	(0.000934)	(0.000934)	(0.000933)	(0.000932)	(0.000958)	(0.000955)	(0.000955)	(0.000954)	(0.000953)
GDP_{t-1}	-1.105	-2.254	-2.259	-2.242	-2.061	-0.159	-1.306	-1.310	-1.307	-1.097
	(3.834)	(3.955)	(3.954)	(3.950)	(3.976)	(3.896)	(3.986)	(3.986)	(3.981)	(4.006)
Urbanization Share	-0.441***	-0.358**	-0.357**	-0.354**	-0.352**	-0.457***	-0.362**	-0.362**	-0.359**	-0.356**
	(0.154)	(0.174)	(0.174)	(0.173)	(0.173)	(0.154)	(0.173)	(0.173)	(0.172)	(0.172)
Export Share	0.0213	0.0149	0.0172	0.0204	0.0185	0.0235	0.0163	0.0180	0.0211	0.0192
	(0.0661)	(0.0664)	(0.0668)	(0.0668)	(0.0668)	(0.0658)	(0.0660)	(0.0663)	(0.0663)	(0.0664)
Public Expenditures Share	0.386**	0.383**	0.383**	0.347**	0.327**	0.379**	0.377**	0.377**	0.342**	0.322**
	(0.158)	(0.158)	(0.158)	(0.159)	(0.159)	(0.157)	(0.157)	(0.157)	(0.158)	(0.158)
Polity2	0.00279	0.00950	0.00956	0.0113	-0.00327	0.00466	0.0119	0.0119	0.0137	-0.000579
	(0.0509)	(0.0505)	(0.0505)	(0.0504)	(0.0508)	(0.0506)	(0.0502)	(0.0502)	(0.0501)	(0.0504)
Educational Inequality		0.156	0.156	0.153	0.149		0.175	0.175	0.172	0.169
		(0.116)	(0.116)	(0.116)	(0.116)		(0.116)	(0.116)	(0.116)	(0.116)
Constant	-0.553	-0.257	-0.259	-0.255	-0.283	1.215	1.854	1.852	1.860	1.835
	(1.166)	(1.191)	(1.191)	(1.190)	(1.196)	(1.900)	(1.939)	(1.939)	(1.939)	(1.941)
N	155	155	155	155	155	155	155	155	155	155
R^2	0.1305	0.1395	0.1395	0.1398	0.1403	0.1410	0.1521	0.1521	0.1523	0.1528

Notes: Migrant Selection regressed on the Gini coefficients between source and host countries and Gini coefficients regressed on oil revenues per capita in a structural equation setup. Migrant selectivity is defined as the difference between the years of schooling of migrants and the average years of schooling in the country of origin. Columns (1) - (10) are estimated based on a 3 SLS procedure with different combinations of covariates. On the first stage, instruments are obtained by regressing endogenous variables on all exogenous variables leading to fitted values. On the second stage, an estimate for the covariance matrix is derived and finally the GLS procedure is applied. In columns (1) to (10) I provide 3SLS estimates while controlling for country pair fixed effects through first differences. Complementarily, specifications in columns (6) to (10) account for time fixed effects. 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 2.5: Simultaneous Equation Model

Apparently, increasing relative oil revenues lead to relatively less dispersed income distributions in light of the estimates above. Based on the theory, an appreciation of the exchange rate crowds out the tradable sector in favor of the non-tradable sector, setting the stage for a contraction of the income distribution. This result is empirically in line with the findings of Fum and Hodler (2010) and Goderis and Malone (2011). While the former find that resource booms lower income inequality as long as the country is ethnically homogenous, the latter conclude that Gini coefficients are generally negatively correlated with resource abundance in the short run. In contrast, Gylfason and Zoega (2003) rely on an endogenous growth model and find a positive correlation between resource dependence measured as the share of natural to total wealth and income inequality. However, theoretically, the authors do not allow for Dutch disease effects in an open economy, and empirically, the authors account for resource dependence in general rather than oil abundance in particular.

In contradiction to Borjas (1987), relative income dispersions only translate into brain drain effects while accounting for lagged rather than contemporaneous Gini coefficients. Nevertheless, based on lagged Gini coefficients, lower skill premia in the source country lead to further brain drain effects. However, the coefficients of the simultaneous equation model should be interpreted cautiously. Firstly, Gini coefficients and covariates are primarily available for high income countries which might lead to a sample selection issue. Secondly, the Borjas model does not exclusively rely on relative income dispersion in order to explain migrant selectivity. Rather, the results of the model are fundamentally based on the income correlation coefficient across countries. As long as income is not sufficiently transferrable, especially between developing and developed countries, a contraction of the income distribution does not necessarily foster brain drain effects. Thirdly, Gini coefficients capture aggregate income inequality whilst the theoretical conjectures exclusively refer to within inequality between skilled and unskilled labor. However, if a political elite appropriates a significant amount of windfall gains aggregate inequality might increase while within inequality between skilled and unskilled labor might see a decline.

Hence, in order to test the robustness of the results, I provide sensitivity checks in the appendix based on different data on migrant selectivity and income inequality, even for contemporaneous relationships. Before, I provide further robustness checks in the following section.

Further Robustness Checks

Confirming the robustness of the results for different model specifications requires several additional checks. First, I have to test whether the results are just limited to oil abundant countries or whether the results can be generalized to different kinds of resources as the title of the paper suggests. In the regression table 2.6 depicted below, I relate the selectivity of migration to an aggregate resource measure based on Haber and Menaldo (2011). Namely, the variable comprises income generated in oil, natural gas, coal, precious metal, and industrial metal industries. Based on aggregate resource revenues, the results are still in line with the baseline specification. Aggregate resource abundance appears to foster brain drain effects. The resources accounted for are all point-source natural resources in line with the theoretical predictions. 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.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity
	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM	GMM
	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell	Blundell
Country Pair Fixed Effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects?	No	No	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Selectivity$_{t-1}$	0.864***	0.973***	0.864***	0.968***	0.874***	0.969***	0.867***	0.970***	1.074***	1.006***	1.077***	1.007***
	(0.0288)	(0.0375)	(0.0296)	(0.0375)	(0.0289)	(0.0376)	(0.0295)	(0.0376)	(0.0442)	(0.0422)	(0.0448)	(0.0424)
Selectivity$_{t-2}$									-0.271***	-0.118***	-0.271***	-0.119***
									(0.0400)	(0.0401)	(0.0397)	(0.0400)
GDP$_{t-1}$	-0.384***	-0.00426	-0.390***	-0.0136	-0.353***	-0.0124	-0.379***	-0.0107	-0.328***	-0.120*	-0.333***	-0.118*
	(0.0674)	(0.0631)	(0.0673)	(0.0634)	(0.0665)	(0.0635)	(0.0672)	(0.0628)	(0.0696)	(0.0656)	(0.0656)	(0.0651)
Civil War	-0.155	-0.114	-0.182	-0.134	-0.246**	-0.146	-0.255**	-0.147	-0.0542	-0.0270	-0.0797	-0.0308
	(0.0961)	(0.0890)	(0.112)	(0.0988)	(0.105)	(0.0988)	(0.113)	(0.100)	(0.107)	(0.0980)	(0.107)	(0.0983)
Quantity Migration	-0.0275	-0.0272	-0.0306	-0.0279	-0.00687	-0.0272	-0.0292	-0.0275	-0.0325	-0.0481**	-0.0439*	-0.0481**
	(0.0268)	(0.0265)	(0.0269)	(0.0260)	(0.0261)	(0.0262)	(0.0265)	(0.0261)	(0.0264)	(0.0219)	(0.0263)	(0.0217)
Polity2	0.00743	0.00726	0.0128***	0.00915**	0.00706	0.00841*	0.00683	0.00901*	-0.00320	0.00316	-0.00275	0.00376
	(0.00489)	(0.00495)	(0.00468)	(0.00459)	(0.00476)	(0.00491)	(0.00493)	(0.00483)	(0.00489)	(0.00499)	(0.00510)	(0.00500)
Polity2 sqrd							0.000144	0.000205			0.000167	0.000189
							(0.000348)	(0.000365)			(0.000336)	(0.000316)
Polity2 sqrd							0.000144	0.000205			0.000167	0.000189
							(0.000348)	(0.000365)			(0.000336)	(0.000316)
Resource Revenues	0.257***	0.135***	0.204***	0.178***	0.266***	0.190***	0.277***	0.184***	0.238***	0.211***	0.241***	0.204***
	(0.0524)	(0.0434)	(0.0456)	(0.0394)	(0.0466)	(0.0429)	(0.0516)	(0.0430)	(0.0527)	(0.0470)	(0.0607)	(0.0456)
Resource Revenues sqrd	-0.0203***	-0.0113***			-0.0231***	-0.00348	-0.0266***	-0.00492	-0.0184***	-0.00493	-0.0177***	-0.00620
	(0.00435)	(0.00404)			(0.00563)	(0.00593)	(0.00669)	(0.00586)	(0.00553)	(0.00565)	(0.00610)	(0.00528)
Resource Revenues × Polity2			0.00874**	0.0106***	-0.00197	0.00925***	-0.00415	0.00794**	0.00123	0.00942**	0.00155	0.00817**
			(0.00366)	(0.00231)	(0.00335)	(0.00322)	(0.00358)	(0.00312)	(0.00460)	(0.00466)	(0.00504)	(0.00413)
Resource Revenues × Civil War			-0.110	-0.110	-0.256**	-0.136	-0.279**	-0.143	-0.244**	-0.158	-0.242**	-0.166*
			(0.109)	(0.0974)	(0.114)	(0.102)	(0.118)	(0.103)	(0.114)	(0.0998)	(0.0993)	(0.100)
Constant	3.561***	0.989	3.576***	1.087	3.151***	1.071	3.522***	1.040	3.340***	2.167***	3.425***	2.127***
	(0.707)	(0.693)	(0.709)	(0.697)	(0.709)	(0.700)	(0.705)	(0.683)	(0.715)	(0.656)	(0.673)	(0.648)
N	929	929	929	929	929	929	929	929	774	774	774	774
Number of Instruments	51	59	52	60	53	61	54	62	65	72	66	73
Hansen J	80.81	61.81	81.48	59.92	81.74	60.58	82.23	61.12	74.73	64.70	74.70	64.84

Notes: Migrant Selection regressed on the difference of resource revenues per capita between source and host countries in a dynamic framework. Time Span: 1910-2009. Migrant selectivity is defined as the difference between the years of schooling of migrants and the average years of schooling in the country of origin. Columns (1) - (12) display system GMM estimates controlling for country pair fixed effects, while the specifications in columns (2), (4), (6), (8), (10), (12) complementarily control for time fixed effects. The columns differ with respect to interactions between resource revenues and the polity2 index as well as between oil revenues and a civil war dummy (columns (3)-(12)), non-linear effects of resource revenues (columns (1)-(2), (5)-(12)) and the polity index (columns (7), (8)) as well as the inclusion of a further lag of the outcome variable (columns (9)-(12)). All bilateral variables besides of GDP and civil wars are accounted for as the difference between source and host countries. GDP and distances between source and host countries are log-transformed. 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 2.6: Dynamic Panel Model

Second, I have to encounter two potential selectivity issues, sample selection biases as well as self-selection biases. Introductorily, I already touched on the latter, self-selection biases, suggesting that bilateral migration streams are not exogenous. Rather, 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 I directly refer to the selectivity of migration, I explicitly allow and account for sample selection with respect to the schooling of migrants. Therefore, this problem is negligible in my 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 I exclusively focus on representative survey data, I do not face any sample selection issues at first sight. But since the data are mainly based on bilateral migration patterns between a selection of countries and not based on all potential source and destination countries, I have to check whether the country selection facilitates external validity. Therefore, I exemplarily compare GDP per capita 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 those for which World Bank (2015) data are available.

Table 2.7: 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.

2.4 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, I illuminate the relationship between resource booms and the selectivity of migration. The main contributions of this chapter are twofold. First, I set out a theoretical framework relating resource shocks and migrant selectivity. Second, I related resource abundance and migrant selectivity empirically based on several panel models. Namely, I 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 brain drain effects. Namely, a resource boom elicits a Dutch disease materializing in an appreciation of the exchange rate which crowds out the tradable in favor of the non-tradable sector. Based on the assumption that the tradable (non-tradable) sector is relatively high-skilled (low-skilled) labor intensive, high-skilled labor is worse off while low-skilled labor is better off post of the resource boom. As long as initial resource transfers do not compensate the decline in the returns to skills of high-skilled labor, the Dutch disease lays the ground for brain drain effects through the lens of the Borjas model.

Empirically, I relied on panel models which account for migrant selectivity between 116 source countries and 23 destination countries between 1910 and 2009. Specifically, I pursued fixed and random effects panel estimates as a baseline setup and carried the empirical analysis forward to dynamic panel estimates and a simultaneous 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 do not refute the theoretical claim that resource booms lead to brain drain effects. These brain drain effects appear to be mediated through distributional effects, as confirmed by sensitivity checks.

Introductorily, I referred to Gylfason (2001) in raising the question whether there is an inverse relationship between natural capital and human capital. According to the 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.

2.5 Appendix: Sensitivity Check Simultaneous Equation Model

In the simultaneous equation model in section 2.3.3.3, I simultaneously related resource abundance, income inequality and migrant selectivity in order to test whether a resource boom leads to brain drain effects mediated through distributional effects. Consistently, as part of a sensitivity analysis, I perform the same steps as in section 2.3.3.3, while accounting for alternative measures of migrant selectivity and income inequality. With respect to migrant selectivity, I rely on a novel brain drain database assembled by the German Institute for Employment Research (IAB) capturing the ratio of migrants with an upper degree relative to the total number of migrants above age 25 between 1980 and 2010 (Bruecker et al. (2013)). In particular, the dataset captures migration patterns into 20 OECD member state countries for 5 year intervals, while classifying and trisecting qualifications in lower, middle and upper final degrees based on national census data. The variable BRAIN DRAIN is accounted for as the change in the stock of migrants with an upper degree relative to the overall number of migrants moving from country i to j in period t. With respect to income inequality, I rely on GINI coefficients provided by the World Bank (World Bank (2015)) for the period 1980 to 2010 in table 2.8 below.

Formally, the analysis makes use of a simultaneous equation model set out and described in section 2.3.3.3, though accounting for different sources for GINI coefficients and migrant selectivity as described above.

$$GINI_{it} - GINI_{jt} = \gamma_i + (RESOURCES_{it} - RESOURCES_{jt})\zeta + \boldsymbol{W'}_{ijt}\alpha + u_{ijt} \tag{2.48}$$

$$BRAINDRAIN_{ijt} = \theta_i + (GINI_{it} - GINI_{jt})\beta + \boldsymbol{X'}_{ijt}\pi + \eta_{ijt} \tag{2.49}$$

which can be written more compactly as

$$\boldsymbol{Y} = \boldsymbol{Z}'\xi + \epsilon \tag{2.50}$$

The following table provides estimates for the coefficients set out above. In columns (1) to (4) I provide pooled 3SLS estimates estimates for different model specifications in order to test the sensitivity of the results. Complementarily, specifications in columns (5) to (8) account for time fixed effects while specifications in columns (9) to (12) account for both source country and time fixed effects. Apparently, the results do not refute the theoretical claim that a resource windfall leads to a decline in income inequality translating into brain drain effects. As opposed to section 2.3.3.3, this even holds for contemporaneous relationships between income inequality and migrant selectivity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Brain Drain	Brain Drain	Brain Drain	Brain Drain	Brain Drain	Brain Drain	Brain Drain	Brain Drain	Brain Drain	Brain Drain	Brain Drain	Brain Drain
	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS	3SLS
Country FE?	No	No	No	No	No	No	No	No	Yes	Yes	Yes	Yes
Time FE?	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Gini	-0.000818***	-0.000945***	-0.000900***	-0.000800**	-0.000975***	-0.00123***	-0.00118***	-0.00111***	-0.00116**	-0.00152**	-0.00168***	-0.00182***
	(0.000307)	(0.000348)	(0.000348)	(0.000349)	(0.000298)	(0.000340)	(0.000341)	(0.000346)	(0.000535)	(0.000622)	(0.000622)	(0.000675)
GDP Growth$_{t-1}$	-0.0140	-0.0217	-0.0201	-0.0251	-0.0102	-0.0163	-0.0144	-0.0165	-0.00912	0.00187	0.00746	0.00866
	(0.0167)	(0.0171)	(0.0171)	(0.0171)	(0.0169)	(0.0173)	(0.0173)	(0.0173)	(0.0257)	(0.0264)	(0.0264)	(0.0265)
Export Share	-0.000334***	-0.000335***	-0.000331***	-0.000369***	-0.000312***	-0.000300***	-0.000296***	-0.000316***	-0.000321**	-0.000278*	-0.000280*	-0.000270*
	(0.0000923)	(0.0000920)	(0.0000919)	(0.0000923)	(0.0000898)	(0.0000895)	(0.0000895)	(0.0000901)	(0.000145)	(0.000147)	(0.000147)	(0.000148)
Polity2		-0.000655*	-0.000497	-0.00105**		-0.000541	-0.000340	-0.000606		-0.00233*	-0.00363***	-0.00380***
		(0.000381)	(0.000385)	(0.000441)		(0.000375)	(0.000380)	(0.000441)		(0.00125)	(0.00126)	(0.00131)
Migrant Stock		0.000632	0.000670	0.000430		-0.000856	-0.000803	-0.000881		-0.00168	-0.00176	-0.00189
		(0.000926)	(0.000925)	(0.000923)		(0.000933)	(0.000933)	(0.000932)		(0.00116)	(0.00116)	(0.00121)
Educational Inequality				-0.000368**				-0.000174				0.000191
				(0.000145)				(0.000146)				(0.000368)
Constant	0.0380***	0.0325***	0.0323***	0.0364***	-0.0363***	-0.0322**	-0.0323**	-0.0275*	-0.0579**	-0.0765**	-0.0908***	-0.101***
	(0.00356)	(0.00913)	(0.00912)	(0.00917)	(0.0130)	(0.0140)	(0.0140)	(0.0144)	(0.0266)	(0.0307)	(0.0307)	(0.0359)
Gini												
Oil Revenues per Capita	-0.00126***	-0.00125***	-0.00127***	-0.00127***	-0.00134***	-0.00133***	-0.00134***	-0.00135***	-0.00116***	-0.00117***	-0.00105***	-0.00105***
	(0.0000823)	(0.0000822)	(0.0000821)	(0.0000822)	(0.0000822)	(0.0000819)	(0.0000816)	(0.0000818)	(0.0000638)	(0.0000638)	(0.0000624)	(0.0000624)
GDP Growth$_{t-1}$	-9.399***	-9.381***	-7.788***	-7.957***	-5.376**	-5.393**	-3.602	-3.674	2.680	2.678	5.946***	5.950***
	(2.300)	(2.300)	(2.364)	(2.365)	(2.344)	(2.344)	(2.392)	(2.393)	(2.121)	(2.121)	(2.061)	(2.061)
Manufacturing Share	-0.188***	-0.187***	-0.193***	-0.193***	-0.190***	-0.190***	-0.195***	-0.195***	-0.181***	-0.181***	-0.154***	-0.153***
	(0.00881)	(0.00881)	(0.00899)	(0.00899)	(0.00879)	(0.00878)	(0.00889)	(0.00890)	(0.00956)	(0.00956)	(0.00956)	(0.00956)
Educational Inequality	0.0210	0.0234	0.0458**	0.0376*	0.0126	0.0144	0.0423*	0.0382*	0.0470	0.0458	0.0603**	0.0620**
	(0.0209)	(0.0209)	(0.0223)	(0.0226)	(0.0206)	(0.0205)	(0.0220)	(0.0223)	(0.0303)	(0.0303)	(0.0291)	(0.0293)
Urbanisation Share	-0.0301*	-0.0307*	-0.0373**	-0.0369**	-0.0460***	-0.0472***	-0.0553***	-0.0550***	-0.155***	-0.154***	-0.148***	-0.148***
	(0.0158)	(0.0158)	(0.0159)	(0.0159)	(0.0157)	(0.0156)	(0.0157)	(0.0158)	(0.0256)	(0.0256)	(0.0246)	(0.0246)
Polity2			0.176***	0.162**			0.212***	0.205***			-0.855***	-0.856***
			(0.0629)	(0.0631)			(0.0620)	(0.0622)			(0.0827)	(0.0827)
Constant	3.407***	3.380***	3.381***	3.443***	-5.930***	-6.008***	-6.913***	-6.811***	-27.89***	-27.82***	-35.20***	-35.26***
	(0.436)	(0.436)	(0.435)	(0.435)	(1.850)	(1.850)	(1.861)	(1.863)	(2.475)	(2.476)	(2.483)	(2.485)
N	1282	1282	1282	1282	1282	1282	1282	1282	1282	1282	1282	1282
R^2	0.3255	0.3254	0.3287	0.3288	0.3617	0.3616	0.3667	0.3667	0.7890	0.7890	0.8054	0.8054

Notes: Brain Drain regressed on the Gini coefficients between source and host countries and Gini coefficients regressed on oil revenues per capita in a structural equation setup making use of alternative data sources. Inequality data from the World Bank and Brain Drain data from the German Institute of Employment Research (IAB). Time span: 1980-2010. The dependent variable Brain Drain is defined as the change in the stock of migrants from country i to country j in period t. Columns (1) - (12) are estimated based on a 3 SLS procedure. On the first stage, instruments are obtained by regressing endogenous variables on all exogenous variables leading to fitted values. On the second stage, an estimate for the covariance matrix is derived and finally the GLS procedure is applied. In columns (1) to (4) I provide pooled 3SLS estimates for different model specifications in order to test the sensitivity of the results. Complementarily, specifications in columns (5) to (12) account for time fixed effects while specifications in columns (9) to (12) account for both source country and time fixed effects. All bilateral variables besides of GDP growth 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 2.8: Sensitivity Analysis Simultaneous Equation Model

3

RESOURCE BOOMS AND THE SELECTIVITY OF INTERNAL MOBILITY

Abstract:

While Chapter 2 was devoted to the selectivity of international migration patterns, Chapter 3 examines the selectivity effects of interstate migration patterns arising as a virtue of resource booms. Theoretically, I show that natural resource booms lower the relative educational background of prospective immigrants. This especially holds if resource abundant states embark on a policy of resource transfers in the course of further fiscal capacity. Empirically, I examine selective interstate mobility patterns, relying on US census data spanning the years between 1940 and 2000. The empirical results are mainly in accordance with the theoretical predictions. Namely, a resource boom lowers the educational background of prospective immigrants and unleashes ambiguous effects on the selectivity of emigration.[1]

[1]This chapter is single-authored and has been submitted to an academic journal.

3.1 Introduction

"The consumer-voter may be viewed as picking that community which best satisfies his preference pattern (...)."

– Tiebout (1956), p. 418.

In Chapter 2, I showed that a resource boom lays the ground for brain drain effects in international migration contexts. The theoretical predictions were based on Dutch disease models (Corden and Neary (1982), Corden (1984)), according to which natural resource booms lead to a real appreciation of the exchange rate (spending effect) along with intersectoral factor movements towards the non-tradable sector (resource movement effects). Due to the distributional effects in the course of the deindustrialisation, the Dutch disease fosters brain drain effects. Complementarily, Chapter 3 examines selectivity effects of US interstate migration patterns in response to resource windfalls. In particular, I raise the following questions: What are the underlying mechanisms in relating resource booms to the skill composition of internal migration patterns? Are the empirical results in line with the theoretical conjectures? Are non-parametric methods appropriate in order to model the multilateral character of migration decisions?

In order to address these questions, I combine a theoretical model with an empirical investigation. Theoretically, I rely on a simple model, according to which the fiscal authority encounters further fiscal capacity in the course of resource booms, setting the stage for resource transfers. As long as low-skilled labor derives a stronger utility gain from resource windfall gains, a resource boom is negatively associated with the selectivity of immigration. Complementarily, a Dutch disease translating into a boom of the service sector and a bust of the tradable sector strengthens this result through intersectoral resource movements. However, as opposed to international migration patterns analyzed in Chapter 2, even regions lacking natural resources might be exposed to factor reallocations as a consequence of exchange rate effects. Hence, Dutch disease models are not an appropriate reference in order to analyze selective regional migration patterns as a consequence of resource booms.

The findings of this chapter are embedded into several strands of literature which shed light on the determinants of (selective) regional migration patterns, especially within the US. In particular, Borjas et al. (1992) relies on the National Longitudinal Survey of Youth and shows that relative returns to skills across US states serve as the main determinant of selective migration patterns. "Persons whose skills are most mismatched with the reward structure offered by their current state of residence are the persons most likely to leave that state, and these persons tend to relocate in states which offer higher rewards for their particular skills." (p. 159) These results are consistent with the theoretical predictions Borjas (1987) raised in his seminal paper. Beyond Borjas et al. (1992), the evidence with respect to the Borjas model is relatively mixed and mainly focuses on cross-country migration, as pointed out in Chapter 2. While Moraga (2011) verifies that relative inequality determines the selectivity of migration in line with the Borjas model, Chiquiar (2005) falsifies the theoretical predictions based on migration patterns between Mexico and the US. Kaestner and Malamud (2014) refer to migration streams between Mexico and the US as well and conclude that Mexican migrants in the US approximate a random sample of the Mexican population. Stolz and Baten (2012) examine selective international migration patterns and confirm the predictions of the Borjas model during the era of mass migration. In accordance with the predictions of his seminal paper, Borjas (2002) analyzes interstate mobility patterns in response to differentials in welfare spending and concludes that welfare spending is negatively associated with the selectivity of internal immigration. According to Razin et al. (2011), this result is externally valid for migration patterns in Europe as well.[2]

Empirically, I rely on US census data capturing migration patterns between 1940

[2]These results are further in line with the findings of Enchautegui (1997), McKinnish (2007) Levine and Zimmerman (1999)

and 2000. States which were exposed to significant oil booms in the respective period include Texas, Alaska, Wyoming and Louisiana. Especially in the second half of the 20th century, the US experienced a sharp increase in oil revenues, initially mainly driven by Texas. Peaking in the oil crisis in 1973, the US saw a fierce decline in oil drilling subsequently, though production was pushed up again transitorily with the completion of the Trans-Alaska pipeline as of 1977. After the second peak in 1977, US oil drilling dropped sharply and persistently. The oil boom corresponded with a substantial influx of workers. For instance, the population in Texas increased from almost 10,000,000 in 1960 to 20,000,000 in 2000.

In order to relate resource booms to the selectivity of interstate migration, I proceed in three steps. In a first step, I construct a selectivity measure based on the years of primary, secondary and college education acquired by internal migrants relative to the average educational attainment in the state of origin. In a second step, I set out an econometric model linking the quantity and selectivity of migration to oil revenues per capita along with several covariates. In a third step, I test the robustness of the results based on a dynamic panel model and account for the relative standard of living through a non-parametric approach. With respect to the latter, I make use of seminal contributions of Douglas and Wall (1993) and Wall (2001), according to which relative net migration serves as a means in order to set out an ordinal ranking of states. Even though migration decisions materialize retrospectively as bilateral decisions, prospectively, migration decisions are multilateral since migrants contrast all potential destination states with each other under consideration of migration costs. Hence, a multilateral approach is of particular importance in order to analyze migration decisions.

Moreover, in order to internalize counterfactual trends in migrant selection, I compare the evolution in migrant selection within oil abundant states with the respective evolution in a control group composed of several US states which have not been exposed to any oil boom. Through all econometric specifications, the results are basically in line with theoretical predictions, i.e. resource booms lower the relative educational background of immigrants, while the effects on the selectivity of emigration are ambiguous. Finally, I verify whether the results are driven by migrants moving into the service sector or by migrants taking up positions in the oil extraction industry.

This chapter is organized as follows. In section 3.2, I provide a theoretical setup relating resource windfalls to the selectivity of migration. In section 3.3, I confront the theoretical predictions with data from interstate migration patterns throughout the US. Section 3.4 concludes.

3.2 Theory

In order to derive the link between resource booms and the skill composition of internal migration, I rely on a multinomial choice model in the spirit of McFadden et al. (1973), McFadden (1978) and Maddala (1983). In particular, I posit an economy which is composed of N individuals, $k \in \mathcal{K} = \{1, ..., N\}$, distributed across M states, $j \in \mathcal{J} = \{1, ..., M\}$. Let V_{kj} denote the indirect utility individual k derives in state j, while individual incomes are made up of a deterministic component, $x'_{kj}\beta$, and a stochastic component, ϵ_{kj}, according to the following equation:

$$V_{kj} = x'_{kj}\beta + \epsilon_{kj} \tag{3.1}$$

Each individual chooses the destination state which maximizes indirect utility, V_{kj}, out of the indirect utility set, $\{\mathrm{V}_{k1}...V_{kM}\}$, while dispensing with migration costs which are modest in internal migration contexts. Formally,

$$Prob(V_k = j) = Prob(V_{kj} = \max\{V_{k1}, ..., V_{kM}\}) \tag{3.2}$$

Assuming a stochastic component which is i.i.d. extreme value distributed, i.e.

$$F(\epsilon_{kj}) = \exp(-\exp(-\epsilon_{kj})) \tag{3.3}$$

carries over to the following probability of individual k choosing state j, $Prob(V_k = j|x_{kj})$,

$$Prob(V_k = j|x_{kj}) = \frac{\exp(x'_{kj}\beta)}{\sum_{j=1}^{M}\exp(x'_{kj}\beta)} \tag{3.4}$$

which goes back to Maddala (1983). Due to the extreme value distribution, the stochastic components of the indirect utility derived in each state are independent of the stochastic components of the indirect utility derived in all other states. This assumption is standard and often referred to as independence of irrelevant alternatives (IIA) in the literature (e.g. Luce (2005)). In addition, it is worth mentioning that individual choices are exclusively determined by aggregate covariates which might be interacted with individual covariates in a conditional logit framework.

Within the conditional logit framework set out above, I assume that state j experiences a resource windfall and provides each inhabitant an unconditional resource transfer, x_{kjr}. The change in the probability of migration into the resource abundant state, j, in response to changes in control x_{kjr} is given by:

$$\frac{\partial Prob(V_k = j|x_{kj})}{\partial x_{kjr}} = Prob(V_k = j|x_{kj})(1 - Prob(V_k = j|x_{kj})\beta_r \tag{3.5}$$

Conspicuously, the effect of resource windfall gains on the immigration probability depends on the impact of resource windfall gains on indirect utility, β_r, and on all covariates, x_{kj}.

In order to evaluate the effect of resource windfall gains on the selectivity of migration, I discuss the general results above based on a specific deterministic utility function. Suppose an agent living in country j chooses consumption, c, and labor, l, in order to maximize utility, $U = c^{\alpha}(1-l)^{\beta}$ with $0 < \alpha < 1$ and $0 < \beta < 1$ subject to his budget constraint, $pc = (1-\tau)wl + \mathcal{R}$. Time is normalized to one and the individual trades off work, l, and leisure, $1-l$. In addition, τ equals a proportional income tax, whilst $\mathcal{R}$ represents resource transfers. The indirect utility individual k derives in state j arising out of this optimization problem is given by:

$$V_{kj} = \left(\frac{(1-\tau_j)w_k}{p}\right)^{\alpha}\left(1+\frac{\mathcal{R}_j}{(1-\tau_j)w_k}\right)^{\alpha+\beta}\frac{\alpha^{\alpha}\beta^{\beta}}{(\alpha+\beta)^{\alpha+\beta}} \tag{3.6}$$

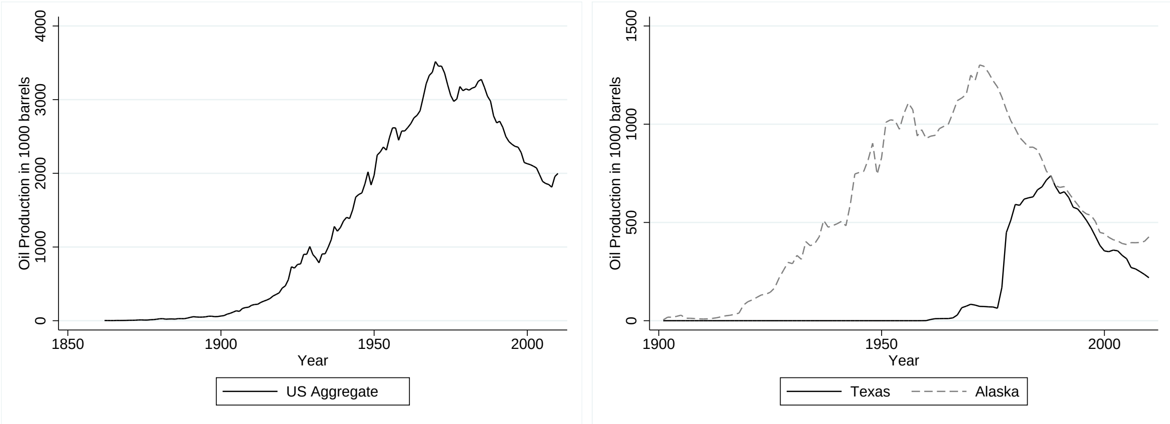
Conspicuously, unconditional resource transfers unambiguously increase the indirect utility across all skill levels. However, the positive association is stronger the lower the net wage, and hence the productivity of the worker under reasonable assumptions due to the decline in marginal utility. Therefore, resource windfall gains are particularly beneficial for low-skilled labor even in the absence of a Dutch disease. However, in light of equation 3.5, a positive association between resource windfall gains and indirect utility is necessary though not sufficient to go along with an increase in the probability of immigration. Rather, the selectivity effects of resource windfall gains also depend on the initial relative attractiveness of the resource abundant state, as individuals make discrete rather than continuous choices. However, as long as the number of alternative countries becomes large, it is reasonable to assume that the probability of low-skilled migration increases more fiercely in the course of resource windfall gains. Besides of direct selectivity effects of unconditional transfers, a resource boom precipitates a Dutch disease which corresponds with a boom in the service sector and a bust in the manufacturing sector. As the service sector is relatively low-skilled labor intensive, low-skilled labor is better off in the course of resource booms. This might contribute to the selectivity effects of immigration as well.

In the following section, I illuminate the relationship between resource booms and the selectivity of interstate migration empirically. In this regard, I make use of static and dynamic panel models as well as a nonparametric approach, accounting for the multilateral character of migration decisions. However, before I proceed with a prescriptive analysis, I provide descriptive statistics in the following section.

3.3 Evidence

3.3.1 Descriptive Analysis

In a first step, I descriptively relate relative resource revenues to the selectivity of migration patterns. With respect to oil revenues, Hamilton (2011) provides data on oil production for US states between 1850 and 2000. US states with substantial oil production throughout the 20th century entail Texas, Alaska, Louisiana, California and Colorado. As displayed in the panel on the left-hand side of figure 3.1 below, aggregate US oil drilling was modest until the beginning of the 20th century and went up subsequently until the first oil crisis in 1973 with 3,400,000 barrels per day, followed by an almost persistent downturn. According to the disaggregated panel on the right hand side of figure 3.1, the increase in aggregate oil production at the beginning of the 20th century was mainly driven by Texas preceding the first oil crisis and by Alaska following the first oil crisis. In Texas, large scale oil drilling began in the 1930's on a fairly low level and peaked in the 1970's with 1,300,000 barrels per day, followed by a persistent decline, while large-scale oil drilling in Alaska began in 1977. With the first oil crisis, rigid legal disputes with respect to the construction of the Transalaska-Pipeline came to an end and the Transalaska Pipeline was completed between 1973 and 1977. With the completion of the Transalaska-Pipeline connecting Prudhoe Bay in the North and Valdez in the south, US aggregate oil production saw a transient increase.



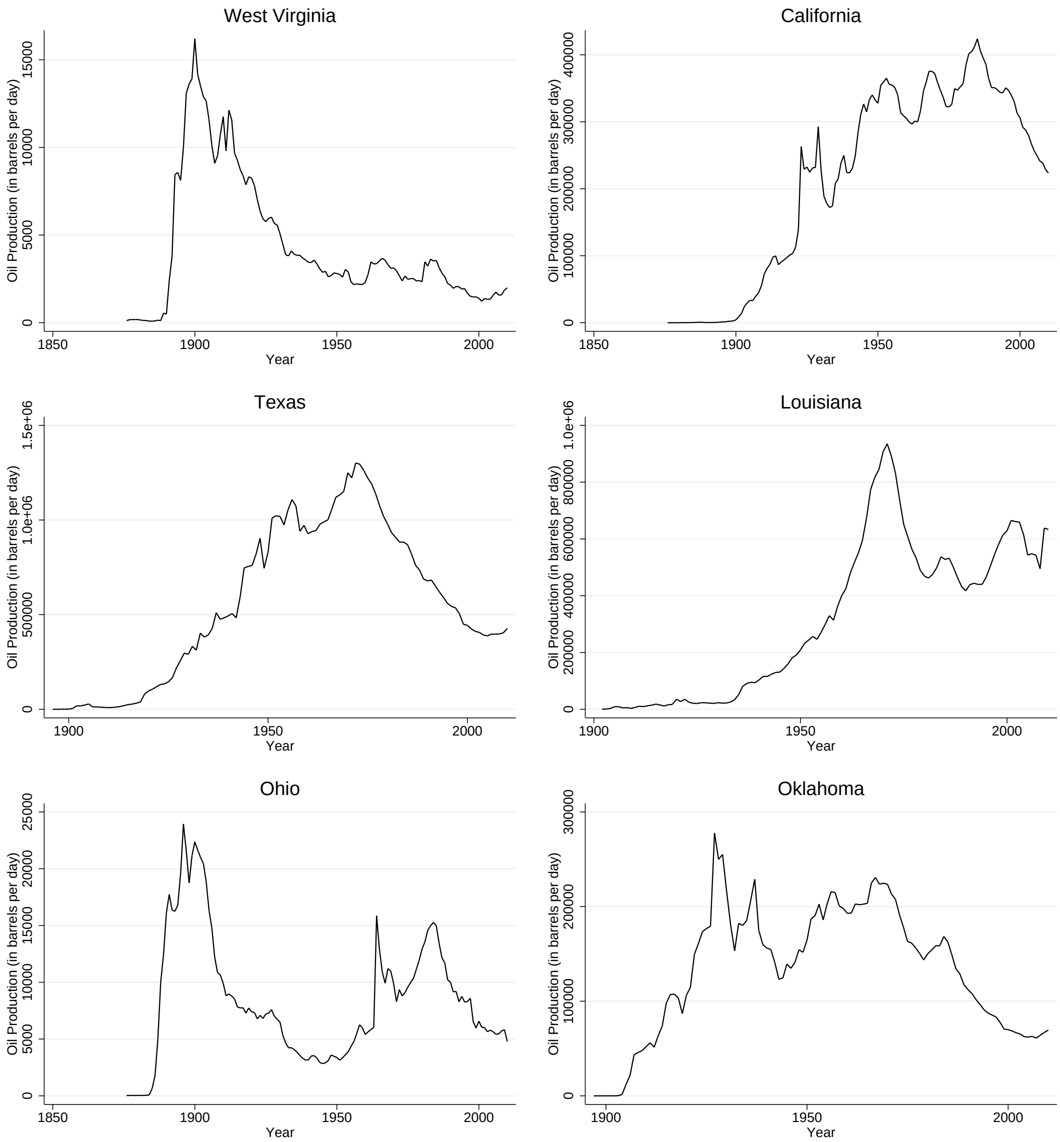
Notes: The figures depict trends in US and state oil production in 1000 barrels per day. Data source: Hamilton (2011).

Figure 3.1: US Oil Drilling

Alaska in particular exhibited some peculiarities. Firstly, production started abruptly rather than steadily after the completion of the pipeline in 1977, setting the stage for a boom in the whole economy. While oil production in Alaska was 63,398 barrels per day in 1976, oil production went up to 169,201 barrels per day in 1977, followed by a steady decline after the second oil crisis in 1979. Secondly, oil production serves as the main propeller for the state economy. Therefore, Alaska is a distinct laboratory in order to shed light on the selectivity effects of emigration and immigration as a consequence of the oil boom. I will make use of the fierce increase in oil production in Alaska in order to ascertain the responses in educational investments among local residents in Chapter 4 while excluding migrants from the sample. However, in order to examine the selectivity effects of immigration in response to oil booms, I draw upon data from all US states with significant oil production throughout the 20th century.[3]

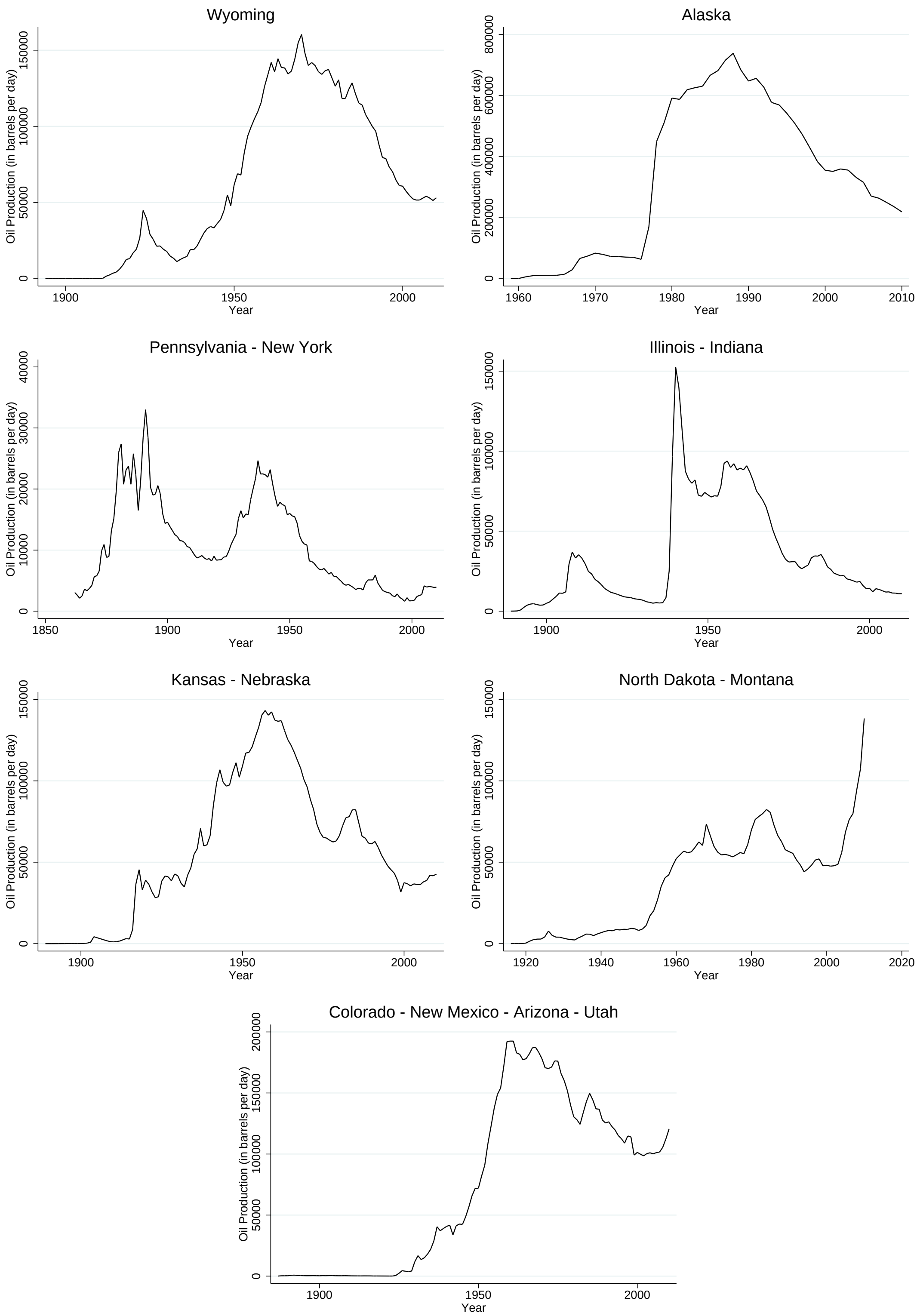
While Texas, Alaska, Louisiana, California, Colorado and Wyoming constitute the states with the largest oil production throughout the 20th century, according to the separate panels in figure 3.2 and 3.3, Indiana, Kansas and North Dakota contributed to aggregate oil drilling as well. In recent years, newly discovered oil fields, especially in Montana, serve as the main contributor to the increase in aggregate oil production.

[3]States with minor oil production might be grouped as suggested by Hamilton (2011).



Notes: The figures depict trends in US state oil production in barrels per day. Data source: Hamilton (2011).

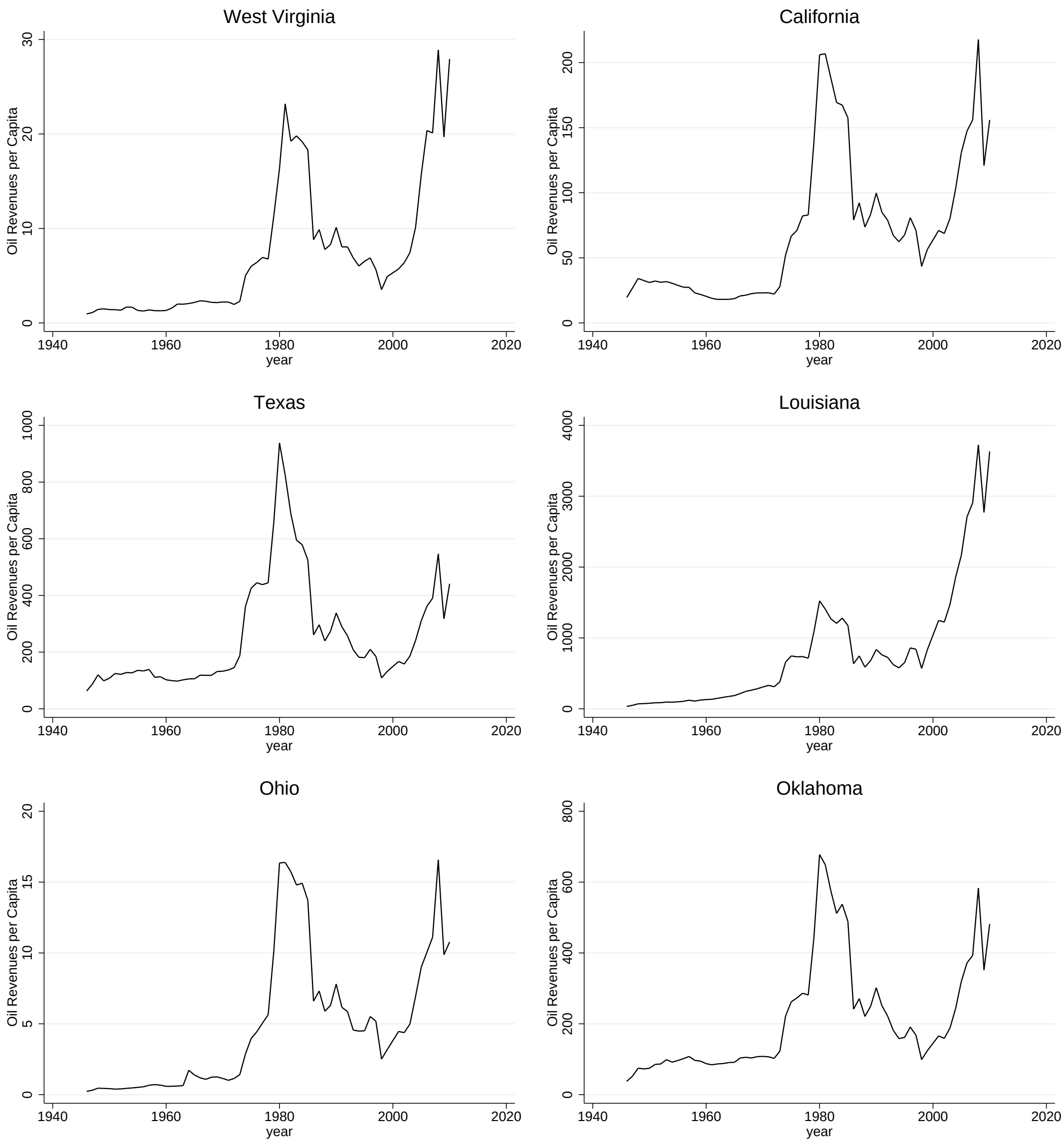
Figure 3.2: Oil Production by US States 1



Notes: The figures depict trends in US state oil production in barrels per day. Data source: Hamilton (2011).

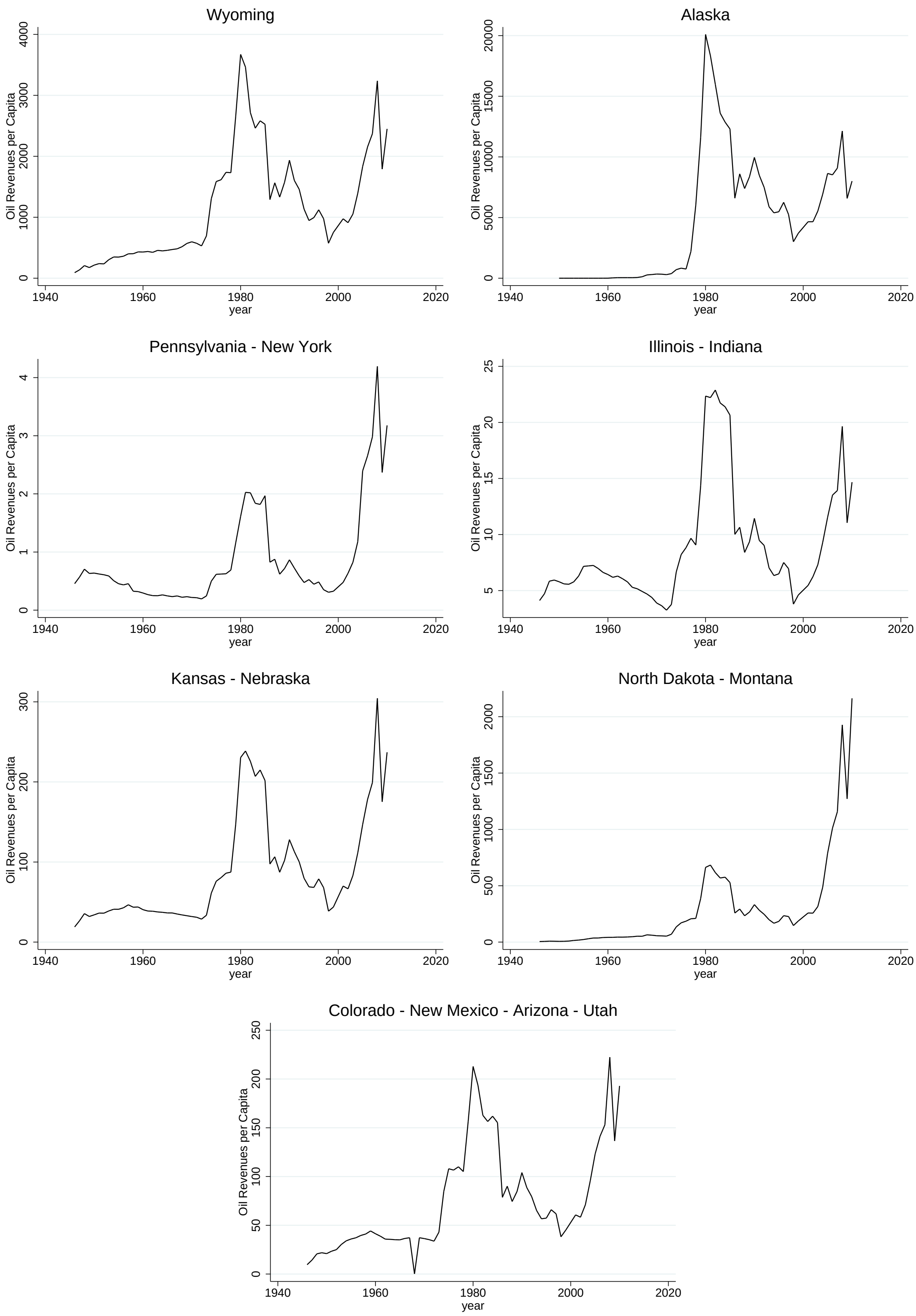
Figure 3.3: Oil Production by US States 2

Complementarily, figures 3.4 and 3.5 display oil revenues per capita on a US state level between 1945 and 2000. While annual oil revenues per capita in Alaska peaked in 1980 with 20,000 USD per capita, oil revenues per capita in Texas reached the maximum of slightly below 1,000 USD in 1980 due to the large population size compared to Alaska. Further states with substantial oil revenues per capita throughout the 20th century include Louisiana, Wyoming and Montana as well as North Dakota.



Notes: The figures depict trends in US oil revenues per capita in annual USD. Data source: Hamilton (2011).

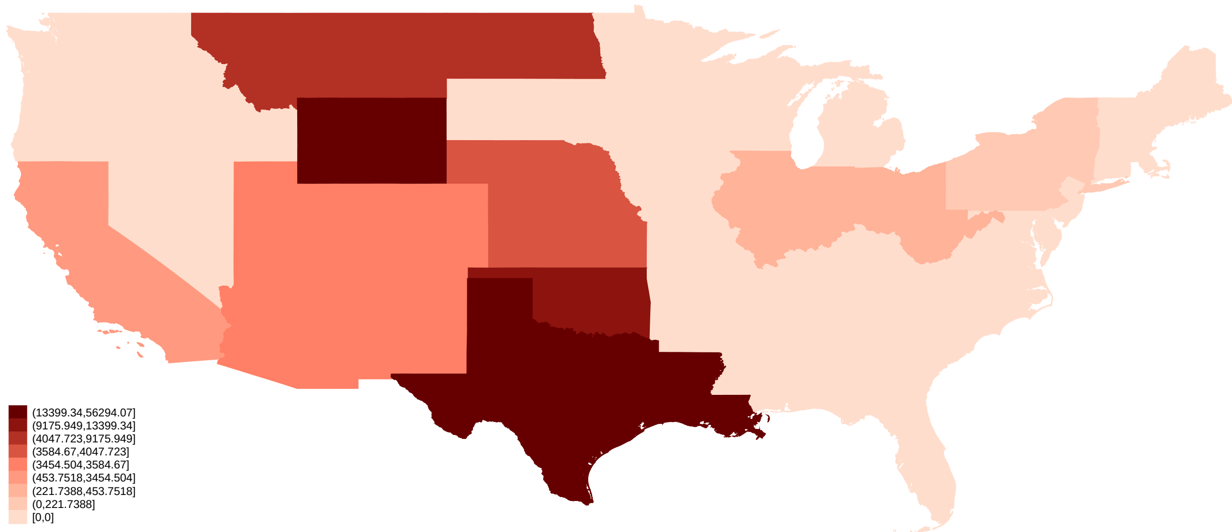
Figure 3.4: Oil Revenues per Capita by US States 1



Notes: The figures depict trends in US oil revenues per capita in annual USD. Data source: Hamilton (2011).

Figure 3.5: Oil Revenues per Capita by US States 2

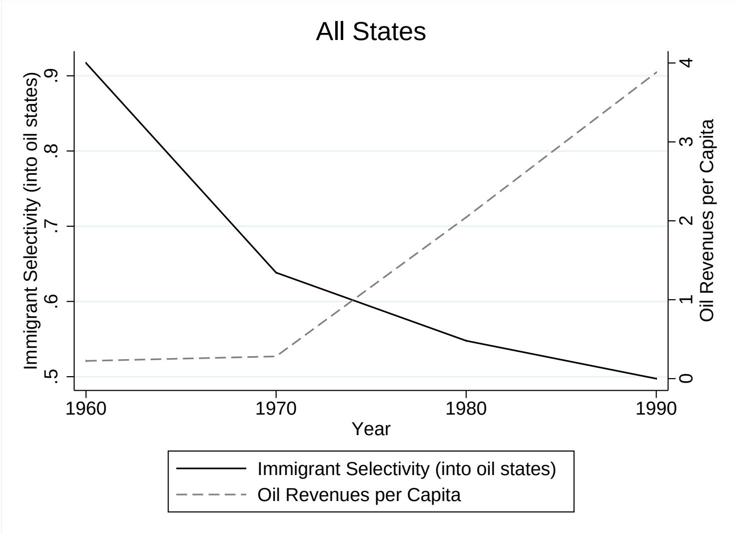
The following map summarizes the sum of oil revenues per capita between 1940 and 2000 for each US state besides Alaska by collapsing the time series above.



Notes: The map depicts the sum of oil revenues per capita by US states over the 20th century. Oil revenues per capita are given as oil revenues per day according to Hamilton (2011) divided by the population size. Data source: Hamilton (2011).

Figure 3.6: US Oil Drilling

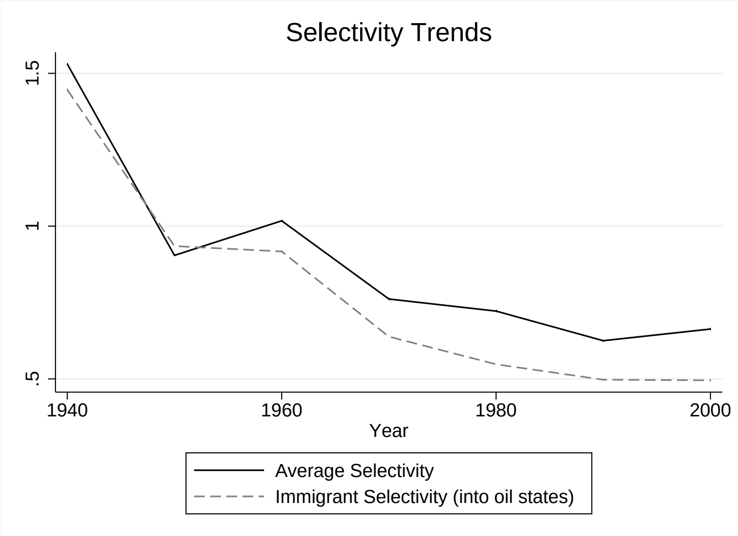
Complementarily, in figure 3.7, I relate the selectivity of interstate immigrants to oil revenues per capita. In particular, the figure refers to the selectivity of migrants moving into oil abundant states as listed in figures 3.2 and 3.3. The selectivity of migration is measured as the difference between the years of schooling of immigrants and the average years of schooling in the state of origin. Again, historical oil production data originate from Hamilton (2011) while data on the selectivity of migration are obtained from Ruggles et al. (2010). In line with the theoretical conjectures, the figure depicts a negative association between oil abundance and the relative educational background of immigrants while oil abundance are measured in oil revenues per day, in accordance with Hamilton (2011).



Notes: The figures depict trends in oil revenues per capita per day and the selectivity of immigration within the US. The selectivity of immigration is measured as the difference in the years of schooling of immigrants and the average years of schooling in the state of origin. Data source: Hamilton (2011), Ruggles et al. (2010).

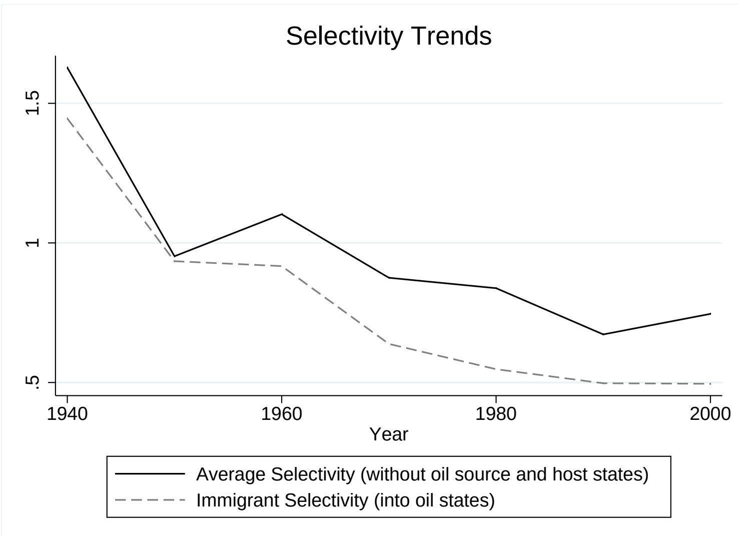
Figure 3.7: Immigrant Selectivity - Oil Revenues

However, the correlations reported in figure 3.7 are insufficient as long as the selectivity of interstate migration decreases throughout the 20th century across all US states, while oil revenues per capita increase. The former might be due to a decline in poverty constraints materializing across all US states or due to an increase in average educational attainment and a given educational background of migrants. Hence, I compare the average selectivity of immigration into oil abundant states with the average selectivity of immigration into all states including oil abundant states in figure 3.8 and into states not engaging in oil drilling in figure 3.9. Apparently, since the 1960's migrant selectivity into oil abundant states fell short of the average migrant selectivity, a shortfall which is even more succinct compared to the selectivity of migration while excluding oil abundant states. Hence, I can conclude that oil revenues per capita are negatively associated with the selectivity of immigration, even compared to a control group approximating a counterfactual. I refer to these counterfactual trends again in the empirical section below. Before I exploit the data structure more carefully by setting out static and dynamic panel models. The latter accounts for dynamic adjustments in the selectivity of migration as well.



Notes: The figure contrasts the selectivity of immigration into oil abundant states with the average selectivity of immigration across all states. The selectivity of immigration is measured as the difference in the years of schooling of immigrants and the average years of schooling in the state of origin. Data source: Hamilton (2011), Ruggles et al. (2010).

Figure 3.8: Relative Selectivity 1



Notes: The figure contrasts the selectivity of immigration into oil abundant states with the average selectivity of immigration across all states while excluding oil abundant states as source and host states. The selectivity of immigration is measured as the difference in the years of schooling of immigrants and the average years of schooling in the state of origin. Data source: Hamilton (2011), Ruggles et al. (2010).

Figure 3.9: Relative Selectivity 2

These panel models are introduced in the next section of this chapter.

3.3.2 Empirical Strategy

In a second step, I examine the selectivity of interstate migration patterns within the US as a consequence of oil abundance in the source and host state based on US census data between 1940 to 2000. In particular, as a baseline setup, I posit the following econometric model, relating the selectivity of migrants moving from state i to j to oil revenues in the source and host state along with further covariates:

$$SELECTIVITY_{ijt} = \alpha_{ij} + \phi OILREVPC_{it} + \pi OILREVPC_{jt} + \boldsymbol{X'}_{it}\gamma + \boldsymbol{X'}_{jt}\lambda + \epsilon_{ijt} \tag{3.7}$$

while the identification again relies on a strict exogeneity assumption:

$$E(\epsilon_{ijt}|X_{ijt}, OILREVPC_{ijt}, \alpha_{ij}) = 0 \tag{3.8}$$

for $t = 1, ..., T$ and X_{ijt} serving as a vector of all covariates in the source and host state and $OILREVPC_{ijt}$ as a vector of oil revenues per capita in the source and host state.

In contrast to Chapter 2, I account for all covariates in the source and host state separately in order to disentangle push and pull factors. In addition, I focus on natural resource booms as a pull factor of immigration rather than as a push factor for emigration. Similar to Chapter 2, the data are collapsed for decades and state pairs, in order to capture long run changes in migrant selectivity. The model is inspired by a gravity equation proposed by Zipf (1946), Egger and Pfaffermayr (2003) as well as Anderson and Van Wincoop (2001) which explains migration and trade by push and pull factors in the source and host state in the case of migration or exporter and importer countries in the case of trade.[4] However, as opposed to gravity equations and the setup in Chapter 2 which focused on international migration, distances are less important for

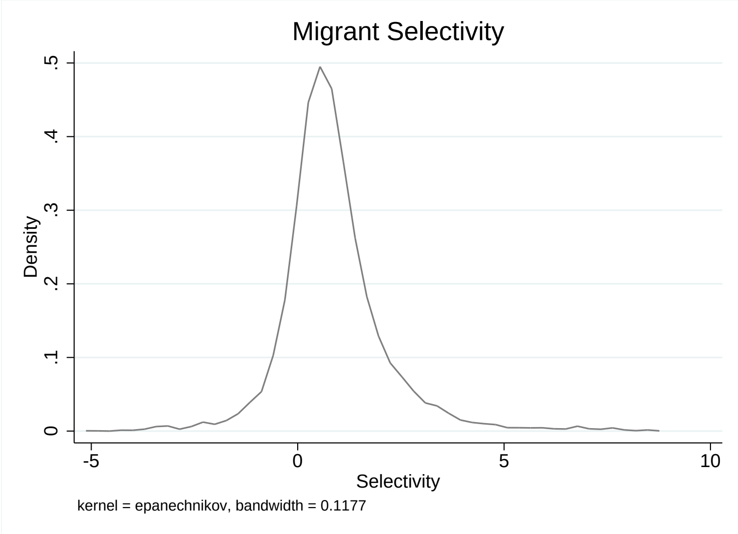
[4] In order to avoid feedback effects, migration patterns are captured within 5 years before the respective census.

interstate migration patterns within a country.

As pointed out previously, the outcome variable, $SELECTIVITY_{ijt}$, is defined as the difference in the years of primary, secondary and college education of migrants moving from state i to j and the average years of schooling in state i, drawn from US census data (Ruggles et al. (2010)). The years of schooling are consistently defined across states and over time, and therefore a reliable and comparable measure for the selectivity of migration. To preclude that the results are driven by families with children moving across US states, I restrict the analysis to individuals above age 25 who are more likely to have completed their education. In addition, I include the average age of migrants as an additional control variable in various specifications. In essence, labor and interstate mobility declines over the life cycle with respect to both skilled and unskilled labor, while overall, the mobility of skilled labor exceeds the mobility of unskilled labor. However, even without restricting the analysis to individuals above 25, the average age shows only moderate differences between oil abundant states with 28.90244 years and non-oil oil abundant states with 29.36241 years (see table 4.1).

Again, in order to ascertain the distribution of the outcome variable, I provide Kernel density estimates of migrant selectivity in figure 3.10, according to which migrant selection in fact approximates a Gaussian normal distribution.[5] Apparently, migrants are on average positively selected, as less educated individuals encounter less opportunities which is reflected in lower mobility (e.g. Abramitzky et al. (2013)).

[5]As set out in Chapter 2, I estimate the density of educational investments based on a non-parametric approach which is standard.



Notes: The figure depicts Kernel density estimates of the average migrant selection across all US states. Data source: Ruggles et al. (2010).

Figure 3.10: Kernel Density Estimate: Migrant Selectivity

The independent variables $OILREVPC_{it}$ and $OILREVPC_{jt}$ are defined as oil revenues per capita in the source state i and host state j, respectively. Oil revenues are defined as the product of state oil production per day on a US state level provided by Hamilton (2011) and the respective oil price which is invariant across states. Again, as the chapter is devoted to the relationship between resource abundance rather than oil dependence and the selectivity of interstate migration, I account for oil revenues per capita rather than per aggregate GDP. The main coefficients of interest are ϕ and π, capturing the relationship between resource abundance and the selectivity of immigration and emigration, respectively. In order to avoid the analysis to be restricted to migration patterns between resource abundant states, I provide separate specifications with oil revenues serving as push and pull factors, respectively. Moreover, I control for state pair fixed effects, α_{ij} in order to control for time constant unobserved heterogeneity across states. I further control for time dummies which is standard in gravity equations (e.g. Egger and Pfaffermayr (2003)) and panel data models in general (e.g. David et al. (2007)). The inclusion of time effects is inevitable in light of figure 3.8 and 3.7 which suggest time specific effects which are invariant across state pairs. While

Egger and Pfaffermayr (2003) proposes a three-way gravity equation with time effects and importer and exporter fixed effects, I account for state pair fixed effects.

In order to improve the efficiency of the estimates and in order to preclude confoundedness, I further control for additional push and pull factors in the source state i and the host state j, X_{it} and X_{jt}, respectively. These covariates entail US state incomes per capita provided by the United States Bureau of Economic Analysis (2017). The role of incomes per capita as a covariate is twofold. Firstly, state incomes per capita mainly reflect pecuniary constraints which confine migration decisions (e.g. Abramitzky et al. (2013)). Secondly, state income per capita serves as an indicator for the relative standard of living, severely affecting migration decisions as well. The relative standard of living might also be affected by the provision of public goods through fiscal expenditures. Hence, I control for fiscal expenditures per capita in the source and host state as well, originating from the United States Census Bureau (2015). In additional robustness checks, I further account for differences in the living standard originating from taxes and transfers as a percentage of state incomes and the population density originating from United States Census Bureau (2015) as well. In order to test the predictions of the Borjas model within a country, I further include income inequality measures for the source and host state through state Gini coefficients provided by Sommeiller and Price (2014). As pointed out in Chapter 2, Borjas (1987) suggests that relative returns to skills between the source and host state determine the selectivity of migration. Namely, under the assumption that incomes are sufficiently correlated across states and the returns to skills in the destination state exceed returns to skills in the source state, a positive selection of immigrants is attracted on average.

Moreover, I control for the quantity of migration between state pairs as well, capturing potential network effects in migration decisions. Workers often self-select themselves into destination states which are populated by people with similar socio-economic and cultural backgrounds, as emphasized by Bartel (1989), Beine and Salomone (2013) as well as McKenzie and Rapoport (2007) in light of international migration patterns into the US. However, since cultural disparities are modest across states within the US, community effects are less relevant for internal migration patterns, in contrast to Chapter 2. Further, a selectivity-quantity trade-off might hold by definition since skilled labor is less abundant compared to unskilled labor.

Table 3.1 provides summary statistics for all covariates, i.e. the number of observations along with the mean and standard deviation as well as the minimum and maximum values of all variables I make use of in the prescriptive analysis below. As the OLS estimator is based on a normal distribution of the error term rather than a normal distribution of independent variables, the consistency of estimates is not affected by the distribution of covariates. However, I provide log-transformations of all independent variables which are greater than zero and not defined as percentages. In line with the descriptive statistics shown in figure 3.2 and 3.3, oil revenues as well as covariates are grouped for certain country pairs, following the definitions of Hamilton (2011). Apparently, though consistently positive, the selectivity of migrants moving into oil abundant states with 0.7511925 falls short of the selectivity of migrants moving into other states with 0.9060558.

		All States					Oil Abundant States					Other States				
Variable	Year	No. Obs.	Mean	Std. Dev.	Min	Max	No. Obs.	Mean	Std. Dev.	Min	Max	No. Obs.	Mean	Std. Dev.	Min	Max
Migrant Selectivity	All	11955	.863049	1.264543	-5.010753	8.644372	3320	.7511925	1.154108	-5.010753	8.505211	8635	.9060558	1.302025	-5.010753	8.644372
Quantity Migration	All	11955	311.6132	858.0879	1	23071	3320	420.6133	1010.818	1	18484	8635	269.7047	787.623	1	23071
Log Quantity Migration	All	3320	4.311144	2.081325	0	9.82466	3320	4.311144	2.081325	0	9.82466	8635	3.915423	1.97019	0	10.04633
Oil Revenues per Capita	All	3181	504.9325	1525.953	.3764766	11113.66	3181	504.9325	1525.953	.3764766	11113.66	0	0	0	0	0
Log Oil Revenues per Capita	All	3181	4.004527	2.439034	-.9768993	9.31593	3181	4.004527	2.439034	-.9768993	9.31593	nd	nd	nd	nd	nd
Log State Income per Capita	All	7684	4.568636	.8354291	.4691133	6.418655	2102	4.567404	.9595492	.4691133	6.10531	5582	4.569101	.7837056	3.00794	6.418655
Gini	All	10791	.474301	.0614441	.3408051	.6377532	2934	.4699843	.0630937	.3425638	.6477804	7989	.4767373	.0613898	.3408051	.6181685
Fiscal Expenditures	All	10301	1181.111	1365.668	17.2483	9422.978	2926	1311.093	1720.065	17.2483	9422.978	7375	1129.541	1192.541	36.84698	4882.155
Log Fiscal Expenditures	All	10301	6.303275	1.371645	2.847714	9.150907	2926	6.315546	1.444522	2.847714	9.150907	7375	6.298407	1.341705	3.606774	8.493342
Log Population Size	All	11955	16.8515	1.354685	11.63514	20.77126	3320	17.14427	1.518246	12.42922	20.77126	8635	16.73894	1.268511	11.63514	19.5139
Density	All	8097	168.4309	238.7819	.4048079	1103.994	1708	83.77992	80.73318	.4048079	274.0076	6389	191.0611	260.9442	2.368351	1103.994
Age	All	11955	29.11674	6.13689	1	83 8635	3320	28.88838	5.789051	1	82	8635	29.20455	6.263598	1	83

Notes: This table reports summary statistics for variables I make use of in the empirical section. However, the empirical part is based on several subsamples and restricts the analysis to migrants above age 25. Oil abundant states include those listed in the descriptive section.

Table 3.1: Summary Statistics

In the following section, I proceed with the discussion of the results of the static panel model.

3.3.3 Results

Static Panel Model

Table 3.2 reports estimates for the relationship between absolute oil abundance in the source and host state and the selectivity of migration based on the econometric model set out in equation 3.7 above. While the specifications in columns (1) to (3) rely on a pooled OLS estimator, the estimates shown in columns (4) to (6) are based on a random effects and the setups in columns (7) to (9) on a fixed effects estimator. However, in light of a Hausman test statistic for the baseline model of $\chi^2 = 109$, the fixed effects estimates serve as the main reference. Complementarily, the estimates in columns (4) to (9) control for state pair fixed effects with clustered standard errors in the sense of Stock and Watson (2008) which is standard in gravity equations. In order to take into account that numerous US states do not generate oil revenues, I provide separate estimates for oil revenues serving as push and pull factors, respectively.

Qualitatively, in line with the theoretical predictions, oil abundance in destination states is significantly and negatively associated with the relative educational background of immigrants throughout all specifications, while the relationship between oil abundance and the selectivity of emigration is insignificant. In general, a reversal in the sign of the coefficient between the pooled OLS model and the random and fixed effects model might be an example of the Simpson's Paradox (Simpson (1951)), according to which a relationship which is apparent on a state level might turn insignificant or even reverses in a pooled sample or vice versa. However, the respective coefficient is consistently insignificant across all specifications. Quantitatively, the coefficients relating oil revenues per capita and migrant selectivity range between -0.0197 and -0.0351, both significant at the 1 percent level.

In contrast to oil revenues, the covariates accounted for are consistently available for all states, and hence do not set the stage for implicit sample selection issues due to missing values. Therefore, I do not provide separate analyses for different sets of covariates in the source and destination state. In essence, the results are at least partially in line with the predictions of the Borjas model, i.e. in the pooled OLS model (column 1) a rise in returns to skills in the destination state corresponds with an increase in the selectivity of immigration. The larger returns to skills in the source state the lower the relative educational background of prospective immigrants. I will elaborate on the empirical evidence for the Borjas model in more detail below.

Moreover, state incomes per capita and fiscal expenditures serve as a pull factor for skilled interstate migration. However, causality might, at least partially, go from the selectivity of migration to state incomes per capita as well. However, these potential feedback effects do not impinge on the relationship of interest, as oil production is exogenous. Further, the results indicate network effects of migration in line with the theoretical conjectures. The larger the amount of interstate migration, the lower the selectivity of prospective immigration. This is remarkable in light of the fact that across US states cultural disparities are modest and migrants do not have to overcome language barriers in contrast to international migration (e.g. Bartel (1989)). However, in a static framework in which skilled labor is less abundant compared to unskilled labor, this might even hold by definition. The scarcity of skilled labor might lead to a decline in the selectivity of migration in the course of additional migration.

Complementarily, in table 3.3, I further control for average ages. Apparently, the average age is negatively associated with the selectivity of migration which might just reflect a strong upward trend in educational investments due to path dependencies. The theoretical predictions referred to resource windfall gains which are particularly valuable for low-skilled labor. One specific instance was the Alaska Permanent Fund established in 1976 which will be studied in more detail in Chapter 4 with respect to the effect on educational investments among local residents. Moreover, all state income taxes were totally abolished in Alaska in 1980, so state income taxes have to be accounted for as well. In order to verify whether the results are sensitive to the inclusion of taxes and transfers, I additionally control for the share of income tax revenues along with the share of transfers relative to total state incomes in table 3.4 below. In line with the estimates reported in table 3.2, the results show that resource abundance pulls down the selectivity of immigration. However, in the fixed effects setup the coefficient turns insignificant. This indicates that the selectivity effects might in fact at least be partially driven by transfers and taxes in line with the theoretical conjectures. This result is consistent with the results derived by Razin et al. (2011), McKinnish (2007) and Levine and Zimmerman (1999). I will further elaborate on the mediating factors in light of a dynamic panel model below.

Moreover, in table 3.5, I additionally control for the unemployment rate in the source and host state. Apparently, though the significance slightly declines, the relationship between relative oil abundance and selective migration is still significant and remains qualitatively unaffected by the inclusion of further covariates. However, the decline in the selectivity might be due to missing values in earlier time periods as well. Finally, table 3.6 tests the sensitivity of the selectivity measure to shifts in the educational indicator. In particular, table 3.6 reports estimates based on a slightly different definition of the years of schooling. In particular, the years of schooling are calculated for individuals above grade 8. This is due to the fact that in the census data years of schooling between grade 4 and 8 are grouped which slightly biases the average years of schooling. However, qualitatively, changes in the definition of the indicator do not impinge on the respective coefficient of interest. As reported in table 3.6, the results are insensitive to different definitions of the educational indicator.

	(1) Selectivity Pooled OLS	(2) Selectivity Pooled OLS	(3) Selectivity Pooled OLS	(4) Selectivity RE	(5) Selectivity RE	(6) Selectivity RE	(7) Selectivity FE	(8) Selectivity FE	(9) Selectivity FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues per Capita	-0.0274***		-0.0351***	-0.0200***		-0.0197***	-0.0315***		-0.0350***
	(0.00858)		(0.0102)	(0.00751)		(0.00678)	(0.00896)		(0.00814)
Oil Revenues per Capita (source)		0.00638	0.00174		-0.00344	-0.00391		-0.0108	-0.0219*
		(0.00741)	(0.0104)		(0.00645)	(0.00872)		(0.00791)	(0.0120)
Population	0.119***	0.208***	0.126***	0.123***	0.204***	0.169***	0.629***	0.388***	0.725***
	(0.0179)	(0.0211)	(0.0233)	(0.0235)	(0.0308)	(0.0328)	(0.146)	(0.128)	(0.171)
Population (source)	0.137***	0.164***	0.102***	0.125***	0.167***	0.149***	0.0886	0.284*	0.619***
	(0.0207)	(0.0211)	(0.0251)	(0.0294)	(0.0293)	(0.0396)	(0.156)	(0.154)	(0.191)
GDP per Capita	0.0535	0.419***	0.0678	0.0740	0.287***	0.153***	0.507***	0.341***	0.698***
	(0.0459)	(0.0889)	(0.0439)	(0.0478)	(0.0572)	(0.0466)	(0.140)	(0.121)	(0.162)
GDP per Capita (source)	0.0441	0.0881**	0.0333	0.0759	0.136***	0.0842	0.117	0.286**	0.548***
	(0.0562)	(0.0424)	(0.0514)	(0.0533)	(0.0422)	(0.0531)	(0.141)	(0.143)	(0.176)
Fiscal Expenditures	0.0673*	0.0630***	0.140***	0.0627*	0.0513**	0.0919**	0.0785*	0.0237	0.0755
	(0.0377)	(0.0238)	(0.0525)	(0.0352)	(0.0216)	(0.0421)	(0.0431)	(0.0325)	(0.0466)
Fiscal Expenditures (source)	-0.0462**	-0.0606	-0.0128	-0.0492**	0.00550	0.0347	-0.0527*	0.0348	0.0758
	(0.0181)	(0.0368)	(0.0525)	(0.0193)	(0.0327)	(0.0455)	(0.0306)	(0.0340)	(0.0488)
Quantity Migration	-0.123***	-0.219***	-0.148***	-0.112***	-0.202***	-0.185***	-0.00433	-0.124*	-0.352***
	(0.0219)	(0.0193)	(0.0229)	(0.0279)	(0.0263)	(0.0294)	(0.106)	(0.0679)	(0.0743)
Gini	2.925*	0.190	2.032	0.838	-0.369	1.252	-1.659	-1.001	2.110
	(1.565)	(0.984)	(2.146)	(1.448)	(0.940)	(1.761)	(1.476)	(1.227)	(1.860)
Gini (source)	0.468	-3.074*	-5.517**	1.337	-2.623*	-4.246**	3.949***	-1.083	-3.597*
	(1.017)	(1.767)	(2.266)	(1.037)	(1.404)	(1.962)	(1.448)	(1.356)	(2.085)
Constant	-2.839***	-1.527*	0.632	-2.071**	-1.103	-0.561	-10.18***	-5.612**	-13.95***
	(0.909)	(0.918)	(1.354)	(0.895)	(0.861)	(1.253)	(2.937)	(2.722)	(4.065)
N	1665	1664	440	1665	1664	440	1665	1664	440
R^2	0.0733	0.158	0.246	0.0550	0.0791	0.2977	0.0699	0.0909	0.348

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state. Migrant selectivity is defined as the difference in the years of schooling of migrants and the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) state pair fixed effects estimates. Following Egger and Pfaffermayr (2003), the specifications control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered for state pairs. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.2: Static Panel Model

	(1) Selectivity Pooled OLS	(2) Selectivity Pooled OLS	(3) Selectivity Pooled OLS	(4) Selectivity RE	(5) Selectivity RE	(6) Selectivity RE	(7) Selectivity FE	(8) Selectivity FE	(9) Selectivity FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues per Capita	-0.0306***		-0.0359***	-0.0233***		-0.0202***	-0.0333***		-0.0366***
	(0.00828)		(0.0102)	(0.00761)		(0.00686)	(0.00922)		(0.00823)
Oil Revenues per Capita (source)		0.00154	0.000360		-0.00528	-0.00480		-0.0119	-0.0235*
		(0.00761)	(0.0103)		(0.00642)	(0.00825)		(0.00788)	(0.0119)
Population	0.115***	0.182***	0.121***	0.123***	0.197***	0.169***	0.643***	0.422***	0.742***
	(0.0178)	(0.0210)	(0.0242)	(0.0229)	(0.0303)	(0.0332)	(0.146)	(0.126)	(0.170)
Population (source)	0.130***	0.162***	0.0993***	0.126***	0.171***	0.148***	0.134	0.291*	0.627***
	(0.0204)	(0.0212)	(0.0254)	(0.0284)	(0.0289)	(0.0395)	(0.152)	(0.155)	(0.194)
GDP per Capita	0.0229	0.376***	0.0588	0.0580	0.278***	0.153***	0.531***	0.374***	0.722***
	(0.0463)	(0.0835)	(0.0428)	(0.0477)	(0.0554)	(0.0462)	(0.140)	(0.120)	(0.161)
GDP per Capita (source)	0.0751	0.104**	0.0384	0.0908*	0.148***	0.0883*	0.157	0.297**	0.562***
	(0.0511)	(0.0408)	(0.0510)	(0.0509)	(0.0412)	(0.0528)	(0.138)	(0.143)	(0.179)
Fiscal Expenditures	0.0732**	0.0383*	0.142***	0.0674*	0.0422**	0.0939**	0.0791*	0.0179	0.0782*
	(0.0359)	(0.0233)	(0.0525)	(0.0346)	(0.0213)	(0.0417)	(0.0427)	(0.0321)	(0.0458)
Fiscal Expenditures (source)	-0.0575***	-0.0571	-0.0127	-0.0564***	-0.00146	0.0332	-0.0580*	0.0312	0.0746
	(0.0175)	(0.0372)	(0.0525)	(0.0187)	(0.0331)	(0.0458)	(0.0300)	(0.0345)	(0.0495)
Age	-0.0444***	-0.0430***	-0.0125*	-0.0378***	-0.0292***	-0.00943*	-0.0282**	-0.0192**	-0.0139**
	(0.00998)	(0.00614)	(0.00678)	(0.0101)	(0.00731)	(0.00526)	(0.0114)	(0.00866)	(0.00589)
Quantity Migration	-0.101***	-0.190***	-0.137***	-0.101***	-0.193***	-0.180***	-0.0579	-0.145**	-0.370***
	(0.0230)	(0.0192)	(0.0244)	(0.0283)	(0.0258)	(0.0298)	(0.107)	(0.0675)	(0.0756)
Gini	2.332	0.475	1.869	0.537	-0.271	1.139	-1.809	-1.028	2.086
	(1.537)	(0.971)	(2.138)	(1.471)	(0.949)	(1.772)	(1.473)	(1.239)	(1.867)
Gini (source)	0.514	-2.108	-5.202**	1.071	-1.981	-4.044**	3.337**	-0.877	-3.468*
	(1.013)	(1.717)	(2.271)	(1.034)	(1.383)	(1.961)	(1.418)	(1.355)	(2.077)
Constant	-1.107	-0.452	1.009	-0.750	-0.539	-0.325	-9.468***	-5.619**	-13.84***
	(0.932)	(0.919)	(1.367)	(0.950)	(0.892)	(1.282)	(2.890)	(2.735)	(4.051)
N	1665	1664	440	1665	1664	440	1665	1664	440
R^2	0.101	0.189	0.250	0.0676	0.0885	0.3011	0.0817	0.100	0.355

Notes: Immigrant regressed on oil revenues per capita in the source and host state while accounting for migration ages. Migrant selectivity is defined as the difference in the years of schooling of migrants and the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) state pair fixed effects estimates. Following Egger and Pfaffermayr (2003), the specifications control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered for state pairs. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.3: Static Panel Model with Ages

	(1) Selectivity Pooled OLS	(2) Selectivity Pooled OLS	(3) Selectivity Pooled OLS	(4) Selectivity RE	(5) Selectivity RE	(6) Selectivity RE	(7) Selectivity FE	(8) Selectivity FE	(9) Selectivity FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues per Capita	-0.366***		-0.546***	-0.321***		-0.492***	0.104		-0.0155
	(0.122)		(0.179)	(0.113)		(0.150)	(0.146)		(0.189)
Oil Revenues per Capita (source)		0.280**	0.371**		0.249**	0.341**		0.365**	0.178
		(0.135)	(0.149)		(0.124)	(0.140)		(0.143)	(0.184)
Population	0.253***	0.270***	0.228***	0.268***	0.303***	0.224***	1.538***	0.705***	0.723*
	(0.0321)	(0.0316)	(0.0542)	(0.0382)	(0.0457)	(0.0736)	(0.290)	(0.210)	(0.417)
Population (source)	0.230***	0.224***	0.0920*	0.257***	0.241***	0.101*	1.105***	1.910***	1.671***
	(0.0305)	(0.0329)	(0.0465)	(0.0372)	(0.0420)	(0.0602)	(0.245)	(0.329)	(0.481)
GDP per Capita	1.303***	1.244***	1.544***	1.152***	1.012***	1.330***	-0.310	0.254	-0.319
	(0.262)	(0.161)	(0.412)	(0.275)	(0.196)	(0.494)	(0.395)	(0.288)	(0.510)
GDP per Capita (source)	-0.806***	-0.761***	-1.197***	-0.791***	-0.619**	-1.017**	-0.590***	-1.136***	-0.599
	(0.129)	(0.272)	(0.365)	(0.153)	(0.282)	(0.403)	(0.225)	(0.400)	(0.488)
Fiscal Expenditures	0.0195	0.00318	0.144**	0.0202	0.0210	0.130**	-0.129**	-0.0161	0.00159
	(0.0372)	(0.0334)	(0.0581)	(0.0387)	(0.0329)	(0.0614)	(0.0529)	(0.0467)	(0.0765)
Fiscal Expenditures (source)	0.0667***	-0.0425	-0.0629	0.0531**	-0.0102	-0.0305	-0.00529	-0.0647	-0.0115
	(0.0257)	(0.0440)	(0.0568)	(0.0238)	(0.0431)	(0.0606)	(0.0331)	(0.0532)	(0.0647)
Age	0.0712***	0.0694***	0.0891***	0.0808***	0.0784***	0.0964***	0.0927***	0.0836***	0.102***
	(0.0143)	(0.0142)	(0.0247)	(0.0130)	(0.0178)	(0.0290)	(0.0123)	(0.0198)	(0.0216)
Quantity Migration	-0.240***	-0.331***	-0.251***	-0.264***	-0.352***	-0.260***	-0.430***	-0.387***	-0.293*
	(0.0305)	(0.0300)	(0.0577)	(0.0350)	(0.0396)	(0.0764)	(0.0962)	(0.106)	(0.152)
Gini	4.933**	-0.439	-1.359	5.331**	-0.792	-0.330	10.28**	-0.694	0.385
	(2.196)	(1.214)	(3.755)	(2.619)	(1.213)	(4.419)	(4.557)	(1.449)	(5.703)
Gini (source)	1.329	-5.264*	-6.339	1.553	-5.530*	-6.866	3.123*	-1.709	-1.017
	(1.048)	(2.722)	(4.189)	(1.111)	(3.025)	(4.774)	(1.765)	(4.241)	(5.279)
Transfers	-23.85*	-41.94***	-44.31*	-20.86	-32.01**	-37.10*	-19.46	-32.62**	-32.15
	(14.32)	(13.95)	(23.25)	(13.34)	(12.69)	(20.83)	(15.77)	(15.47)	(19.60)
Transfers (source)	-2.629	30.82**	22.81	4.040	6.155	-2.407	31.31	-10.99	-20.03
	(11.97)	(14.99)	(22.77)	(12.49)	(13.05)	(18.83)	(20.83)	(15.28)	(18.00)
Taxes	1.947	9.426***	-7.857*	4.883**	7.899***	-6.173	21.51***	5.247	-0.762
	(2.054)	(2.288)	(4.138)	(2.278)	(2.707)	(5.230)	(5.197)	(5.391)	(7.086)
Taxes (source)	-0.934	-8.790***	-15.19***	-2.155	-3.906	-10.99**	0.00370	18.04***	14.21**
	(1.773)	(2.444)	(4.602)	(2.217)	(2.555)	(5.215)	(5.573)	(6.287)	(6.120)
Constant	-17.59***	-11.52***	-11.44***	-18.50***	-11.14***	-10.59***	-54.82***	-51.08***	-45.43***
	(1.424)	(2.398)	(3.579)	(1.742)	(2.470)	(3.891)	(7.587)	(9.026)	(12.95)
N	792	790	120	792	790	120	792	790	120
R^2	0.271	0.310	0.623	0.0814	0.0689	0.6399	0.307	0.276	0.615

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state with extended covariates. Migrant selectivity is defined as the difference in the years of schooling of migrants and the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) fixed effects estimates. Following Egger and Pfaffermayr (2003), the specifications control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered for state pairs. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.4: Static Panel Model with Taxes and Transfers

State Pair FE?	(1) Selectivity Pooled OLS No	(2) Selectivity Pooled OLS No	(3) Selectivity Pooled OLS No	(4) Selectivity RE Yes	(5) Selectivity RE Yes	(6) Selectivity RE Yes	(7) Selectivity FE Yes	(8) Selectivity FE Yes	(9) Selectivity FE Yes
Oil Revenues per Capita	-0.0259*		-0.00635	-0.0426***		-0.0115	-0.0673**		-0.0379*
	(0.0150)		(0.0204)	(0.0123)		(0.0140)	(0.0298)		(0.0223)
Oil Revenues per Capita (source)		0.0228*	0.0355**		0.0149*	0.0262**		0.0109	0.0119
		(0.0131)	(0.0149)		(0.00883)	(0.0115)		(0.0182)	(0.0303)
Population	0.333***	0.280***	0.250***		0.298***	0.256***		0.212	1.116**
	(0.0494)	(0.0366)	(0.0641)		(0.0450)	(0.0812)		(0.349)	(0.502)
Population (source)	0.141***	0.229***	-0.0412		0.237***	-0.0276		0.396	0.853
	(0.0427)	(0.0406)	(0.0551)		(0.0489)	(0.0652)		(0.393)	(0.586)
GDP per Capita	0.722**	1.144***	0.294	0.534	1.003***	0.386	2.180**	0.0644	1.517*
	(0.365)	(0.176)	(0.393)	(0.355)	(0.207)	(0.378)	(0.991)	(0.350)	(0.834)
GDP per Capita (source)	-0.487***	-0.568**	-1.331***	-0.614***	-0.481**	-1.208***	-0.986***	-0.384	-0.591
	(0.185)	(0.251)	(0.287)	(0.194)	(0.241)	(0.300)	(0.345)	(0.618)	(1.021)
Fiscal Expenditures per Capita	0.141***	-0.00312	0.204***	0.0766	0.0162	0.201***	0.301***	0.0442	0.142
	(0.0472)	(0.0390)	(0.0599)	(0.0478)	(0.0390)	(0.0589)	(0.0943)	(0.0618)	(0.113)
Fiscal Expenditures per Capita (source)	0.0220	-0.0217	0.00588	0.0248	0.00305	0.0284	-0.0126	0.0424	0.00338
	(0.0377)	(0.0533)	(0.0716)	(0.0332)	(0.0522)	(0.0642)	(0.0435)	(0.0716)	(0.0839)
Age	-0.0491***	-0.0277**	-0.0418	-0.0341*	-0.0161	-0.0232	-0.0225	0.00533	0.0100
	(0.0171)	(0.0127)	(0.0310)	(0.0174)	(0.0172)	(0.0319)	(0.0214)	(0.0271)	(0.0280)
Quantity Migration	-0.0897**	-0.278***	-0.0459	0.0672*	-0.296***	-0.0714	0.0391	-0.191	-0.0487
	(0.0436)	(0.0312)	(0.0445)	(0.0388)	(0.0336)	(0.0533)	(0.182)	(0.125)	(0.187)
Gini	-4.415	-0.202	-8.052**	0.485	-0.333	-6.440*	-4.155	-1.441	1.096
	(2.788)	(1.249)	(3.799)	(2.958)	(1.299)	(3.548)	(4.823)	(1.880)	(6.120)
Gini (source)	1.614	-3.170	-6.001	2.217	-3.192	-5.380	3.480*	-5.670	-3.354
	(1.430)	(3.119)	(4.527)	(1.466)	(3.343)	(4.129)	(2.075)	(5.136)	(6.733)
Unemployment	0.0644*	-0.103***	0.0929**	0.0599**	-0.0691***	0.0883**	0.0952*	0.0103	0.0808
	(0.0343)	(0.0228)	(0.0458)	(0.0272)	(0.0213)	(0.0348)	(0.0486)	(0.0281)	(0.0564)
Unemployment (source)	-0.0131	0.0395**	0.0287	-0.0174	0.0178	0.00513	-0.0151	-0.0183	-0.0195
	(0.0180)	(0.0154)	(0.0289)	(0.0173)	(0.0137)	(0.0239)	(0.0210)	(0.0208)	(0.0301)
Constant	-6.599***	-6.524***	-1.324	-3.179**	-6.488***	-2.480	-7.727	-5.064	-34.09**
	(1.589)	(2.206)	(3.390)	(1.591)	(2.219)	(2.822)	(5.399)	(7.886)	(13.32)
N	592	593	90	592	593	90	592	593	90
R^2	0.194	0.317	0.630	0.0501	0.0125	0.3082	0.0906	0.0387	0.410

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state with extended covariates. Migrant selectivity is defined as the difference in the years of schooling of migrants and the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) state pair fixed effects estimates. Following Egger and Pfaffermayr (2003), the specifications control for time effects as well. Robust standard errors in parentheses. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Standard errors in the fixed effects model are clustered for state pairs. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.5: Static Panel Model with Unemployment Rates

	(1) Selectivity Pooled OLS	(2) Selectivity Pooled OLS	(3) Selectivity Pooled OLS	(4) Selectivity RE	(5) Selectivity RE	(6) Selectivity RE	(7) Selectivity FE	(8) Selectivity FE	(9) Selectivity FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues per Capita	-0.0311***		-0.0359***	-0.0236***		-0.0200***	-0.0334***		-0.0363***
	(0.00841)		(0.0108)	(0.00775)		(0.00701)	(0.00932)		(0.00827)
Oil revenues per Capita (source)		0.00779	0.00677		-0.00958	-0.00978		-0.0106	-0.0222*
		(0.00761)	(0.0103)		(0.00648)	(0.00854)		(0.00793)	(0.0121)
Population	0.106***	0.181***	0.118***	0.114***	0.197***	0.169***	0.640***	0.424***	0.739***
	(0.0179)	(0.0211)	(0.0243)	(0.0228)	(0.0307)	(0.0337)	(0.147)	(0.127)	(0.168)
Population (source)	0.112***	0.140***	0.0746***	0.102***	0.129***	0.103**	-0.210	-0.0442	0.295
	(0.0205)	(0.0211)	(0.0257)	(0.0281)	(0.0287)	(0.0401)	(0.154)	(0.155)	(0.197)
GDP per Capita	0.0142	0.377***	0.0607	0.0486	0.279***	0.153***	0.528***	0.377***	0.720***
	(0.0477)	(0.0842)	(0.0478)	(0.0489)	(0.0561)	(0.0475)	(0.140)	(0.120)	(0.161)
GDP per Capita (source)	0.0153	0.0705*	0.00188	0.0311	0.0762*	0.00781	-0.185	-0.0685	0.199
	(0.0504)	(0.0403)	(0.0486)	(0.0496)	(0.0407)	(0.0509)	(0.139)	(0.143)	(0.182)
Fiscal Expenditures	0.0783**	0.0383	0.144***	0.0713**	0.0425*	0.0930**	0.0801*	0.0175	0.0768*
	(0.0358)	(0.0238)	(0.0540)	(0.0343)	(0.0217)	(0.0412)	(0.0426)	(0.0324)	(0.0455)
Fiscal Expenditures (source)	-0.0295*	-0.0538	-0.00743	-0.0424**	0.0135	0.0484	-0.0597**	0.0401	0.0839*
	(0.0174)	(0.0374)	(0.0530)	(0.0184)	(0.0329)	(0.0450)	(0.0300)	(0.0347)	(0.0500)
Age	-0.0489***	-0.0423***	-0.00795	-0.0408***	-0.0279***	-0.00565	-0.0289**	-0.0185**	-0.0122*
	(0.0106)	(0.00650)	(0.00705)	(0.0105)	(0.00767)	(0.00487)	(0.0113)	(0.00887)	(0.00615)
Quantity Migration	-0.0845***	-0.190***	-0.134***	-0.0853***	-0.194***	-0.182***	-0.0525	-0.149**	-0.379***
	(0.0229)	(0.0195)	(0.0252)	(0.0282)	(0.0267)	(0.0307)	(0.106)	(0.0683)	(0.0763)
Gini	2.054	0.497	1.840	0.397	-0.268	1.184	-1.807	-1.032	2.135
	(1.500)	(0.976)	(2.072)	(1.418)	(0.953)	(1.635)	(1.470)	(1.250)	(1.827)
Gini (source)	0.168	-2.681	-5.912***	0.717	-3.041**	-5.252***	3.012**	-2.984**	-5.603***
	(1.006)	(1.717)	(2.265)	(1.017)	(1.375)	(1.927)	(1.416)	(1.361)	(2.081)
Constant	-7.115***	-6.465***	-4.995***	-6.765***	-6.270***	-6.063***	-12.54***	-8.069***	-16.23***
	(0.921)	(0.918)	(1.349)	(0.917)	(0.889)	(1.240)	(2.927)	(2.734)	(4.002)
N	1665	1664	440	1665	1664	440	1665	1664	440
R^2	0.294	0.350	0.525	0.3847	0.4620	0.7315	0.397	0.468	0.749

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state based on the years of schooling above grade 8. Educational investments are measured in years of schooling above grade 8. Migrant selectivity is defined as the difference in the years of schooling of migrants and the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) fixed effects estimates. Following Egger and Pfaffermayr (2003), the specifications control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered for state pairs. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.6: Static Panel Model Robustness Educational Indicator

Thus far, I dispensed with sector specific disparities in the relationship between resource abundance and the selectivity of interstate migration. Therefore, in table 3.7, I restrict the sample to migrants taking up position in the oil extraction industry. Apparently, the baseline results are not driven by migrants moving into the oil extraction industry. Rather, neither the selectivity of emigration nor the selectivity of immigration is consistently associated with oil abundance based on the restricted sample of workers while the number of observations is reduced. This suggests that the selectivity effects are not directly induced by employment effects in the oil extraction industry which is consistent with the fact that oil extraction is not very labor intensive (e.g. Auty (1993))

Complementarily, in table 3.8, I restrict the sample to migrants taking up positions in the service sector. Obviously, migrants taking up positions in the service sector contribute to the selectivity effects of migration shown in the baseline results. Consistently through all specifications, a rise in oil revenues per capita lowers the selectivity of immigrants working in the service sector which is significant at the 1 percent level. With coefficients ranging between -0.0287 and -0.0518, the effect of oil revenues per capita on selective migration is even stronger compared to the baseline specification. This result is in line with the theoretical conjecture that a resource boom translates into an expansion of the non-tradable sector which is relatively low-skilled labor intensive and a contraction of the tradable sector which is relatively high-skilled labor intensive.

In addition, in tables 3.9 and 3.10, I provide panel estimates while excluding Alaska and Texas, respectively, which exhibit the highest rates of oil drilling in the US throughout the 20th century. Accordingly, the results are still consistent with the theoretical predictions. Excluding Alaska and Texas lowers the relative educational background of immigrants in response to oil booms even further. On the one hand, Alaska abolished all state income taxes as a consequence of further fiscal capacity which was particularly beneficial for skilled labor. On the other hand, Alaska implemented a Alaska Permanent Fund which is particularly beneficial for unskilled labor. I will further elaborate on the case of Alaska in Chapter 4 with respect to the educational investments of local residents.

Moreover, in the appendix, I perform the same empirical steps, though restricting the sample to in- and out-migration based on individual data. Again, in order to avoid missing values while accounting for resource revenues in the source and host state, I provide separate analyses for resource revenues serving as push and pull factors. Consistently, the main results remain unaffected, i.e. oil revenues lower the selectivity of immigration and might increase the selectivity of emigration, a result which is mainly driven by immigrants working in the service sector rather than the oil extraction sector.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity
	Pooled OLS	Pooled OLS	Pooled OLS	RE	RE	RE	FE	FE	FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues per Capita	0.0268		-0.0448	-0.00339		-0.0693	-0.0248		-0.0907
	(0.0394)		(0.0558)	(0.0381)		(0.0523)	(0.0500)		(0.0715)
Oil Revenues per Capita (source)		0.0740**	-0.00840		0.0470	-0.0213		-0.0722*	-0.0888*
		(0.0371)	(0.0465)		(0.0349)	(0.0424)		(0.0418)	(0.0465)
Population	0.349***	0.232**	0.161	0.263**	0.199*	0.113	-0.760	-1.232	-1.742
	(0.0924)	(0.106)	(0.135)	(0.104)	(0.119)	(0.153)	(1.090)	(0.937)	(1.377)
Population (source)	0.306***	0.158	0.167	0.287***	0.138	0.154	-1.356*	1.204	1.556
	(0.0893)	(0.102)	(0.121)	(0.0957)	(0.113)	(0.129)	(0.810)	(1.103)	(1.259)
GDP per Capita	0.153	0.534**	0.340	0.149	0.517*	0.336	-0.713	-0.733	-1.235
	(0.192)	(0.271)	(0.277)	(0.200)	(0.290)	(0.290)	(1.051)	(0.922)	(1.292)
GDP per Capita (source)	0.235	-0.106	0.172	0.263	-0.0553	0.189	-1.170	1.117	1.503
	(0.303)	(0.325)	(0.338)	(0.320)	(0.332)	(0.353)	(0.762)	(1.032)	(1.140)
Fiscal Expenditures	0.0169	0.186*	0.291	0.0746	0.171	0.338	0.195	0.170	0.427
	(0.205)	(0.109)	(0.318)	(0.186)	(0.126)	(0.291)	(0.197)	(0.211)	(0.261)
Fiscal Expenditures (source)	0.112	-0.139	0.133	0.129	-0.0748	0.145	0.318	0.266	0.119
	(0.0889)	(0.197)	(0.267)	(0.100)	(0.198)	(0.253)	(0.220)	(0.258)	(0.276)
Quantity Migration	-0.134*	-0.111	-0.00203	-0.101	-0.122	0.00107	0.394	-0.139	0.257
	(0.0727)	(0.0800)	(0.109)	(0.0751)	(0.0890)	(0.118)	(0.384)	(0.361)	(0.461)
Gini	0.937	-0.0100	4.487	4.004	1.412	7.214	6.785	7.886	16.43
	(8.815)	(5.495)	(13.69)	(8.684)	(5.809)	(13.49)	(10.72)	(11.61)	(13.50)
Gini (source)	-4.711	-13.46	-8.392	-6.536	-12.40	-6.433	-11.23	-10.12	4.601
	(4.534)	(9.031)	(11.51)	(4.939)	(8.799)	(9.878)	(9.251)	(11.64)	(13.06)
Constant	-3.419	4.615	1.148	-2.441	4.637	0.0495	23.20	5.663	-5.340
	(4.630)	(5.055)	(7.818)	(4.528)	(5.191)	(7.166)	(15.20)	(16.34)	(21.01)
N	706	541	299	706	541	299	706	541	299
R^2	0.0480	0.0666	0.0868	0.0218	0.0185	0.0810	0.0422	0.0525	0.124

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state. The sample is restricted to workers in the oil extraction industry. Migrant selectivity is defined as the difference in the years of schooling of migrants and the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) fixed effects estimates. Following Egger and Pfaffermayr (2003), the specifications control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered for state pairs. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.7: Static Panel Model Oil Extraction Sector

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity
	Pooled OLS	Pooled OLS	Pooled OLS	RE	RE	RE	FE	FE	FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues per Capita	-0.0376***		-0.0473***	-0.0287***		-0.0334***	-0.0387***		-0.0518***
	(0.00937)		(0.0129)	(0.00895)		(0.0114)	(0.0105)		(0.0140)
Oil Revenues per Capita (source)		-0.000229	0.000572		-0.00622	-0.00157		-0.0120	-0.0132
		(0.00981)	(0.0120)		(0.00721)	(0.00779)		(0.00892)	(0.0131)
Population	0.125***	0.210***	0.150***	0.134***	0.207***	0.179***	0.803***	0.372**	0.999***
	(0.0220)	(0.0245)	(0.0309)	(0.0276)	(0.0344)	(0.0390)	(0.175)	(0.174)	(0.258)
Population (source)	0.129***	0.212***	0.130***	0.130***	0.226***	0.160***	0.227	0.345**	0.463*
	(0.0241)	(0.0231)	(0.0313)	(0.0326)	(0.0326)	(0.0435)	(0.167)	(0.171)	(0.249)
GDP per Capita	0.118***	0.377***	0.102*	0.127***	0.270***	0.152***	0.698***	0.294*	0.952***
	(0.0357)	(0.0860)	(0.0545)	(0.0364)	(0.0681)	(0.0582)	(0.163)	(0.172)	(0.235)
GDP per Capita (source)	0.0208	0.0764*	0.0113	0.0388	0.126***	0.0366	0.195	0.305*	0.387*
	(0.0591)	(0.0461)	(0.0537)	(0.0585)	(0.0488)	(0.0599)	(0.158)	(0.157)	(0.231)
Fiscal Expenditures	0.0805*	0.0270	0.137**	0.0666	0.0265	0.108*	0.0568	0.0150	0.0924
	(0.0418)	(0.0258)	(0.0621)	(0.0416)	(0.0268)	(0.0619)	(0.0502)	(0.0478)	(0.0767)
Fiscal Expenditures (source)	-0.0571***	-0.0354	-0.0392	-0.0507***	0.0385	0.00816	-0.0410	0.0935**	0.0865
	(0.0196)	(0.0449)	(0.0545)	(0.0197)	(0.0388)	(0.0469)	(0.0338)	(0.0430)	(0.0565)
Quantity Migration	-0.0935***	-0.218***	-0.145***	-0.0935***	-0.207***	-0.159***	-0.0846	-0.111	-0.355**
	(0.0238)	(0.0223)	(0.0327)	(0.0288)	(0.0295)	(0.0375)	(0.118)	(0.0809)	(0.143)
Gini	4.099**	1.465	4.365	2.356	0.973	3.260	-0.449	-0.260	3.887
	(1.724)	(1.152)	(2.695)	(1.707)	(1.203)	(2.583)	(1.703)	(1.737)	(2.795)
Gini (source)	1.439	-3.449*	-3.279	2.120*	-3.680**	-2.936	4.781***	-1.831	-2.031
	(1.077)	(1.816)	(2.359)	(1.115)	(1.513)	(2.064)	(1.667)	(1.517)	(2.061)
Constant	-2.912***	0.310	-1.277	-2.431***	0.0667	-1.320	-9.962***	-3.776	-11.48**
	(0.948)	(1.113)	(1.508)	(0.928)	(1.013)	(1.480)	(2.653)	(2.790)	(4.851)
N	1651	1647	440	1651	1647	440	1651	1647	440
R^2	0.0660	0.128	0.180	0.0380	0.0506	0.1252	0.0543	0.0667	0.187

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state. The sample is restricted to workers in the service sector. Migrant selectivity is defined as the difference in the years of schooling of migrants compared to the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) fixed effects estimates. Following Egger and Pfaffermayr (2003), the specifications control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered for state pairs. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.8: Static Panel Model Service Sector

State Pair FE?	(1) Selectivity Pooled OLS No	(2) Selectivity Pooled OLS No	(3) Selectivity Pooled OLS No	(4) Selectivity RE Yes	(5) Selectivity RE Yes	(6) Selectivity RE Yes	(7) Selectivity FE Yes	(8) Selectivity FE Yes	(9) Selectivity FE Yes
Oil Revenues per Capita	-0.0311***		-0.0359***	-0.0236***		-0.0200***	-0.0334***		-0.0363***
	(0.00841)		(0.0108)	(0.00775)		(0.00701)	(0.00932)		(0.00827)
Oil revenues per Capita (source)		0.00779	0.00677		-0.00958	-0.00978		-0.0106	-0.0222*
		(0.00761)	(0.0103)		(0.00648)	(0.00854)		(0.00793)	(0.0121)
Population	0.106***	0.181***	0.118***	0.114***	0.197***	0.169***	0.640***	0.424***	0.739***
	(0.0179)	(0.0211)	(0.0243)	(0.0228)	(0.0307)	(0.0337)	(0.147)	(0.127)	(0.168)
Population (source)	0.112***	0.140***	0.0746***	0.102***	0.129***	0.103**	-0.210	-0.0442	0.295
	(0.0205)	(0.0211)	(0.0257)	(0.0281)	(0.0287)	(0.0401)	(0.154)	(0.155)	(0.197)
GDP per Capita	0.0142	0.377***	0.0607	0.0486	0.279***	0.153***	0.528***	0.377***	0.720***
	(0.0477)	(0.0842)	(0.0478)	(0.0489)	(0.0561)	(0.0475)	(0.140)	(0.120)	(0.161)
GDP per Capita (source)	0.0153	0.0705*	0.00188	0.0311	0.0762*	0.00781	-0.185	-0.0685	0.199
	(0.0504)	(0.0403)	(0.0486)	(0.0496)	(0.0407)	(0.0509)	(0.139)	(0.143)	(0.182)
Fiscal Expenditures	0.0783**	0.0383	0.144***	0.0713**	0.0425*	0.0930**	0.0801*	0.0175	0.0768*
	(0.0358)	(0.0238)	(0.0540)	(0.0343)	(0.0217)	(0.0412)	(0.0426)	(0.0324)	(0.0455)
Fiscal Expenditures (source)	-0.0295*	-0.0538	-0.00743	-0.0424**	0.0135	0.0484	-0.0597**	0.0401	0.0839*
	(0.0174)	(0.0374)	(0.0530)	(0.0184)	(0.0329)	(0.0450)	(0.0300)	(0.0347)	(0.0500)
Age	-0.0489***	-0.0423***	-0.00795	-0.0408***	-0.0279***	-0.00565	-0.0289**	-0.0185**	-0.0122*
	(0.0106)	(0.00650)	(0.00705)	(0.0105)	(0.00767)	(0.00487)	(0.0113)	(0.00887)	(0.00615)
Quantity Migration	-0.0845***	-0.190***	-0.134***	-0.0853***	-0.194***	-0.182***	-0.0525	-0.149**	-0.379***
	(0.0229)	(0.0195)	(0.0252)	(0.0282)	(0.0267)	(0.0307)	(0.106)	(0.0683)	(0.0763)
Gini	2.054	0.497	1.840	0.397	-0.268	1.184	-1.807	-1.032	2.135
	(1.500)	(0.976)	(2.072)	(1.418)	(0.953)	(1.635)	(1.470)	(1.250)	(1.827)
Gini (source)	0.168	-2.681	-5.912***	0.717	-3.041**	-5.252***	3.012**	-2.984**	-5.603***
	(1.006)	(1.717)	(2.265)	(1.017)	(1.375)	(1.927)	(1.416)	(1.361)	(2.081)
Oil revenues per Capita (source)		0.00779	0.00677		-0.00958	-0.00978		-0.0106	-0.0222*
		(0.00761)	(0.0103)		(0.00648)	(0.00854)		(0.00793)	(0.0121)
Constant	-7.115***	-6.465***	-4.995***	-6.765***	-6.270***	-6.063***	-12.54***	-8.069***	-16.23***
	(0.921)	(0.918)	(1.349)	(0.917)	(0.889)	(1.240)	(2.927)	(2.734)	(4.002)
N	1665	1664	440	1665	1664	440	1665	1664	440
R^2	0.294	0.350	0.525	0.0780	0.0993	0.3029	0.397	0.468	0.749

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state. Alaska is excluded from the sample. Migrant selectivity is defined as the years of schooling of migrants compared to the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) fixed effects estimates. Following Egger and Pfaffermayr (2003), the specifications control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered for state pairs. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.9: Static Panel Model without Alaska

	(1) Selectivity Pooled OLS	(2) Selectivity Pooled OLS	(3) Selectivity Pooled OLS	(4) Selectivity RE	(5) Selectivity RE	(6) Selectivity RE	(7) Selectivity FE	(8) Selectivity FE	(9) Selectivity FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues per Capita	-0.0320***		-0.0371***	-0.0251***		-0.0232***	-0.0317***		-0.0370***
	(0.00923)		(0.0120)	(0.00815)		(0.00807)	(0.00934)		(0.00851)
Oil revenues per Capita (source)		0.00402	0.00182		-0.00582	-0.00560		-0.0115	-0.0179
		(0.00834)	(0.0117)		(0.00668)	(0.00927)		(0.00806)	(0.0133)
Population	0.115***	0.173***	0.122***	0.125***	0.190***	0.168***	0.582***	0.442***	0.732***
	(0.0195)	(0.0221)	(0.0278)	(0.0242)	(0.0317)	(0.0366)	(0.190)	(0.138)	(0.235)
Population (source)	0.126***	0.167***	0.0980***	0.121***	0.171***	0.138***	0.119	0.259	0.416
	(0.0215)	(0.0233)	(0.0295)	(0.0297)	(0.0310)	(0.0448)	(0.167)	(0.189)	(0.253)
GDP per Capita	0.0197	0.380***	0.0690	0.0511	0.285***	0.154***	0.478***	0.407***	0.732***
	(0.0465)	(0.0899)	(0.0478)	(0.0483)	(0.0605)	(0.0499)	(0.175)	(0.131)	(0.219)
GDP per Capita (source)	0.0769	0.107**	0.0436	0.0884	0.145***	0.0728	0.149	0.268	0.371
	(0.0543)	(0.0414)	(0.0566)	(0.0549)	(0.0426)	(0.0599)	(0.152)	(0.171)	(0.234)
Fiscal Expenditures	0.0888**	0.0365	0.153**	0.0877**	0.0425*	0.118**	0.0848*	0.0152	0.0794
	(0.0398)	(0.0252)	(0.0604)	(0.0384)	(0.0233)	(0.0498)	(0.0487)	(0.0350)	(0.0617)
Fiscal Expenditures (source)	-0.0597***	-0.0604	-0.0175	-0.0599***	0.00541	0.0434	-0.0668**	0.0386	0.100
	(0.0184)	(0.0402)	(0.0594)	(0.0190)	(0.0352)	(0.0522)	(0.0312)	(0.0401)	(0.0638)
Age	-0.0435***	-0.0445***	-0.0122*	-0.0376***	-0.0302***	-0.00820	-0.0277**	-0.0200**	-0.0130**
	(0.0103)	(0.00643)	(0.00686)	(0.0104)	(0.00750)	(0.00599)	(0.0118)	(0.00882)	(0.00525)
Quantity Migration	-0.0968***	-0.185***	-0.120***	-0.0955***	-0.190***	-0.161***	-0.0638	-0.151**	-0.399***
	(0.0243)	(0.0202)	(0.0274)	(0.0293)	(0.0267)	(0.0323)	(0.113)	(0.0733)	(0.0879)
Gini	1.659	0.109	1.253	-0.276	-0.315	0.370	-2.016	-0.744	2.472
	(1.670)	(1.043)	(2.516)	(1.622)	(1.023)	(2.024)	(1.713)	(1.340)	(2.449)
Gini (source)	0.232	-2.629	-5.622**	0.854	-2.397*	-5.135**	3.646**	-1.267	-5.412*
	(1.099)	(1.793)	(2.571)	(1.135)	(1.406)	(2.338)	(1.533)	(1.510)	(2.909)
Constant	-0.636	0.0615	1.424	-0.255	-0.233	0.470	-8.271**	-5.531*	-10.66*
	(1.007)	(0.964)	(1.600)	(1.035)	(0.941)	(1.521)	(3.679)	(3.121)	(5.564)
N	1514	1512	360	1514	1512	360	1514	1512	360
R^2	0.0962	0.186	0.230	0.0630	0.0841	0.2751	0.0746	0.0958	0.326

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state. Texas is excluded from the sample. Migrant selectivity is defined as the years of schooling of migrants compared to the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) fixed effects estimates. Following Egger and Pfaffermayr (2003), the specifications control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.10: Static Panel Model without Texas

Controlling for Counterfactual Trends

Thus far, I relied on a selectivity measure which was defined as the years of schooling of migrants net the average years of schooling in the source state. However, the selectivity of migration might follow some path dependencies. For instance, for a given educational background of migrants the selectivity of migration might decline if the average educational attainment increases in the source state. Alternatively or additionally, the average educational attainment of migrants might have declined relative to the state average. In order to preclude that the estimates are driven by a general decline in the average selectivity of interstate migrants throughout the 20th century, table 3.11 reports estimates of the baseline setup, while accounting for the relative selectivity, RELSELECTIVITY, which is defined as the difference in migrant selectivity into oil abundant states and the average migrant selectivity between states not engaging in oil drilling. The difference in the selectivity of migration is displayed in the descriptive section in figures 3.8 and 3.9, while relying on a pooled sample of states. Apparently, the selectivity of immigration decreases even relative to the average selectivity of migrants across non-oil abundant states. In fact, as bilateral migration patterns are preceded by multilateral comparisons of all potential destination states, the control group is not totally untreated. Rather, the control group is in the choice set of each individual, and hence partially treated. Therefore, the control group should be interpreted as an approximation as part of a robustness check. Complementarily, I will make use of a non-parametric approach, in order to account for the multilateral character of migration decisions below. Before, I rely on the following econometric framework:

$$\begin{aligned} RELSELECTIVITY_{ijt} &= \alpha_{ij} + \phi OILREVPC_{it} \\ &+ \pi OILREVPC_{jt} + \boldsymbol{X'}_{it}\gamma + \boldsymbol{X'}_{jt}\lambda + \epsilon_{ijt} \end{aligned} \tag{3.9}$$

which coincides with the previous model except with respect to the outcome variable. In line with the baseline specification, the results indicate a decline in the relative selectivity of immigration. This result is robust for the inclusion of state pair fixed effects as well (columns (5) - (8)). Hence, I can conclude that the baseline relationship is not driven by a general decline in the selectivity of immigration.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative Selectivity	Relative Selectivity	Relative Selectivity	Relative Selectivity	Relative Selectivity	Relative Selectivity	Relative Selectivity	Relative Selectivity
Time Effects?	No	No	No	No	Yes	Yes	Yes	Yes
Oil Revenues per Capita	-0.0266***	-0.0486***	-0.0473**	-0.0566**	-0.0245**	-0.0449**	-0.0473**	-0.0566**
	(0.00994)	(0.0172)	(0.0194)	(0.0259)	(0.0103)	(0.0178)	(0.0194)	(0.0259)
Population	0.116***	0.179***	0.152**	0.163	0.116***	0.167***	0.152**	0.163
	(0.0218)	(0.0644)	(0.0673)	(0.106)	(0.0217)	(0.0634)	(0.0673)	(0.106)
Population (source)	0.113***	0.187***	0.172***	0.124**	0.118***	0.185***	0.172***	0.124**
	(0.0237)	(0.0486)	(0.0502)	(0.0611)	(0.0241)	(0.0485)	(0.0502)	(0.0611)
GDP per Capita	0.0287	1.146***	1.252***	1.703***	0.0588	1.120***	1.252***	1.703***
	(0.0696)	(0.334)	(0.434)	(0.647)	(0.0685)	(0.338)	(0.434)	(0.647)
GDP per Capita (source)	0.0472	-0.507**	-0.476**	-0.491*	0.0182	-0.561**	-0.476**	-0.491*
	(0.0632)	(0.211)	(0.232)	(0.288)	(0.0692)	(0.219)	(0.232)	(0.288)
Fiscal Expenditures	0.0780*	0.0630	0.0680	0.110	0.0770*	0.0630	0.0680	0.110
	(0.0441)	(0.0654)	(0.0678)	(0.0748)	(0.0459)	(0.0672)	(0.0678)	(0.0748)
Fiscal Expenditures (source)	-0.0517**	0.0357	0.0951**	0.0716	-0.0415*	0.0483	0.0951**	0.0716
	(0.0208)	(0.0357)	(0.0371)	(0.0439)	(0.0213)	(0.0370)	(0.0371)	(0.0439)
Age	-0.0427***	-0.0301						
	(0.0134)	(0.0222)						
Quantity Migration	-0.0854***	-0.143***	-0.140***	-0.105**	-0.105***	-0.142***	-0.140***	-0.105**
	(0.0267)	(0.0498)	(0.0494)	(0.0485)	(0.0255)	(0.0489)	(0.0494)	(0.0485)
Gini	1.827	0.756	0.779	-3.668	2.246	0.720	0.779	-3.668
	(1.845)	(3.973)	(3.987)	(4.470)	(1.872)	(4.007)	(3.987)	(4.470)
Gini (source)	0.788	0.685	0.266	1.182	0.961	0.892	0.266	1.182
	(1.217)	(1.517)	(1.617)	(1.716)	(1.225)	(1.542)	(1.617)	(1.716)
Density (source)		0.000155	0.000292*	0.000204		0.000162	0.000292*	0.000204
		(0.000180)	(0.000161)	(0.000171)		(0.000180)	(0.000161)	(0.000171)
Density		0.000902	0.00104	0.00188*		0.000881	0.00104	0.00188*
		(0.000673)	(0.000733)	(0.00106)		(0.000678)	(0.000733)	(0.00106)
Taxes (source)		-0.303	0.862	0.810		-0.618	0.862	0.810
		(2.745)	(2.898)	(3.186)		(2.883)	(2.898)	(3.186)
Taxes		-9.369*	-8.502*	-13.88**		-8.839*	-8.502*	-13.88**
		(4.990)	(4.863)	(6.459)		(5.037)	(4.863)	(6.459)
Transfers (source)			-49.81**	-46.23*			-49.81**	-46.23*
			(21.99)	(26.16)			(21.99)	(26.16)
Transfers			-16.56	-19.81			-16.56	-19.81
			(24.23)	(27.03)			(24.23)	(27.03)
Unemployment rate				0.0215				0.0215
				(0.0501)				(0.0501)
Unemployment rate (source)				0.0218				0.0218
				(0.0181)				(0.0181)
Constant	-1.693	-0.505	0.427	4.094	-3.125***	-1.656	0.427	4.094
	(1.152)	(2.760)	(3.663)	(5.270)	(1.183)	(3.058)	(3.663)	(5.270)
N	1193	566	566	421	1193	566	566	421
R^2	0.105	0.156	0.156	0.167	0.0819	0.146	0.156	0.167

Notes: Relative immigrant selectivity regressed on oil revenues per capita in the source and host state state. Relative Selectivity is defined as the difference in immigrant selectivity into oil abundant states relative to states lacking oil revenues. The specifications in columns (1) to (8) report pooled OLS estimates. Complementarily, the specifications in columns (5) to (8) account for time fixed effects. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered for state pairs. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.11: Static Panel Model based on Relative Selectivity

In the next section, I complement the static panel models with a dynamic panel setup.

Dynamic Panel Model

In the baseline model, I did not allow for partial adjustments in the outcome variable. In order to account for path dependencies in migrant selection even across US states, I augment the baseline specification similarly to Chapter 2 as follows:[6]

$$\begin{aligned} SELECTIVITY_{ijt} =& \alpha_{ij} + \beta SELECTIVITY_{ijt-1} + \\ & \phi OILREVPC_{it} + \pi OILREVPC_{jt} + \boldsymbol{X'}_{it}\gamma + \boldsymbol{X'}_{jt}\lambda + \epsilon_{ijt} \end{aligned} \tag{3.10}$$

Again, the identification rests on the strict exogeneity assumption,

$$E(\epsilon_{ijt}|X_{ijt}, \alpha_{ij}) = 0 \tag{3.11}$$

for $t = 1, ..., T$ where X_{ijt} comprises all covariates in the source and host state. As already pointed out in Chapter 2, the strict exogeneity assumption implies that the idiosyncratic error term is uncorrelated with all covariates in each period. Due to the dynamics, the standard deviations-from-means and random effects estimators lead to inconsistent estimates. Again, basically three estimators might serve as a remedy in dynamic panel setups. The estimator suggested by Anderson and Hsiao (1982) makes use of a further lag of the lagged dependent variable as an instrument for the first lag. Alternatively, in the approach proposed by Arellano and Bond (1991) all available additional lags of the lagged dependent variable serve as instruments. Finally, Blundell and Bond (1998) construct instruments composed of a system of further lagged differences and levels of the lagged dependent variable in order to improve the efficiency of the estimates.

[6] This model is similar to the one set out in Steinberg (2017) in international migration contexts.

In table 3.12, I report system GMM estimates proposed by Blundell and Bond (1998) (columns (1) to (9)), relating relative oil abundance to the selectivity of migration patterns in a dynamic setup. Again, in order to preclude implicit sample selection issues due to missing data, I provide separate specifications with oil revenues per capita serving as pull factors in the destination state (columns (1), (4), (7)), as push factors in the source state (columns (2), (5), (8)) and for specifications with oil revenues serving as push and pull factors (columns (3), (6), (9)). Moreover, the specifications in columns (4) to (6) control for income tax revenues as a percentage of income and the specifications in columns (7) to (9) complementarily control for time effects following Egger and Pfaffermayr (2003) and transfers as a percentage of state incomes. With respect to the coefficient of interest, in line with the static panel model above, the results indicate that resource abundance lowers the selectivity of immigration, whilst the estimates even indicate brain drain effects when dispensing with taxes and transfers. The coefficients range between 0.0260 and 0.0535 which is slightly above the estimates in the previous specifications. Conversely to the previous specifications, accounting for taxes and transfers in the dynamic panel model does not reduce the significance of the coefficient attached to the selectivity of immigration.

With respect to covariates, in light of the summary statistics in table 3.1, it became apparent that the population density differs between resource abundant states and non-resource abundant states. In order to preclude that the results are affected by disparities in population density, I control for the population density rather than population size in the dynamic panel model. Apparently, the population densities in the source and host state are consistently positively associated with selected migration which suggests that skilled labor is more mobile across densely populated states while population density might be positively associated with opportunities. However, the main coefficient of interest remains still significant. In addition, the estimates do not point at a clear pattern with respect to path dependencies in the selectivity of migration as most of the estimates are insignificant.

Additionally, the results again indicate a quantity-selectivity trade-off in migration, in coherence with the static panel model. However, the estimates are partially, though not fully consistent with the predictions of the Borjas model. An increase in income inequality in the source state lowers the selectivity of emigration. This indicates that returns to skills in fact impinge on the selectivity of migration, even though the estimate is not highly significant. In particular, an increase in returns to skills in the source state is particularly beneficial for skilled labor, lowering the average selectivity of emigration.

Again, in tables 3.13 and 3.14, I further separate the specifications for internal migrants taking up positions in the oil extraction sector and the service sector, respectively. Consistently with the static panel models, the selectivity effects of immigration are not driven by migrants moving into the oil extraction industry. Rather, the estimates suggest that migrants taking up positions in the service sector contribute to the selectivity effects of internal migration.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity
	System GMM	System GMM	System GMM	System GMM	System GMM	System GMM	System GMM	System GMM	System GMM
State Pair FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Selectivity$_{t-1}$	0.0579	0.143*	-0.116	0.0600	0.151**	-0.150	0.0705	0.169**	-0.142
	(0.0696)	(0.0760)	(0.0946)	(0.0678)	(0.0757)	(0.0995)	(0.0686)	(0.0717)	(0.0917)
Oil Revenues per Capita	-0.0260***		-0.0384***	-0.0310***		-0.0483***	-0.0311***		-0.0535***
	(0.00993)		(0.00963)	(0.0105)		(0.0102)	(0.0110)		(0.00917)
Oil Revenues per Capita (source)		0.0216***	0.0105		0.0113	0.00144		0.0119	0.00368
		(0.00749)	(0.00991)		(0.00847)	(0.0116)		(0.00903)	(0.0130)
Density	0.00136***	0.000800***	0.00190**	0.00163***	0.00181***	0.00346***	0.00164***	0.00166***	0.00330***
	(0.000416)	(0.000134)	(0.000779)	(0.000470)	(0.000420)	(0.000740)	(0.000465)	(0.000347)	(0.000728)
Density (source)	0.000303**	0.00126***	0.000589	0.000302**	0.000607	0.000311	0.000306**	0.000834	0.000252
	(0.000146)	(0.000410)	(0.000606)	(0.000140)	(0.000696)	(0.000915)	(0.000136)	(0.000636)	(0.000855)
GDP per Capita	0.702***	0.962***	1.055***	0.820***	0.683***	1.316***	0.858***	0.740***	1.525***
	(0.173)	(0.162)	(0.240)	(0.172)	(0.174)	(0.256)	(0.194)	(0.176)	(0.263)
GDP per Capita (source)	-0.330**	-0.512***	-0.516**	-0.392**	-0.263	-0.427	-0.422**	-0.198	-0.515*
	(0.166)	(0.163)	(0.217)	(0.164)	(0.188)	(0.266)	(0.178)	(0.204)	(0.275)
Fiscal Expenditures	0.0929*	-0.0495	0.106**	0.0843*	-0.00288	0.0483	0.0885	0.0314	0.106*
	(0.0500)	(0.0312)	(0.0531)	(0.0480)	(0.0414)	(0.0485)	(0.0553)	(0.0434)	(0.0571)
Fiscal Expenditures (source)	-0.0302	-0.0836**	0.0520	-0.0237	-0.0916**	0.0261	-0.0230	-0.0628	0.0472
	(0.0352)	(0.0412)	(0.0831)	(0.0347)	(0.0451)	(0.0828)	(0.0353)	(0.0513)	(0.0933)
Quantity Migration	0.00481	-0.129***	-0.0855**	-0.00454	-0.0965***	-0.159***	-0.00369	-0.115***	-0.167***
	(0.0351)	(0.0259)	(0.0403)	(0.0339)	(0.0312)	(0.0455)	(0.0336)	(0.0261)	(0.0446)
Gini	-5.215**	-2.192*	0.793	-5.353**	-3.144**	2.658	-5.562**	-4.180***	-0.438
	(2.129)	(1.227)	(2.668)	(2.090)	(1.456)	(2.558)	(2.353)	(1.483)	(3.201)
Gini (source)	-0.245	0.598	-7.981**	-0.325	0.743	-9.379**	-0.408	-1.831	-10.42**
	(1.245)	(1.888)	(4.058)	(1.253)	(2.078)	(4.011)	(1.413)	(2.468)	(4.612)
Taxes				-6.756*	4.755*	-19.52***	-6.528*	7.357***	-16.18***
				(3.525)	(2.591)	(6.158)	(3.412)	(2.384)	(6.002)
Taxes (source)				1.536	-5.421	-14.49**	1.822	-4.532	-12.94**
				(2.918)	(3.447)	(6.169)	(2.983)	(3.098)	(6.232)
Transfers							-5.322	-53.22***	-38.49*
							(17.49)	(18.01)	(23.26)
Transfers (source)							-0.0457	-15.90	-11.99
							(16.53)	(15.18)	(17.22)
Constant	0.920	-1.491	0.655	0.551	0.329	1.175	0.449	2.538	2.460
	(1.374)	(1.394)	(1.927)	(1.360)	(1.612)	(2.185)	(1.539)	(2.118)	(2.612)
N	783	788	120	783	788	120	783	788	120
Hansen J	41.36	26.53	14.98	7.59	30.59	9.17	7.59	30.59	9.17

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state in a dynamic panel model. Migrant selectivity is defined as the years of schooling of migrants compared to the average years of schooling in the source state. All specifications are based on a System GMM approach proposed by Blundell and Bond (1998). Following Egger and Pfaffermayr (2003), the specifications (4) - (9) control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Clustered robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.12: Dynamic Panel Model

	(1) Selectivity System GMM	(2) Selectivity System GMM	(3) Selectivity System GMM	(4) Selectivity System GMM	(5) Selectivity System GMM	(6) Selectivity System GMM	(7) Selectivity System GMM	(8) Selectivity System GMM	(9) Selectivity System GMM
State Pair FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Selectivity$_{t-1}$	-0.0280	-0.0928	-0.0930	-0.0166	-0.117	-0.132**	-0.0228	0.0376	-0.0829
	(0.0715)	(0.0743)	(0.0716)	(0.0842)	(0.0719)	(0.0654)	(0.0718)	(0.0880)	(0.0758)
Oil Revenues per Capita	0.0637*		0.0348	0.0229		-0.0240	0.0304		0.0530
	(0.0374)		(0.0487)	(0.0556)		(0.0499)	(0.0368)		(0.0576)
Oil revenues per Capita (source)		0.0426	0.0304		0.00401	-0.0287		0.00809	0.0284
		(0.0430)	(0.0473)		(0.0449)	(0.0440)		(0.0400)	(0.0399)
Population	0.498***	0.306**	0.283*	0.0815	0.350**	0.262*	0.639***	0.326***	0.232
	(0.113)	(0.134)	(0.156)	(0.972)	(0.137)	(0.156)	(0.169)	(0.123)	(0.155)
Population (source)	0.311***	0.210	0.260*	2.685*	0.237*	0.243*	0.246**	0.242	0.00838
	(0.108)	(0.129)	(0.133)	(1.446)	(0.129)	(0.134)	(0.116)	(0.190)	(0.201)
GDP per Capita	0.370*	0.767***	0.643**	0.298	0.932***	0.702**	0.541**	0.953***	0.840***
	(0.209)	(0.249)	(0.251)	(0.533)	(0.300)	(0.298)	(0.223)	(0.272)	(0.277)
GDP per Capita (source)	0.185	-0.142	0.00419	1.453	-0.0266	0.0299	0.0567	0.00879	-0.0971
	(0.256)	(0.273)	(0.277)	(0.928)	(0.335)	(0.339)	(0.250)	(0.289)	(0.280)
Fiscal Expenditures	0.0837	0.176*	0.114	-0.450	0.176*	0.235	0.0988	0.293**	-0.00777
	(0.218)	(0.0996)	(0.258)	(0.575)	(0.102)	(0.253)	(0.210)	(0.116)	(0.257)
Fiscal Expenditures (source)	0.152*	0.156	0.150	0.617**	0.276	0.309	0.0294	0.258	-0.00359
	(0.0908)	(0.232)	(0.245)	(0.292)	(0.234)	(0.236)	(0.122)	(0.242)	(0.256)
Quantity Migration	-0.0927	-0.0317	0.0512	-0.833	-0.0912	0.0175	-0.0463	0.000136	0.106
	(0.0846)	(0.109)	(0.119)	(0.585)	(0.108)	(0.119)	(0.0882)	(0.109)	(0.120)
Gini	-12.32*	4.620	-2.010	19.88	3.559	6.169	-7.386	-1.256	3.076
	(6.549)	(5.642)	(8.465)	(23.72)	(6.677)	(9.913)	(6.651)	(5.507)	(8.468)
Gini (source)	-4.554	-19.07**	-13.21	-4.660	-20.26**	-8.846	-4.663	-22.47**	-9.022
	(4.531)	(8.223)	(8.291)	(7.681)	(10.06)	(9.401)	(4.900)	(9.091)	(8.519)
Density							-0.00548**		
							(0.00227)		
Density (source)							0.00117***	-0.000336	0.00360
							(0.000425)	(0.00239)	(0.00239)
Taxes							59.27	-92.05*	-19.37
							(40.83)	(49.80)	(52.85)
Taxes (source)							93.28	-5.639	1.421
							(56.89)	(75.28)	(67.15)
Transfers							0.497	-3.550	-13.75
							(13.58)	(12.01)	(13.87)
Transfers (source)							-22.03**	-26.65*	-41.66**
							(9.808)	(14.18)	(16.93)
Constant	0.861	3.927	3.607	-38.02*	6.036	-0.657	-2.717	9.383*	4.571
	(4.057)	(4.443)	(5.453)	(21.15)	(6.026)	(6.268)	(4.610)	(5.138)	(5.735)
N	483	345	239	483	345	239	483	345	239
Hansen J	20.31	26.92	22.06	8.44	16.88	16.96	21.21	63.98	25.86

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state in a dynamic panel model. The sample is restricted to workers in the oil extraction industry. Migrant selectivity is defined as the years of schooling of migrants compared to the average years of schooling in the source state. All specifications are based on a System GMM approach proposed by Blundell and Bond (1998). Following Egger and Pfaffermayr (2003), the specifications (4) - (9) control for time effects as well. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Clustered robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.13: Dynamic Panel Model Oil Extraction Sector

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity	Selectivity
	System GMM	System GMM	System GMM	System GMM	System GMM	System GMM	System GMM	System GMM	System GMM
State Pair FE?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Selectivity$_{t-1}$	0.0676	0.105**	0.0277	0.121**	0.181***	0.191	0.0728	0.291***	-0.0514
	(0.0444)	(0.0509)	(0.0952)	(0.0472)	(0.0553)	(0.124)	(0.0445)	(0.0472)	(0.115)
Oil revenues per Capita	-0.0156**		-0.0289***	-0.0241***		-0.0269**	-0.0133*		-0.0239***
	(0.00756)		(0.00928)	(0.00925)		(0.0116)	(0.00747)		(0.00926)
Oil Revenues per Capita (source)		-0.00186	0.00568		0.00199	0.00404		0.00593	0.0143*
		(0.00593)	(0.00773)		(0.00691)	(0.00845)		(0.00632)	(0.00838)
Population	0.146***	0.199***	0.201***	0.0394	0.169***	0.162***	0.0712*	0.0859***	0.121**
	(0.0284)	(0.0303)	(0.0364)	(0.189)	(0.0285)	(0.0352)	(0.0368)	(0.0265)	(0.0508)
Population (source)	0.113***	0.199***	0.164***	0.112	0.166***	0.122***	0.0862***	0.0789**	0.0192
	(0.0310)	(0.0280)	(0.0409)	(0.238)	(0.0270)	(0.0362)	(0.0316)	(0.0372)	(0.0814)
GDP per Capita	0.134***	0.296***	0.177***	0.0169	0.224***	0.0770	0.0647**	0.230***	0.144***
	(0.0262)	(0.0532)	(0.0456)	(0.115)	(0.0701)	(0.0602)	(0.0313)	(0.0598)	(0.0522)
GDP per Capita (source)	0.110***	0.132***	0.106***	-0.00275	0.0931*	0.0185	0.0523	0.107**	0.0301
	(0.0424)	(0.0410)	(0.0380)	(0.127)	(0.0487)	(0.0506)	(0.0506)	(0.0439)	(0.0556)
Fiscal Expenditures	0.0786**	0.0497*	0.148***	0.0719	0.0439*	0.148***	0.0568	0.0729***	0.136**
	(0.0368)	(0.0257)	(0.0528)	(0.0553)	(0.0262)	(0.0574)	(0.0417)	(0.0246)	(0.0680)
Fiscal Expenditures (source)	-0.0540***	0.00480	-0.0173	-0.0281	-0.0231	-0.0146	-0.0642**	-0.0285	-0.0462
	(0.0195)	(0.0339)	(0.0403)	(0.0443)	(0.0356)	(0.0420)	(0.0255)	(0.0400)	(0.0540)
Quantity Migration	-0.0800***	-0.190***	-0.156***	-0.0382	-0.160***	-0.121***	-0.0526*	-0.117***	-0.114***
	(0.0272)	(0.0262)	(0.0390)	(0.128)	(0.0257)	(0.0400)	(0.0273)	(0.0233)	(0.0391)
Gini	-3.329***	-0.496	-0.929	0.179	0.793	-0.742	-2.194	-1.575*	0.244
	(1.290)	(1.001)	(1.938)	(2.449)	(1.087)	(2.413)	(1.562)	(0.935)	(2.669)
Gini (source)	-0.718	-5.396***	-4.856***	1.847	-3.180**	-3.345*	0.172	-4.139***	-4.168**
	(0.948)	(1.179)	(1.600)	(1.253)	(1.383)	(1.956)	(1.002)	(1.398)	(1.774)
Density							0.000112	0.000780*	0.00189**
							(0.000112)	(0.000414)	(0.000898)
Density (source)							0.000748*	0.000638***	0.000880
							(0.000390)	(0.000126)	(0.000634)
Taxes							16.47	-9.192	-29.24**
							(15.61)	(10.51)	(13.02)
Taxes (source)							16.87	-28.18**	3.329
							(11.72)	(11.04)	(18.02)
Transfers							4.771**	-1.684	-4.106
							(2.131)	(2.892)	(5.183)
Transfers (source)							3.692	9.986***	5.936
							(2.709)	(1.614)	(3.855)
Constant	1.769**	1.931**	1.560	0	0.258	0	1.207	3.966***	3.343***
	(0.741)	(0.814)	(0.979)	(.)	(0.981)	(.)	(0.955)	(0.980)	(1.231)
N	1626	1627	440	1626	1627	440	1626	1627	440
Hansen J	54.54	60.04	31.56	4.88	35.70	24.82	42.37	166.10	30.09

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state in a dynamic panel model. The sample is restricted to workers in the service sector. Migrant selectivity is defined as the years of schooling of migrants compared to the average years of schooling in the source state. All specifications are based on a System GMM approach proposed by Blundell and Bond (1998). Following Egger and Pfaffermayr (2003) the specifications (4) - (9) control for time effects as well. the specifications in columns (4) to (9) account for time fixed effects. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Clustered robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.14: Dynamic Panel Model Service Sector

In the following section, I make use of a nonparametric approach in order to account for the multilateral character of migration decisions.

3.3.4 Multilateral Approaches

The static and dynamic panel model build upon a bilateral approach, according to which the selectivity of migration is exclusively determined by push and pull factors in the source and destination state. However, migration decisions are prospectively multilateral decisions, even though they materialize retrospectively as bilateral migration patterns. In addition, although I controlled for time and state pair fixed effects along with several covariates in the static and dynamic panel models above, the relative standard of living is partially intangible. Yet, if individuals vote with their feet, the relative net migration serves as a means in order to account for the relative standard of living. This especially holds for internal mobility patterns which are not exposed to explicit migration restrictions. Moreover, within a country, emigration and immigration patterns are captured centrally through census data and net migration rates can easily be determined. In order to explicitly account for the relative standard of living, I follow the approach proposed by Douglas and Wall (1993) and Wall (2001), relying on bilateral net migration streams.[7]

In this regard, I refer to equation 3.1 which was set out in the theoretical section, though dispensing with individual specific indices for the sake of parsimony. I posit that indirect utility in state j, V_j, is composed of non-pecuniary amenities, A_j, and pecuniary income, Y_j, according to the following function:

$$V_j = \alpha \ln A_j + \beta \ln Y_j + \epsilon_j \tag{3.12}$$

with $\alpha > 0$ and $\beta > 0$. Since migration is exclusively determined by the indirect utility in the source state and all potential host states while dispensing with migration costs,

[7] I henceforth dispense with time indexes for the sake of parsimony.

relative net migration might be described by the following model:

$$\Omega_{ij} = \mu_j - \mu_i + \beta \ln \left(\frac{Y_j}{Y_i} \right) + \epsilon_{ij} \tag{3.13}$$

with $\mu_i = \alpha A_i$ and Ω_{ij} representing net migration rates between states i to state j. As the potential for migration increases with the population size in the source and host state, net migration rates are defined relative to the product of the population size in state i and j, respectively (e.g. Zipf (1946), Wall (2001)). Formally,

$$\Omega_{ij} = \frac{m_{ij} - m_{ji}}{P_i P_j} \tag{3.14}$$

where $m_{ij} - m_{ji}$ equals the net migration between state i and j and P_i and P_j represent the population size in state i and j, respectively. In this model, relative net migration serves as a measure for the relative standard of living. Under the assumption that individuals self-select themselves into the state which provides them the highest utility, the relative standard of living might be approximated multilaterally through accounting for all bilateral net migration streams. In this regard, I define a variable, d_j, which is 1 (-1) if the relative bilateral net migration between i and j is positive (negative) and 0 otherwise. As I control for common pecuniary push and pull factors, in the following model proposed by Douglas and Wall (1993), the coefficient attached to the variable, λ, serves as an approximation for the relative standard of living:

$$\Omega_{ij} = \sum_{j=1}^{M} \lambda_j d_j + \beta ln \left(\frac{Y_j}{Y_i} \right) + \epsilon_{ij} \tag{3.15}$$

with

$$\sum_{j=1}^{M} \lambda_j = 0 \tag{3.16}$$

Controlling for the relative standard of living leads to the estimates displayed in table 3.15 below. All specifications control for state fixed effects based on the relative net migration as defined above, while the net migration indicator sums up to 0. In order to internalize this restriction, the estimates are derived through constrained regressions. In contrast to the previous static and dynamic panel estimates, all covariates are captured as the difference between the host and source state. As I focus on the quantity of migration rather than the selectivity of migration in the framework set out above, I have to contrast selectivity levels below and above the state average. In particular, the specifications in columns (1) to (4) depict estimates based on a restricted sample of migrants who exhibit a selectivity below the average, while the estimates shown in columns (5) to (8) are restricted to migrants who characterized by a selectivity above the state average. Further, the specifications differ with respect to the covariates controlled for. Consistently, relative oil revenues per capita serve as a strong pull factor for negatively selected migrants (columns (1) to (4)), while positively selected migrants are not significantly attracted by relative oil abundance (columns (5) to (8)). These results are in line with the theoretical predictions and previous findings.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Net Migration	Net Migration	Net Migration	Net Migration	Net Migration	Net Migration	Net Migration	Net Migration
	Constrained Regression	Constrained Regression	Constrained Regression	Constrained Regression	Constrained Regression	Constrained regression	Constrained Regression	Constrained Regression
Sample?	Below Average	Below Average	Below Average	Below Average	Above Average	Above Average	Above Average	Above Average
Oil Revenues per Capita	0.0438*	0.0512*	0.0554*	0.0526**	0.00404	-0.00429	-0.00731	-0.0160
	(0.0155)	(0.0181)	(0.0188)	(0.0206)	(0.0121)	(0.0157)	(0.0156)	(0.0164)
GDP per Capita	-0.0442*	-0.0472*	-0.0534*	-0.0506*	-0.0475*	-0.0468*	-0.0445*	-0.0358**
	(0.0118)	(0.0123)	(0.0145)	(0.0161)	(0.0131)	(0.0127)	(0.0131)	(0.0160)
Fiscal Expenditures	-0.0492	-0.0557	-0.0732	-0.0760	0.106**	0.127**	0.143*	0.132**
	(0.0551)	(0.0571)	(0.0574)	(0.0571)	(0.0459)	(0.0550)	(0.0544)	(0.0567)
Gini	-0.00108	-0.00100	-0.000706	-0.000519	-0.000535	-0.000105	-0.000387	-0.000101
	(0.00153)	(0.00151)	(0.00150)	(0.00151)	(0.00103)	(0.00122)	(0.00124)	(0.00117)
Income Taxes		0.00456***	0.00288	0.00314		-0.00295	-0.00260	-0.00117
		(0.00270)	(0.00262)	(0.00267)		(0.00224)	(0.00227)	(0.00269)
Transfers			0.0165	0.0161			-0.00888	-0.00446
			(0.0126)	(0.0128)			(0.00669)	(0.00688)
Density				-0.000132				-0.000308
				(0.000212)				(0.000189)
Constant	-0.0000278	-0.0000259	-0.0000297	-0.0000268	0.00000465	0.00000384	0.00000276	-0.00000530
	(0.0000350)	(0.0000348)	(0.0000340)	(0.0000347)	(0.0000271)	(0.0000270)	(0.0000271)	(0.0000252)
N	220	220	220	220	220	220	220	220

Notes: Net Migration regressed on the difference in oil revenues per capita between the host and source state. All specifications account for state fixed effects which make use of relative net migration as an indicator for the relative standard of living. The specifications in columns (1) to (4) report estimates for the relationship between relative oil abundance and net migration for negatively selected migrants (selectivity < 0.5), while the specifications in columns (5) to (8) rely on a sample of positively selected migrants (selectivity > 0.5). Covariates are accounted for as the difference between values in the state of residence and the state of origin. Robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.15: Nonparametric Migration Model

3.4 Conclusion

Introductorily, I raised the question whether natural resource booms impinge on the selectivity of immigration and emigration patterns within the US. In order to tackle this question, I combined a theoretical analysis with an empirical investigation.

Theoretically, I set out a simple multinomial choice model in the spirit of McFadden et al. (1973) and Maddala (1983), according to which oil windfall gains ease the household budget constraint. However, as low-skilled labor derives a stronger utility gain from resource windfall gains compared to skilled labor, a resource windfall lowers the relative educational background of prospective immigrants. These selectivity effects are strengthened by the boom in the service sector throughout the whole economy due to a Dutch disease.

Empirically, I relied on static and dynamic panel models inspired by a gravity equation to relate the selectivity of migration to relative resource abundance based on US census data between 1940 and 2000. In order to internalize path dependencies in the selectivity of migration, I further compare changes in selective migration into oil abundant states with the average change of migrant selection across other US states. Complementarily, in order to account for multilateral migration decisions, I made use of a nonparametric approach based on the relative net migration across states. In essence, the results are in line with the theoretical predictions, i.e. resource abundance is negatively associated with the selectivity of immigration. These selectivity effects are driven by migrants taking up positions in the service sector rather than the oil extraction industry.

While Chapter 2 shows that a resource boom translating into a Dutch disease might lead to brain drain effects internationally, this paper suggests that selective migration effects of resource booms might even materialize regionally. Moreover, Chapter 2 pointed at resource shocks serving as a push factor, while Chapter 3 highlights the role of resource shocks serving as a pull factor.

3.5 Appendix: Robustness Checks Individual Data

	(1) Selectivity Pooled OLS	(2) Selectivity Pooled OLS	(3) Selectivity Pooled OLS	(4) Selectivity RE	(5) Selectivity RE	(6) Selectivity RE	(7) Selectivity FE	(8) Selectivity FE	(9) Selectivity FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues	-0.0220***		-0.0168***	-0.0519***		-0.0386***	-0.0492***		-0.0441***
	(0.00175)		(0.00220)	(0.00196)		(0.00287)	(0.00328)		(0.00347)
Oil Revenues per Capita (source)		0.0202***			-0.00339*			0.00474*	
		(0.00167)			(0.00188)			(0.00245)	
Population	0.163***	0.218***	0.155***	0.137***	0.228***	0.140***	0.719***	0.582***	0.738***
	(0.00331)	(0.00306)	(0.00431)	(0.00346)	(0.00307)	(0.00440)	(0.0310)	(0.0256)	(0.0373)
Population (source)	0.00841**	0.0783***	0.00466	0.0289***	0.0440***	0.0100***	0.00816*	0.0203***	0.00904**
	(0.00331)	(0.00333)	(0.00333)	(0.00327)	(0.00349)	(0.00336)	(0.00448)	(0.00502)	(0.00449)
GDP per Capita	0.0826***	0.221***	0.0583***	0.133***	0.288***	0.140***	0.618***	0.493***	0.664***
	(0.00589)	(0.00711)	(0.00630)	(0.00721)	(0.00861)	(0.00793)	(0.0286)	(0.0249)	(0.0372)
GDP per Capita (source)	0.0222***	-0.0119*	-0.000519	0.103***	0.0645***	0.0948***	0.0177*	0.0339***	0.0215**
	(0.00768)	(0.00629)	(0.00781)	(0.00931)	(0.00776)	(0.00941)	(0.0101)	(0.00839)	(0.0103)
Fiscal Expenditures	0.128***	0.239***	0.0914***	0.192***	0.284***	0.138***	0.170***	0.0376***	0.162***
	(0.00706)	(0.00494)	(0.00828)	(0.00766)	(0.00546)	(0.0105)	(0.0125)	(0.00964)	(0.0137)
Fiscal Expenditures (source)	-0.0866***	-0.0755***	-0.104***	-0.0232***	-0.0310***	-0.0900***	0.00527	-0.0167*	0.00451
	(0.00498)	(0.00610)	(0.00548)	(0.00524)	(0.00680)	(0.00574)	(0.00680)	(0.00891)	(0.00682)
Quantity Migration	-0.117***	-0.179***	-0.108***	-0.115***	-0.182***	-0.108***	-0.143***	-0.215***	-0.142***
	(0.00273)	(0.00239)	(0.00276)	(0.00272)	(0.00240)	(0.00278)	(0.00439)	(0.00360)	(0.00442)
Gini	-2.462***	-0.769***	-1.604***	2.128***	1.125***	1.883***	-3.154***	-3.776***	-2.700***
	(0.228)	(0.138)	(0.238)	(0.274)	(0.153)	(0.278)	(0.336)	(0.274)	(0.390)
Gini (source)	-1.048***	-6.298***	-0.804***	1.232***	-2.562***	0.652***	0.215	-0.490*	0.297
	(0.150)	(0.203)	(0.157)	(0.166)	(0.242)	(0.169)	(0.213)	(0.271)	(0.216)
Population Density	0.000329***		0.000202***			0.000176***			-0.000567***
	(0.0000124)		(0.0000137)			(0.0000137)			(0.000121)
Population Density (source)			-0.000230***			-0.000334***			0.000439**
			(0.0000524)			(0.0000548)			(0.000171)
Age	0.0705***	0.0669***	0.0706***	0.0707***	0.0669***	0.0706***	0.0710***	0.0687***	0.0710***
	(0.000209)	(0.000178)	(0.000209)	(0.000209)	(0.000178)	(0.000209)	(0.000209)	(0.000180)	(0.000209)
Constant	-1.333***	-0.676***	-2.191***	-3.613***	-2.001***	-3.189***	-5.618***	-4.665***	-5.966***
	(0.134)	(0.127)	(0.141)	(0.153)	(0.145)	(0.155)	(0.333)	(0.330)	(0.426)
N	1141714	1321019	1141714	1144263	1321019	1141714	1144263	1321019	1141714
R^2	0.149	0.145	0.150	0.149	0.146	0.151	0.159	0.162	0.159

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state based on individual data. Migrant selectivity is defined as the years of schooling of migrants compared to the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) fixed effects estimates. Complementarily, the specifications in columns (1) to (9) account for time fixed effects. GDP per Capita, Fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.16: Static Panel Model Micro

	(1) Selectivity Pooled OLS	(2) Selectivity Pooled OLS	(3) Selectivity Pooled OLS	(4) Selectivity RE	(5) Selectivity RE	(6) Selectivity RE	(7) Selectivity FE	(8) Selectivity FE	(9) Selectivity FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues per Capita	0.0756***		0.0343	0.0570**		-0.0223	0.00605		0.0108
	(0.0218)		(0.0261)	(0.0237)		(0.0309)	(0.0349)		(0.0361)
Oil revenues per Capita (source)		0.0836***			0.0744***			-0.0285	
		(0.0217)			(0.0235)			(0.0313)	
Population	0.324***	0.369***	0.365***	0.318***	0.368***	0.326***	-0.567	-0.560	-1.436**
	(0.0463)	(0.0517)	(0.0730)	(0.0464)	(0.0517)	(0.0760)	(0.474)	(0.448)	(0.660)
Population Source	0.0689	0.0559	0.0225	0.0802*	0.0693	0.0395	0.305	0.892*	0.156
	(0.0449)	(0.0487)	(0.0502)	(0.0451)	(0.0496)	(0.0508)	(0.405)	(0.489)	(0.480)
GDP per Capita	0.221***	0.386***	0.281***	0.221**	0.279**	0.258**	-0.511	-0.543	-1.300**
	(0.0788)	(0.0940)	(0.0846)	(0.103)	(0.118)	(0.120)	(0.466)	(0.443)	(0.642)
GDP per Capita (source)	0.0463	0.0164	-0.0426	0.00798	-0.0836	-0.0921	0.192	0.715	0.0670
	(0.0868)	(0.0888)	(0.0915)	(0.106)	(0.110)	(0.110)	(0.387)	(0.468)	(0.460)
Fiscal Expenditures	-0.0373	0.293***	0.0371	-0.00414	0.314***	0.202	0.0166	0.0781	0.0848
	(0.117)	(0.0578)	(0.125)	(0.121)	(0.0603)	(0.133)	(0.155)	(0.107)	(0.157)
Fiscal Expenditures (source)	0.195***	-0.132	0.168***	0.214***	-0.0668	0.184***	0.293**	0.204	0.261*
	(0.0495)	(0.108)	(0.0504)	(0.0504)	(0.111)	(0.0511)	(0.122)	(0.149)	(0.136)
Quantity Migration	0.0212	0.0145	0.0404	0.0122	-0.00580	0.0142	-0.0429	-0.195***	-0.0289
	(0.0393)	(0.0481)	(0.0447)	(0.0403)	(0.0489)	(0.0457)	(0.0687)	(0.0714)	(0.0694)
Gini	-5.260	-5.745**	-4.065	-3.106	-8.207***	0.901	3.586	-2.284	3.668
	(3.276)	(2.497)	(3.303)	(4.293)	(3.120)	(4.482)	(5.877)	(5.086)	(7.708)
Gini (source)	-5.264**	-5.275	-5.018**	-5.115**	-8.001*	-4.082	-1.529	1.532	-2.112
	(2.175)	(3.368)	(2.286)	(2.502)	(4.120)	(2.547)	(4.253)	(5.439)	(4.544)
Age	0.00865***		0.00768**			0.00767**	0.00580*		0.00579*
	(0.00336)		(0.00336)			(0.00338)	(0.00336)		(0.00337)
Density (source)			0.000862***			0.000883***			0.00196
			(0.000277)			(0.000282)			(0.00221)
Density			-0.00270**			-0.00256**			0.00653
			(0.00119)			(0.00127)			(0.00498)
Transfers (source)			33.30**			27.34**			-9.044
			(13.37)			(13.40)			(20.93)
Transfers			62.53***			35.04			100.9**
			(24.07)			(25.06)			(47.12)
Taxes (source)			-12.73***			-12.82***			-4.583
			(3.773)			(3.824)			(10.83)
Taxes			-4.642			-13.22*			-8.890
			(6.540)			(7.110)			(14.22)
Constant	1.780	2.506	0.825	0.838	3.535	-1.626	2.695	-1.180	10.35
	(1.630)	(1.757)	(1.924)	(2.254)	(2.377)	(2.490)	(7.183)	(7.710)	(9.391)
N	5328	4473	5328	5328	4473	5328	5328	4473	5328
R^2	0.0226	0.0278	0.0284	0.0234	0.0291	0.0308	0.0567	0.0676	0.0581

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state based in individual data. The sample is restricted to workers in the oil extraction industry. Migrant selectivity is defined as the years of schooling of migrants compared to the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) fixed effects estimates. Complementarily, the specifications in columns (1) to (9) account for time fixed effects. GDP per Capita, fiscal expenditures and the quantity of migration are log-transformed. Robust standard errors in parentheses. Standard errors in the fixed effects model are clustered. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.17: Static Panel Model Micro Oil Extraction Sector

	(1) Selectivity Pooled OLS	(2) Selectivity Pooled OLS	(3) Selectivity Pooled OLS	(4) Selectivity RE	(5) Selectivity RE	(6) Selectivity RE	(7) Selectivity FE	(8) Selectivity FE	(9) Selectivity FE
State Pair FE?	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Oil Revenues per Capita	-0.0418***		-0.0358***	-0.0532***		-0.0411***	-0.0552***		-0.0527***
	(0.00213)		(0.00243)	(0.00240)		(0.00338)	(0.00427)		(0.00449)
Oil Revenues per Capita (source)		0.000267			-0.0126***			-0.0117***	
		(0.00181)			(0.00206)			(0.00348)	
Population	0.170***	0.248***	0.143***	0.139***	0.257***	0.131***	0.833***	0.719***	0.754***
	(0.00391)	(0.00361)	(0.00566)	(0.00417)	(0.00364)	(0.00580)	(0.0390)	(0.0327)	(0.0537)
Population (source)	0.0697***	0.115***	0.0482***	0.0706***	0.0889***	0.0476***	0.251***	0.596***	0.348***
	(0.00414)	(0.00399)	(0.00431)	(0.00417)	(0.00416)	(0.00436)	(0.0347)	(0.0389)	(0.0392)
GDP per Capita	0.0971***	0.235***	0.0827***	0.126***	0.298***	0.126***	0.713***	0.627***	0.636***
	(0.00751)	(0.00892)	(0.00776)	(0.00935)	(0.0110)	(0.0100)	(0.0359)	(0.0317)	(0.0509)
GDP per Capita (source)	0.0988***	0.0468***	0.0521***	0.140***	0.119***	0.102***	0.216***	0.503***	0.305***
	(0.00954)	(0.00812)	(0.00985)	(0.0118)	(0.0102)	(0.0122)	(0.0329)	(0.0353)	(0.0369)
Fiscal Expenditures	0.162***	0.229***	0.119***	0.164***	0.255***	0.114***	0.217***	0.0254**	0.249***
	(0.00790)	(0.00599)	(0.00935)	(0.00875)	(0.00671)	(0.0122)	(0.0158)	(0.0128)	(0.0174)
Fiscal Expenditures (source)	-0.0871***	-0.0277***	-0.126***	-0.0721***	-0.0207***	-0.127***	-0.0770***	0.0311**	-0.0816***
	(0.00525)	(0.00679)	(0.00567)	(0.00556)	(0.00761)	(0.00586)	(0.0121)	(0.0137)	(0.0123)
Quantity Migration	-0.120***	-0.175***	-0.110***	-0.106***	-0.175***	-0.103***	-0.142***	-0.164***	-0.140***
	(0.00353)	(0.00314)	(0.00363)	(0.00356)	(0.00316)	(0.00367)	(0.00517)	(0.00445)	(0.00518)
Gini	-3.628***	-1.193***	-2.072***	0.639**	0.581***	0.759**	-3.014***	-2.078***	-4.117***
	(0.263)	(0.160)	(0.297)	(0.318)	(0.176)	(0.341)	(0.384)	(0.330)	(0.547)
Gini (source)	-0.327*	-6.438***	0.714***	1.793***	-2.893***	2.014***	0.917***	-0.846**	0.581*
	(0.168)	(0.234)	(0.180)	(0.186)	(0.277)	(0.193)	(0.340)	(0.330)	(0.350)
Age	0.0117***		0.0119***			0.0120***	0.0126***		0.0126***
	(0.000289)		(0.000290)			(0.000290)	(0.000290)		(0.000290)
Density (source)			0.000201***			0.000184***			-0.00120***
			(0.0000146)			(0.0000146)			(0.000144)
Density			0.0000311			0.0000183			0.00127***
			(0.0000624)			(0.0000655)			(0.000276)
Transfers (source)			16.63***			16.45***			-8.245***
			(1.084)			(1.086)			(1.522)
Transfers			11.20***			6.727***			28.71***
			(2.375)			(2.492)			(3.972)
Taxes (source)			3.732***			3.063***			2.343***
			(0.297)			(0.301)			(0.890)
Taxes			1.668***			1.177**			2.428*
			(0.512)			(0.593)			(1.271)
Constant	1.466***	2.341***	0.424**	-0.324*	0.956***	-0.766***	-6.944***	-9.484***	-6.938***
	(0.162)	(0.155)	(0.177)	(0.186)	(0.178)	(0.193)	(0.563)	(0.540)	(0.775)
N	540739	629733	540739	540739	629733	540739	540739	629733	540739
R^2	0.0101	0.0147	0.0119	0.00746	0.0156	0.0126	0.0255	0.0377	0.0258

Notes: Immigrant and emigrant selectivity regressed on oil revenues per capita in the source and host state state based on individual data. The sample is restricted to workers in the service sector. Migrant selectivity is defined as the years of schooling of migrants compared to the average years of schooling in the source state. The specifications in columns (1) to (3) report pooled OLS estimates, the specifications in columns (4) to (6) random effects estimates and the specifications in columns (7) to (9) fixed effects estimates. Complementarily, the specifications in columns (1) to (9) account for time fixed effects. Robust standard errors in parentheses. GDP per Capita, Fiscal expenditures and the quantity of migration are log-transformed. Standard errors in the fixed effects model are clustered. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 3.18: Static Panel Model Micro Service Sector

4

INCOME WINDFALLS AND EDUCATIONAL SHORTFALLS - EVIDENCE FROM THE ALASKA OIL BOOM

Abstract:

While Chapters 2 and 3 analyzed selective migration patterns as a consequence of resource booms, this chapter is devoted to educational investments of local residents. Theoretically, I make use of a simple model of human capital formation, showing that resource windfall gains might lower labor supply and the returns to skills. Moreover, the results suggest that investing the additional resource revenues into the quality of the education system is more conducive to human capital development than easing the household budget constraint through transfers. Empirically, I make use of an enormous oil boom in Prudhoe Bay, Alaska, where a large oil field was discovered in the 1960's. The results of a difference-in-differences model based on US census data spanning the years from 1940 and 2010 indicate that the resource windfall gave rise to a shortfalls of human capital development compared to a control group composed of several US states. The shortfall of average years of schooling even materializes in comparison to a synthetic control group.[1]

[1]This chapter is single-authored and has been submitted to an academic journal.

4.1 Introduction

"Lottery winners slightly increased their family size after the lottery more than non-winners, but were not more likely to send their children to school."

– Bleakley and Ferrie (2016), p. 1455.

The skill composition of a population is affected by educational investments of local residents as well as by the selectivity of immigration and emigration. While Chapter 2 and 3 were devoted to selective migration patterns as a consequence of resource booms, Chapter 4 aims at determining the educational investments of local residents in response to income windfalls. Gylfason (2001) hypothesized that natural capital might crowd out human capital, and thereby impede economic development in the long run. The latter might be part of a curse of natural resources more generally (e.g. Baten (2016)). Theoretical models of human capital formation have a long tradition in economics, arising out of seminal contributions of Schultz (1961) and Becker (1962). Unlike static models of human capital development (e.g. Andersson and Konrad (2003)), endogenous growth models highlight the importance of human capital investments for economic prosperity (e.g. Lucas (1988), Romer (1986), Rebelo (1990)).

Referring to Gylfason (2001), Stijns (2006) questions whether the negative association between resource abundance and educational investments is robust to various measures of educational attainment and resource abundance. In contrast to the findings of Gylfason (2001), "subsoil wealth and resource rents per capita are shown to be significantly correlated with improved indicators of human capital accumulation." (Stijns (2006), p. 1060) However, beyond cross-sectional correlations, the literature still lacks a coherent theory and a causal analysis relating resource abundance and educational investments. Therefore, I raise the following questions: How can the relationship between resource abundance and human capital investments be theoretically explained?

Does the relationship between natural and human capital depend on the specific character of policy interventions? Are supply and demand side effects equally important for promoting human capital investments? How can the effect of resource abundance on educational attainment be empirically identified? In order to tackle these questions, I combine a theoretical model with an empirical specification.

Theoretically, I set out a simple framework of educational investments, according to which individuals maximize life-time utility subject to an intertemporal budget constraint. I show that resource booms mitigate human capital investments of local residents under certain conditions. In essence, resource windfall gains which are easing the household budget constraint through lump sum transfers affect educational investments through two channels. First, as pointed out in Chapter 2, a Dutch disease leads to a deindustrialisation along with intersectoral factor movements from the tradable towards the non-tradable sector (Corden and Neary (1982), Corden and Neary (1982)). On the one hand the deindustrialisation leads to a decline in returns to skills and on the other hand the boom in the service sector makes unskilled labor better off.[2] Hence, a Dutch disease might disincentivize educational investments. Second, unconditional resource transfers might lower labor supply and returns to skills in the future, setting the stage for lower educational investments at the present. The larger the share of resource revenues forwarded to individuals, the stronger the human capital responses.

Alternatively, the government encountering further fiscal capacity might contemplate to cut taxes. Lowering proportional labor income taxes is neutral regarding human capital investments as costs and returns of human capital investments are equally affected (Eaton and Rosen (1980), Trostel (1993)).[3] However, lowering taxes on interest income unleashes negative effects on human capital investments since investments in physical capital are incentivized at the costs of human capital (Heckman (1976), Trostel

[2]Goderis and Malone (2011) study Gini coefficients and find that Gini coefficients contract in the course of a resource boom.

[3]In contrast, Rebelo (1990) finds a negative relationship between taxation and human capital accumulation as educational costs are not fully deductible.

(1993)). Investing resource revenues into the quality of the education system is conducive to human capital investments as long as the costs of educational investments are reduced.

Empirically, I refer to the Alaska oil boom, in order to test the theoretical predictions. In 1968, a large oil field was discovered in Prudhoe Bay, Alaska, which affected the economy through various channels. Firstly, the oil boom unleashed employment effects both in the oil extraction industry as well as in secondary sectors. Secondly, the oil boom set the stage for further fiscal capacity which might have been invested in public goods in general. In light of resource windfall gains, the state government elicited a fundamental tax enactment in 1980. As part of the tax reform, both personal income taxes as well as the sales taxes were totally repealed. The tax reform directly impinged on expected lifetime incomes, and therefore might have affected human capital investments as well. In addition, a school tax established in 1949 was abolished in 1980. Further, the Alaska Permanent Fund was put in place in 1976 after the state government encountered allegations that resource rents had not been sustainably invested. 25 percent of annual revenues have been invested into the Alaska Permanent Fund while 50 percent of annual profits from interests are disbursed to local residents. Though modest, annual payments as part of the Alaska Permanent Fund might be considered as unconditional transfers potentially affecting human capital investments as well.

In an effort to relate educational investments to resource abundance, I compare trends in educational investments of local residents in Alaska with the corresponding educational investments in a control group composed of several US states not exposed to any oil boom. In particular, as the main variable of interest, I draw upon the average years of primary, secondary and college education. Positing a parallel counterfactual trend in educational attainment between Alaska and the control group, I base the analysis on a difference-in-differences setup. In order to preclude confoundedness through migration and self-selection into the treatment group, I exclude interstate migrants in the respective period. The results show that the income windfall led to a shortfall of human capital development in Alaska compared to the control group. These results are consistent with Gylfason (2001) in the sense that resource booms trigger crowding out effects of human capital investments.

The paper which is empirically closest to my empirical setup is the one provided by Kumar (2014) for Texas in the 1970's. The author compares human capital investments in regions which were exposed to oil booms and those which were not exposed to oil booms pre and post of the oil boom in the 1970's within Texas. In contrast, I am referring to income windfall gains irrespective of the fact whether the individual is directly involved into the oil industry which is quite modest in terms of employment. As Alaska saw a sharp and tremendous increase in oil revenues which were forwarded to the household budget constraint through the Alaska Permanent Fund, it serves as a perfect laboratory. Similarly, Bleakley and Ferrie (2016) make use of random wealth allocated to families in order to investigate the intergenerational transmission of human capital. However, the authors can not detect major educational disparities between treated and untreated families.

The chapter is organized as follows. In section 4.2, I set out a theoretical model capturing the effect of income windfalls on educational investments. In section 4.3, I descriptively lay out the details of the Alaska oil boom and various dimensions through which the state economy was affected. In addition, I prescriptively make use of a difference-in-differences setup in order to test the theoretical predictions. Section 4.4 concludes.

4.2 Theory

In order to derive the theoretical link between the returns to skills and human capital formation, I proceed in two steps. In a first step, I assume that returns to skills are exogenous with respect to the resource boom in a closed economy. In a second step, the economy is opened up for trade and returns to skills become endogenous.

4.2.1 Closed Economy: Exogenous Returns to Skills

I posit a representative agent maximizing life-time utility over two periods, $t = 1, 2$, within a closed economy.[4] In *period 1* resource windfall gains, $\mathcal{R}$, are easing the budget constraint and the individual trades off human capital investments, h, and labor supply, $n_1 = 1 - h$. Educational costs are made up of both forgone earnings and direct educational costs, $C(h) > 0$. Without loss of generality, following Rea Jr (1977), I postulate a linear cost function for human capital formation, $C(h) = \alpha h$. Educational investments translate into further productivity and labor income in the future, according to the following function, $w_2 = \phi(h)$ while incomes in period 1 are totally exogenous, $w_1 \leq w_2$. Similar to Eaton and Rosen (1980), I assume that the returns to human capital investments are positive, $\phi'(h) > 0$, but decreasing, $\phi''(h) < 0$. In *period 2*, time is exclusively devoted to labor supply, $n_2 = 1$, in the first place. However, in a second scenario discussed below, the individual trades of labor supply and leisure in period 2, which implies that $n_2 = 1 - l$. In light of this framework, without loss of generality, individuals decide self-responsibly about educational investments rather than delegating educational decisions to parents.

Formally, the representative agent chooses consumption in period 1 and 2, c_t, and

[4] Similar models were set out by Becker (1962), Heckman (1976), Eaton and Rosen (1980), Rea Jr (1977) and Acemoglu (2017).

educational investments in period 1, h, in order to maximize life-time utility,

$$\max_{c_t,h} \quad \sum_{t=1}^{2} \beta^{t-1} \log c_t \tag{4.1}$$

subject to his life-time budget constraint

$$\sum_{t=1}^{2} \frac{c_t}{(1+r)^{t-1}} + C(h) - \sum_{t=1}^{2} \frac{(1-\tau)w_t}{(1+r)^{t-1}} n_t - \mathcal{R} = 0 \tag{4.2}$$

where β^{t-1} equals the discount factor and τ represents a proportional labor income tax rate which is time invariant. Apparently, human capital investments exclusively impinge on the earnings potential such that educational investments do not depend on the specific functional form of utility. This is commonly referred to as separation theorem, originally laid out by Hirshleifer (1970). The first order conditions are given by:

$$\frac{c_1}{c_2} = \left(\frac{1}{\beta(1+r)}\right) \tag{4.3}$$

$$\frac{\Phi'(h)(1-\tau)}{1+r} n_2 = \alpha + (1-\tau)w_1 \tag{4.4}$$

Equation 4.3 equates the intertemporal marginal rate of substitution and the relative price, whilst equation 4.4 indicates that the optimal investment in human capital is characterized by the equality of returns to educational investments and marginal educational costs. The latter are made up of direct educational costs, α, as well as opportunity costs of educational investments, $(1-\tau)w_1$.

In light of further fiscal capacity in the course of a resource boom, the state government might lower educational costs or might ease the household budget constraint through unconditional transfers or a decline in proportional tax rates. The educational effects of these policy options are discussed below in the course of three propositions.

Proposition 1: *A resource windfall which lowers educational costs promotes edu-*

cational investments.

Proof: Totally differentiating equation 4.4 with respect to α while taking into account that $n_2 = 1$ yields

$$\frac{\partial h}{\partial \alpha} = \frac{(1+r)}{(1-\tau)\Phi''(h)} < 0 \tag{4.5}$$

According to this inequality, resource windfall gains which are invested into the quality of the educational system are unambiguously conducive to human capital investments as long as marginal educational costs are reduced since $\Phi''(h) < 0$. ■

Proposition 2: *A resource windfall spilling into unconditional transfers might lead to a decline in educational investments as long as labor supply is endogenous.*

Proof: Since the individual simultaneously decides upon human capital investments and labor supply, the effects of lump sum resource transfers on educational investments and labor supply have to be evaluated concurrently. After differentiating equation 4.4 with respect to windfall gains while taking into account that the time devoted to work in period 2 is made up of the residual $n_2 = 1 - l$ under endogenous leisure (l denotes the time devoted to leisure) and $\frac{\partial U}{\partial l} > 0$, I wind up with the following equation:

$$\Phi'(h)\frac{\partial l}{\partial \mathcal{R}} = \Phi''(h)\frac{\partial h}{\partial \mathcal{R}}(1-l) \tag{4.6}$$

Accordingly, human capital investments and resource windfall gains are negatively associated, $\frac{\partial h}{\partial \mathcal{R}} < 0$, as long as the demand for leisure and resource windfall gains are positively related, $\frac{\partial l}{\partial \mathcal{R}} > 0$. This holds under the sufficient condition that returns to skills are positive but decreasing. If leisure is a normal good, exogenous resource windfall gains lower labor supply and returns to skills in the future. While encountering lower returns to skills, individuals invest less in education at the present. Therefore, resource windfall gains serve as an impediment rather than a propeller for human capital development. ■

Proposition 3: *A resource windfall leading to a decline in proportional tax rates is neutral regarding educational investments under exogenous labor supply and conducive to educational investments under endogenous labor supply (if educational costs are fully deductible in both cases).*

Proof: I have to separate two cases. In the first case, labor supply is exogenous in period 2, $l = 0$. Totally differentiating equation 4.4 with respect to τ yields

$$\frac{\partial h}{\partial \tau} = -\frac{w_1(1+r)}{\Phi''(h)(1-\tau)} + \frac{\Phi'(h)}{\Phi''(h)(1-\tau)} \tag{4.7}$$

As the first order conditions imply that $w_1(1+r) = \Phi'(h)$ if educational costs are fully deductible, it directly follows that

$$\frac{\partial h}{\partial \tau} = 0 \tag{4.8}$$

Conspicuously, proportional labor income taxes are neutral regarding educational investments. The neutrality of labor income taxation is due to the fact that the costs of educational investments, forgone wages, and the benefits of educational investments, gained wages, are equally affected through proportional labor income taxation. This result has been similarly derived by Eaton and Rosen (1980).

In the second case, labor supply is endogenous, $n_2 = 1 - l$. Again, totally differentiating equation 4.4 with respect to $\mathcal{R}$ while taking into account that $n_2 = (1 - l)$ yields

$$\Phi'(h)(1-\tau)\frac{\partial l}{\partial \tau} + \Phi'(h)(1-l) - w_1(1+r) = \Phi''(h)\frac{\partial h}{\partial \tau}(1-\tau)(1-l) \tag{4.9}$$

However, as long as educational costs are fully deductible, $\Phi'(h)(1-l)$ and $w_1(1+r)$ coincide and $\frac{\partial h}{\partial \tau}$ as well as $\frac{\partial l}{\partial \tau}$ are negatively associated. Namely, under endogenous leisure, taxation unequally affects the opportunity costs of acquiring human capital at the present and the returns to human capital acquirement in the future. Returns to skills are directly affected by labor income taxation and indirectly through a decline in labor supply. Hence, the abrogation of labor income taxes unfolds neutral (exogenous labor supply) or even positive (endogenous labor supply) educational effects. The latter are strengthened even more if educational costs are not fully deductible (King and Rebelo (1990), Rebelo (1990)). ■

The policy interventions in response to resource booms discussed above are particularly relevant for the specific case of Alaska. As a consequence of further fiscal capacity in the course of the oil boom, Alaska put in place the Alaska Permanent Fund which is equivalent to an unconditional transfer scheme. Moreover, the state government enacted several tax reforms which were supposed to abrogate all state income taxes. While the theory suggests a decline in educational investments as a consequence of the Alaska Permanent Fund, abolishing progressive income taxes is conducive to educational attainment as net returns to skills are increased in the future.

Thus far, I exclusively focused on a closed economy. However, in an open economy, resource windfalls lead to further dampening effects on educational investments. These effects are discussed in the following section.

4.2.2 Open Economy: Endogenous Returns to Skills

In the previous subsection, I postulated that the returns to skills, $\phi(h)$, are exogenous, and hence not affected in the course of resource windfalls. However, in an open economy a resource boom sets the stage for a Dutch disease materializing in an appreciation of the exchange rate (spending effect) along with intersectoral factor movements from the tradable to the non-tradable sector (resource movement effect) as pointed out in Chapter 2. Correspondingly, the boom of the non-tradable sector and the squeeze of the tradable sector promotes heterogenous effects on educational premia across the skill distribution. Namely, if the tradable sector is skilled labor intensive, skilled labor incomes go down in nominal as well as in real terms due to the Stolper-Samuelson-theorem. Again, in light of reduced skill premia in the future, individuals might invest less in education at the present.

In order to derive the educational effects emerging as a consequence of a Dutch disease, I have to augment the setup of the previous section. In a first step, I draw upon the framework set out in Chapter 2, in order to derive the relationship between resource booms and the returns to skills. Accordingly, the timing of the model is as follows: In period 1, the economy experiences a resource windfall, while resource windfall gains are forwarded to the household budget constraint. At the same time, individuals might engage in educational investments, $h = 1$, at educational costs, α, in order to become skilled, H, while individuals not investing in education remain unskilled, L. Hence, without loss of generality, skills are binary rather than continuous. Moreover, I assume that individuals neither trade off labor supply and educational investments in period 1 nor labor supply and leisure in period 2. Rather, educational attainment exclusively induces pecuniary costs. In period 2, skilled labor earns a wage w_H, whilst unskilled labor still earns w_L. According to the separation theorem, individuals choose educational investments in order to maximize life-time income (e.g. Acemoglu (2017)):[5]

$$\sum_{t=1}^{2} \frac{w_L}{(1+r)^{t-1}} + 1\{h=1\} \left(\frac{w_H - w_L}{(1+r)} - \alpha \right) + \mathcal{R} \tag{4.10}$$

where $1\{h = 1\}$ is 1 if the individual acquires human capital and becomes skilled, $h = 1$. For the sake of parsimony, I dispense with time indices in the first place. In light of this framework, I proceed with proposition 4.

Proposition 4: A Dutch disease leads to a crowding out of educational investments.

[5] Again, time is normalized to 1.

Proof: As laid out in proposition 1 of Chapter 2, a Dutch disease leads to a contraction of skill prima, $w_H - w_L$. In light of proposition 2 of Chapter 2, subsequent changes in the returns to skills are not compensated for by initial resource transfers under reasonable assumptions. According to the separation theorem it is sufficient to evaluate human capital responses based on the life-time income. Apparently, in light of the life-time income,

$$\sum_{t=1}^{2} \frac{w_L}{(1+r)^{t-1}} + 1\{h > 0\} \left(\frac{w_H - w_L}{(1+r)} - \alpha \right) + \mathcal{R} \tag{4.11}$$

human capital is acquired as long as $\frac{w_H - w_L}{1+r} > \alpha$. As $w_H - w_L$ contracts due to the Stolper-Samuelson theorem, a Dutch disease leads to a crowding out of educational investments. This holds even more if individuals encounter income losses along with educational costs in the course of educational investments as in the previous model. ■

According to proposition 4, a Dutch disease leads to a crowding out of the tradable sector in favor of the non-tradable sector. As long as the tradable (non-tradable) sector is skilled (unskilled) labor intensive, skilled labor is worse off while unskilled labor is better off. In light of the previous propositions set out above, a Dutch disease might deteriorate educational investments through two channels. First, the opportunity costs of acquiring human capital at the present increase as unskilled labor incomes go up. Second, the returns to skills in the future decrease as skilled labor incomes go down. In combination, a Dutch disease leads to a crowding out of educational investments.

Thus far, the analysis was based on the assumption that households do not face any credit constraints while acquiring human capital. I dispense with this assumption in the following proposition.

Proposition 5: *Credit constraints lower the crowding out of educational effects in* *the course of a Dutch disease.*

Proof: Following Acemoglu (2017), under credit constraints savings are strictly non-negative and the budget constraint becomes

$$0 \leq s \leq Y + \mathcal{R} - 1\{h = 1\}\alpha - c_1 \tag{4.12}$$

in period 1 (while s represents savings and Y exogenous income in period 1) and

$$c_2 \leq w_L + 1\{h = 1\}(w_H - w_L) + (1 + r)s \tag{4.13}$$

in period 2. Individuals not investing in education wind up with utility

$$U(h = 0|Y, \mathcal{R}) = \log w_L + \log(Y + \mathcal{R}) \tag{4.14}$$

while individuals investing in education end up with utility

$$U(h = 1|Y, \mathcal{R}) = \log w_H + \log(Y + \mathcal{R} - \alpha) \tag{4.15}$$

. Contrasting the individual utilities leads to the conclusion that individuals acquire human capital as long as

$$\alpha \leq \frac{w_H - w_L}{w_H}(Y + \mathcal{R}) \tag{4.16}$$

Apparently, under consideration of credit constraints, a Dutch disease unfolds reverse effects on educational attainment. Firstly, a resource boom lowers the returns to skills which disincentivizes educational investments in light of proposition 4. Secondly, resource windfall gains increase the capacity to bear educational costs which incentivizes educational investments. Hence, the net educational effects of a Dutch disease are ambiguous and depend on the relative size of both effects.[6] ∎

[6]The result is based on the assumption that resource windfall gains are equally distributed across skills in line with the Alaska Permanent Fund which is studied in the empirical section.

In the following section, I rely on a quasi-randomized experiment as part of an empirical investigation.

4.3 Evidence

4.3.1 Descriptive Analysis

The Alaska Oil Boom

In order to verify or falsify theoretical predictions, I confront theory with data while relying on a difference-in-differences setup. In particular, I make use of an exogenous variation arising out of an enormous oil boom in Alaska. In 1968, a large oil and gas field was discovered in Prudhoe Bay which is part of the North Slope Boroughin located at the Arctic Ocean in Northern Alaska.[7] With 25 billion barrels estimated in 1968, Prudhoe Bay was supposed to be the largest oil field discovered in the United States and among the 20 largest oil fields in the world.[8] Figure 4.1 visualizes the state of Alaska with Prudhoe Bay situated at the North Slope Boroughin.

[7] Along with oil, large gas fields were discovered in Prudhoe Bay. Beyond Prudhoe Bay, gas was discovered in the Kenai Peninsula on the South Coast of Alaska as well where exploitation started in 1964. In this paper I mainly focus on the variation originating from the oil boom rather than the gas boom as it was much more succinct.

[8] The general information regarding the Alaska Oil Boom and the institutional background are drawn from Alaska Oil and Gas Association (2014).

Figure 4.1: Map Alaska

In an effort to ship oil to the market, the Transalaska-Pipeline was completed between 1974 and 1977. By means of the pipeline, oil could have been shipped to Valdez, 1287 km to the south of Prudhoe Bay and the nearest harbor which is clear of ice. The construction of the pipeline was a consequence of an oil embargo in 1973, which pushed the oil price up from 3 to 12 USD per barrel between 1973 and 1974. With oil prices soaring up, domestic oil production in Prudhoe Bay became economically beneficial, following persistent legal disputes between oil companies and the state administration by 1973. Due to the construction of the pipeline, full-scale production in Prudhoe Bay began with some retardation, according to data from the US Energy Information Administration. Namely, production started in 1977, following a linear increase peaking in 1988 with a production of 2 billion barrels per day. However, as of 1988, Alaska experienced a sharp and persistent decline in oil drilling for more than two decades. Meanwhile, 26.61 billion barrels of oil are so far undiscovered but technically recoverable, according to estimates from the Minerals Management Services (MMS). Similar to Chapter 3, figure 4.2 displays the development of oil drilling in the US in general in the panel on the left-hand side and Alaska in particular in the panel on the right-hand side.

(a) Trends in US Oil Production (b) Trends in US State Oil Production

Notes: The figures depict trends in US state Oil production. Data source: Hamilton (2011).

Figure 4.2: Trends US Oil Production

In contrast to Alaska, oil drilling in the US as a whole began already in 1859, though documentation started in 1900 on a fairly low level, followed by a rapid increase until 1970, a year marked by the oil crisis. Since 1970 oil production dropped fiercely, followed by a further transient increase. This increase is due to the oil embargo in 1973 which laid the ground for additional oil drilling in Alaska where the Transalaska-Pipeline was completed by 1977. Until 1973, oil production was mainly driven by Texas and California, though drilling dropped sharply in Texas and modestly in California over the final quarter of the 20th century. Since the decline of oil production in Texas and California was not compensated by other states between 1980 and 2005, US oil production saw a steady decline. Driven by the discovery of additional oil fields, production went up again as of 2005. Today, the US is the third largest producer of oil following Russia and Saudi-Arabia. Alaska in particular is outnumbered by Texas, the Gulf of Mexico, North Dakota as well as California with respect to oil production. Currently, oil revenues mainly originate from North Dakota and Texas. In 2015 the share of oil drilling in North Dakota was 12.46 percent of the total US oil production, whereas Texas contributed with 36.41 percent, according to the US Energy Information Administration.

As reported in figure 4.3, the oil boom set the stage for a deceleration of human capital development. While the panel on the left hand side shows trends in the years of schooling of local residents living in the same state 5 years ago, the panel on the right hand side visualizes trends in the years of schooling of local residents living even in the same house 5 years ago. Along with the educational trends in Alaska, I visualize educational trends in a control group made up of all US states which were not exposed to any oil boom in the 20th century. Namely, the control group consists of US states excluding Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. The educational trends are based on an indicator capturing the completed years of schooling up to grade 17, which is consistently defined for the treatment and control group.[9] Apparently, parallel educational trends between the treatment and control group prior to the oil boom are followed by converging trends post of the oil boom. In particular, local residents in Alaska acquired more human capital than residents in the control group prior to the oil boom, however, post of the oil boom the educational trends are converging, and finally the control group took over in terms of human capital development in 1973. The volatility of educational investments in the short run in both the treatment and control group might be due to business cycle effects. Mainly, in a recession, students often contemplate to further enroll in educational institutions, waiting for the next boom.

[9]In order to avoid that the results are driven by a rise in the number of children, I restrict the analysis to individuals above age 25. Moreover, as graduation years can be retraced only for years of schooling above grade 8, I henceforth rely on the years of schooling above grade 8.

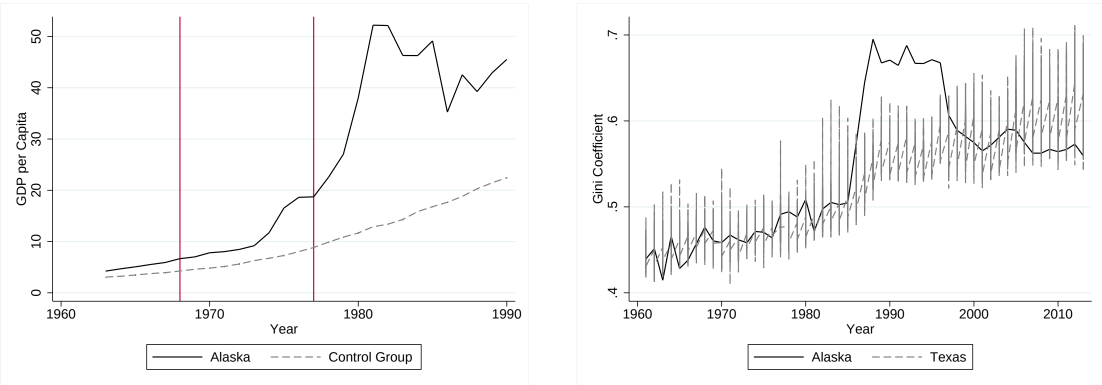
(a) No Migration 5 Years Ago (b) Same House 5 Years Ago

Notes: The figures depict trends in US state educational attainment in Alaska and a control group. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Data source: Ruggles et al. (2003).

Figure 4.3: Educational Trends

Beyond education, there are several channels through which the Alaska oil boom impinged on the local economy in a broad sense. Primarily, the oil boom served as a propeller for the whole economy which is reflected in a massive increase in state income. The following figure 4.4 displays trends in the state income per capita in Alaska and the control group defined above. Apparently, especially after the completion of the pipeline in 1977, state incomes per capita saw a fierce upward deviation in the treatment group compared to the control group. The increase in state incomes per capita was accompanied by several tax reforms. In 1949, a personal income tax has been established which amounted to 10 percent of federal tax income liabilities elevated to 16 percent by 1961. Another tax reform in 1967 aimed at disentangling tax rates from federal income liabilities at given progressive tax rates in the range between 3.5 percent and 14.5 percent with roughly neutral revenue effects. Finally, in 1980, the personal income tax has been repealed due to further fiscal capacity. Established in 1949, an additional school tax asked each wage earner to contribute with 10 USD to a fund supporting schools. Along with the personal income tax, school taxes were abolished in 1980 in light of further fiscal capacity. Among others, these tax enactments set the stage for a transient increase in income inequality in the 1980's. This shift becomes apparent in the panel on the right hand side of figure 4.4, displaying the development of Gini coefficients in Alaska as well as the control group. Especially in the course of the oil boom, Gini coefficients saw a sharp increase until the 1990's and declined subsequently.

(a) Trends in US State GDP per Capita (b) Trends in Gini Coefficients



Notes: The figures depict time trends of GDP per Capita and Gini coefficients for Alaska and a control group. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Data source: Sommeiller and Price (2014).

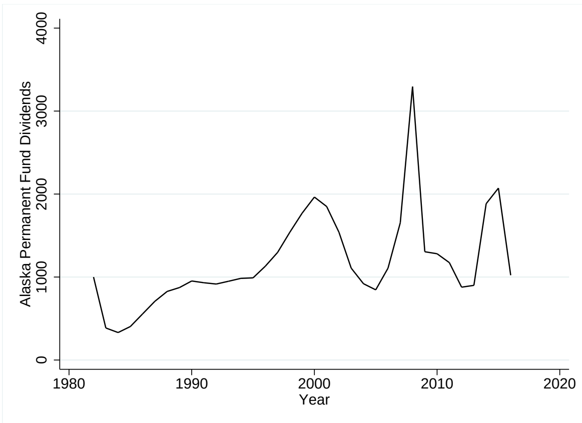
Figure 4.4: GDP per Capita and Gini coefficients

The oil boom also fed into direct and indirect employment effects. Employment effects entail the primary employment as well as secondary employment in jobs which are generally related to the oil and gas industry. Further, there might be additional employment effects arising out of a booming economy as a consequence of the resource windfall. Again, based on data from the Alaska Oil and Gas Association (2014), the primary employment effect amounts to 5,335 individuals and 4,700 residents, whilst the jobs broadly related to the primary companies make up 51,000 individuals in 2013. However, one third of the jobs in Alaska are related to the oil industry in a very broad sense. The actual and anticipated employment effects set the stage for factor movements towards Alaska. In the long run, population went up from 72,000 inhabitants in 1940 to 710,000 individuals in 2010 based on US census data as already emphasized in Chapter 3. In the short run, Alaska experienced two sharp deviations from the upward trend. The first major deviation materialized between 1973 and 1977 during the construction of the Transalaska-Pipeline connecting Purdoe Bay and Valdez. In particular, population went up from 330,000 to 403,000 during the construction period, persisted on a constant level and went up again between 1980 and 1988 to 544,000. The latter boom was due to an extended period of job creation and fiscal expansion as a consequence of the resource windfall. The increase in population in the 1970's and 1980's has been mainly driven by migration rather than reproduction. Hence, I exclude migrants from the sample in order to examine the educational investments among local residents in response to the oil boom. Since the 1990's population growth slowed down as growth rates were primarily driven by reproduction rather than migration. Apparently, even though the population followed a clear upward trend over the 20th century, changes in the trend of population growth did not immediately follow the discovery of oil reserves in 1968. This retardation is due to legal disputes and discussions preceding the construction of the Transalaska-Pipeline and exploited as part of the identification below. Starting with the construction of the Transalaska-Pipeline in 1974, population went up steadily. Today, Alaska is the 47th most populous state and is less densely populated than any other state in the United States.

Furthermore, oil companies pay taxes, thereby setting the stage for further fiscal capacity both on a state as well as on a local level.[10] According to the Alaska Oil and Gas association (2014), in 2013, taxes from oil companies made up 47 percent of total state revenues in Alaska, while 56 percent of the operating budget of the administration originates from the oil and gas industry. In addition, oil companies paid into an unrestricted general fund which contributes, among others, to 80 percent of the budget for public safety and 77 percent of education and early development. Solely between 1980 and 1981 total state revenues more than doubled, from 1.6 billion up to 3.4 billion USD. However, the unprecedented boom in the first half of the 1980's was followed by a serious bust in the second half.

[10]According to the Alaska Oil and Gas Association, the 13 primary companies entail Alyeska Pipeline Service Company, Apache Corporation, BP Exploration Inc., eni petroleum, ExxonMobil Production Company, Flint Hills Resources, Hilcorp, Petro Star Inc., Pioneer Natural Resources Alaska Inc., Repsol EP USA, Shell Exploration Production Company, Statoil, Tesoro Alaska Company, XTO Energy Inc..

The enhanced fiscal capacity had a serious impact on the local economy as well. Namely, a basic income scheme was placed in 1977 shortly before the completion of the Transalaska Pipeline. The purpose of the so-called "Alaska Permanent Fund" was twofold. Firstly, it was intended to set aside at least 25 percent of annual oil revenues in order to partially redistribute oil windfall gains intergenerationally. Secondly, it was a response to criticism the local state government faced when the revenues emerging in the first round through oil field leasing contracts peaked 900 million USD but were not sustainably invested. As a consequence, a referendum was held asking for the implementation of the Alaska Permanent Fund. The following figure depicts annual dividends of the Permanent Fund which started in 1982.

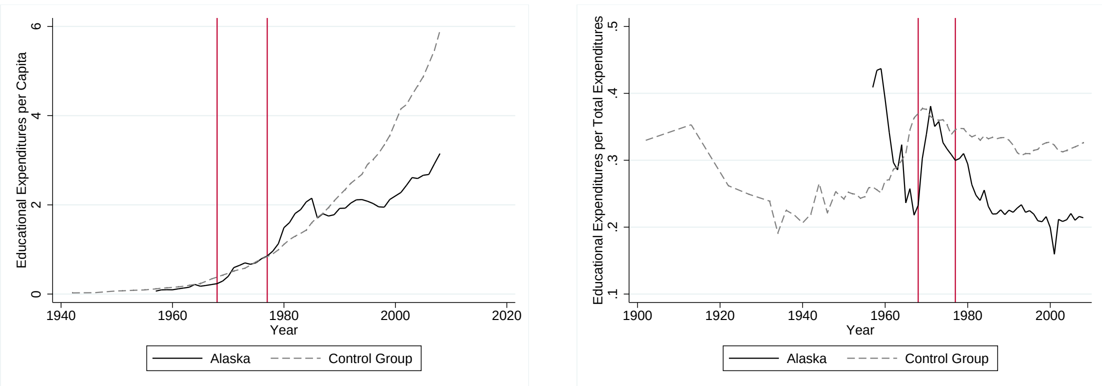


Notes: The figures depicts trends in dividends of the Alaska Permanent Fund. Data source: Alaska Permanent Fund (2017).

Figure 4.5: Alaska Permanent Fund Dividends

Enhanced fiscal capacity might feed into further government expenditures in general and educational expenditures in particular. In the panel on the left hand side of figure 4.6, I contrast educational expenditures per capita in Alaska and the control group prior to and post of the oil boom. According to the figure, government expenditures roughly follow a parallel trend prior to the oil boom, but exhibit a divergence post of the oil boom in 1968 and post of the completion of the pipeline in 1977. While figure 4.6 displays a progression for the control group, the progression is even more distinct in Alaska, especially after the exploration of the oil field and the completion of the pipeline. However, since 1984 educational expenditures per capita saw a sharp decline in Alaska and finally fell short of educational expenditures in the control group. Since the 1960's set the stage for an enormous educational expansion throughout industrial countries, I go a step further and account for the share of educational relative to total fiscal expenditures depicted in figure 4.6. The figure displays a sharp increase in the ratio of educational to total expenditures following the discovery of oil in Prudhoe Bay in 1968. To make matters more concrete, the share of educational expenditure relative to total expenditures increased by more than 10 percentage points. This is remarkable in light of the fact that oil production increased moderately until the completion of the Transalaska-Pipeline in 1977.

(a) Educational Expenditures per Capita (b) Educational per Total Expenditures



Notes: The figures depicts trends in educational expenditures per capita (panel on the left-hand side) and per total expenditures (panel on the right-hand side) in Alaska and control group. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Data source: United States Census Bureau (2015).

Figure 4.6: Trends in Relative Educational Expenditures

Before I provide summary statistics of the covariates of interest, I proceed with a brief description of the educational system in the US.

The Educational System in the US

Mandatory schooling in the US was established in 1852 and was followed by several educational reforms throughout the 20th century. After the implementation of compulsory schooling in general, several additional reforms were devoted to educational federalism. For instance, the Elementary and Secondary Education Act (ESEA) imposed in 1965, requested centralized examinations on a state level, though prohibiting a uniform curriculum. Hence, the reform strengthened the independence, and therefore the competition between the educational systems across US states. Further educational reforms entailed the implementation of similar educational standards throughout the US.

In the US in general, each state is independently in charge of educational policies. Depending on the state, mandatory schooling essentially starts between age 5 and 6 and ends between age 16 and 18. As most of the states request 12 compulsory years of schooling today, the school system is traditionally referred to as K-12-system. Compulsory schooling consists of elementary schools ranging from kindergarten in grade 1 serving students between age 5 and 6 up to the 4th grade via a middle school ranging from grade 5 and 8 to the upper high school between grade 9 and 12. As a substitute for middle schools, some states instead rely on junior and senior high schools. Upon secondary school completion, students normally have to pass a standardized exam administered and organized by the state government. Public schools are supplemented by private schools which commonly preselect their students based on their previous achievement. However, private schools have to be approved by the state government and all students enrolled in private as well as public schools have to participate in standardized tests. Complementarily, students might further enroll in a college in order to advance their academic skills in the course of post secondary education.

In Alaska in particular, students are obliged to attend school for at least 9 years before turning 16 excluding kindergarten which is not required in Alaska. Even though population density is comparatively low, higher education is provided by the University of Alaska which serves students through 10 campuses on a community level complemented by 3 university campuses on an urban level in Fairbanks and Juneau. Hence, even though population density is modest, it does not affect the potential of acquiring higher education.

In the following section I provide summary statistics of all variables I make use of below.

Summary Statistics

In order to sum up, I report descriptive statistics of outcome variables as well as covariates I make use of in the empirical section below. In particular, the table below provides information on the mean, the standard deviation, the minimum and maximum value for each variable. The variables considered entail the years of schooling on the demand side, educational expenditures and the teacher-student-ratio on the supply side, state income per capita, the Gini coefficient, population size as well as the age and a dummy for male graduates. However, in contrast to disparities in levels, I am interested in changes in these levels in response to the Alaska oil boom. These changes are examined in the following sections.

		All States					Alaska				Control			
Variable	Year	No. Obs.	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max
Average Years of Schooling Residence	All	6721	12.37562	1.241036	9	17	12.27891	1.170245	9	17	12.35506	1.238129	9	17
Average Years of Schooling	All	5689	12.31724	1.184018	9	17	13.25387	.9256215	9	17	13.21563	1.014508	9	17
Age	All	22,168,330	34.9176	20.2168	0	100	31.11775	17.09677	0	100	34.99156	20.30858	0	100
Male	All	22,168,330	.4841	.4997485	0	1	.5213	.4996	0	1	.4829	.4997	0	1
Gini	All	4862	.4838442	.0783653	.2314301	.7474164	.5397558	.0809489	.4146556	.6951078	.4831415	.0773676	.2314301	.7114252
Teacher-Student-Ratio	All	1326	.05024	.0072	.0039	.07657	.05370	.0072	.0449	.070001	.0502197	.0072564	.0039307	.0765676
Log GDP per Capita	All	1428	9.028596	.7099012	1.342597	11.08803	9.751805	.8982623	8.350068	10.86304	9.008474	.6655736	7.586766	11.08803
Log Educational Expenditures per Capita	All	2884	4.563799	2.064567	-2.864722	9.686259	6.14986	1.077903	3.70626	7.488822	4.596414	2.087324	-1.464771	9.686259
Population Size	All	3549	4,242,502	.4810418	113000	37,000,000	432053,5	175439.9	135000	710231	3964342	3669316	113000	19400000
Log Population	ALL	3550	14.73773	1.069084	11.63514	20.71725	12.88335	.4515303	11.81303	13.47335	14.82647	.9974852	11.63514	17.43327

Notes: State Income in Millions of current US Dollars. Years of schooling are completed years of schooling rather than current years of schooling which are accounted for individuals above age 25.

Table 4.1: Descriptive Statistics

The following section describes the empirical strategy in order to ascertain the link between resource booms and educational attainment.

4.3.2 Empirical Strategy

In order to illuminate the link between resource booms and human capital investments empirically, I compare human capital development in Alaska prior to and post of the oil boom with the human capital development in a control group made up of several US states based on a difference-in-differences setup. Formally, following the notation in Roller and Steinberg (2017), let $g \in \{0, 1\}$ denote a regional dummy which equals 1 for the treatment group (Alaska) and 0 for a control group legitimized below, whilst $t \in \{0, 1\}$ is a time dummy which equals 1 for graduation years post of the oil boom and 0 for graduation years prior to the oil boom. For the sake of parsimony, I initially assume that there is just one period observable prior to and one period observable post of the oil boom.[11] Let $Y^N_{g,t}$ denote the potential years of schooling of a graduate at time t who belongs to group g not exposed to the oil boom and $Y^I_{g,t}$ the potential outcome of graduates exposed to the oil boom. In an effort to estimate the educational effects in response to the oil boom, I refer to the average treatment effect (ATE), defined as the expected difference between potential years of schooling of treated and untreated graduates. Formally,

$$ATE_t = E\left[Y^I_t - Y^N_t\right] \tag{4.17}$$

In contrast, the average treatment effect on the treated (ATET) is defined as the expected difference between the years of schooling in the treatment group:

$$ATET_t = E\left[Y^I_{1,t} - Y^N_{1,t}\right] \tag{4.18}$$

while ATE and the ATET coincide if the oil boom is unrelated to the expected difference between the potential years of schooling in the control and the treatment group.

[11] In the course of several robustness checks, I adapt the timing below.

As the oil boom is not totally random, I identify the ATET rather than the ATE.

I only capture graduates in Alaska or the control group. In particular, I observe the treated outcome in the treatment group at $t = 1$, $E\left[Y_{1,1}^{I}\right]$, and the untreated outcome at $t = 0$, $E\left[Y_{1,0}^{N}\right]$ while the counterfactuals $Y_{1,0}^{I}$ and $Y_{1,1}^{N}$ are unknown for Alaska. The difference-in-differences strategy might serve as a remedy which becomes obvious by restating the ATET as follows:

$$ATET_1 = E\left[Y_{1,1}^{I} - Y_{1,1}^{N}\right] = E\left[Y_{1,1}^{I}\right] - E\left[Y_{1,1}^{N} - Y_{1,0}^{N}\right] - E\left[Y_{1,0}^{N}\right] \tag{4.19}$$

The only unknown part of equation 4.19 is $E\left[Y_{1,1}^{N} - Y_{1,0}^{N}\right]$, which is the expected change in the potential untreated years of schooling in the treatment group. However, under the assumption that the expected change in the potential untreated outcome in the treatment group is the same as the change in the potential treated outcome in the control group, $E\left[Y_{1,1}^{N} - Y_{1,0}^{N}\right] = E\left[Y_{0,1}^{I} - Y_{0,0}^{I}\right]$, equation 4.19 might be reformulated as follows:[12]

$$ATET_0 = E\left[Y_{1,0}^{I} - Y_{1,0}^{N}\right] = E\left[Y_{1,1}^{I}\right] - E\left[Y_{0,1}^{I} - Y_{0,0}^{I}\right] - E\left[Y_{1,0}^{N}\right] \tag{4.20}$$

which depends exclusively on observed outcomes. The latter assumption is often referred to as common-trend assumption and legitimized below.

Parametrically, I can estimate the $ATET_1$ based on the following regression:

$$Y_{i,t} = \alpha + \phi g_i + \eta t + \rho I_{i,t} + \epsilon_i \tag{4.21}$$

where $Y_{i,t}$ captures the educational investment of student i at time t and $I_{i,t}$ is an indicator taking the value 1 if the individual was actually treated in t. If ALASKA is a regional dummy variable which is 1 for Alaska and 0 otherwise and TIME69 is a time

[12]The difference-in-differences approach is standard in the literature while the notation in this chapter has been introduced in Roller and Steinberg (2017).

dummy variable which is 0 prior to the oil boom and 1 post of the oil boom, variable $I_{i,t}$ equals ALASKA $\times$ TIME69. The $ATET_1$ is then equal to the coefficient ρ. As I have annual observations, students in Alaska are treated for graduation years post of the oil boom and untreated for graduation years prior to the oil boom. In light of the econometric specification, I postulate that the educational effects are primarily driven by the rise in income on the state level rather than employment effects on an individual level. This particularly holds in light of modest direct employment effects in the oil industry as pointed out in the descriptive section. In an effort to further take into account subsequent policy changes as a response to the oil boom, i.e. the completion of the Transalaska-Pipeline and payments of the Alaska Permanent Fund post of 1982, I complementarily provide estimates for adjusted timing variables. Yet, adjusting the timing of the model requires additional parallel trend assumptions with respect to the outcome variables prior to subsequent interventions. I discuss the identifying assumptions in more detail below.

Regarding the outcome variable, $Y_{g,t}$, I have to differentiate between the educational investments on the demand side and educational expenditures on the supply side. With respect to the demand side, I make use of the years of primary, secondary and college education which are available between 1940 and 2010, henceforth denoted as years of schooling. Even though the decennial census does not provide information on the year of graduation, an approximation is derived by tracing back the graduation year based on the individual age, the census year, the average school starting age and the individual years of schooling. Yet, the graduation year can only be retraced for school years above grade 8 as classes are grouped between grade 4 and 8. However, due to mandatory years of schooling above grade 8 this assumption is not restrictive. Further, I account for the ratio of pupils who completed at least one year of college relative to the overall number of graduates based on the years of schooling. The respective ratio is denoted as college ratio. With respect to the supply side, I make use of two outcome variables as well, educational expenditures per capita and per total expenditures. The former might reflect both further fiscal capacity or additional educational priority while the latter primarily signifies educational priority. In fact, the outcome variables have a unit root as educational investments saw a steady increase over the 20th century due to path dependencies in educational investments. Further, the oil boom in the 1960's coincided with an educational expansion in the USA in particular and industrial countries in general. However, as the educational expansion and the unit roots materialized in both the treatment and control group, unit roots and educational expansions do not undermine or even violate the main identification. Yet, according to Bertrand et al. (2002), in case of unit roots in the outcome variable and more than 2 periods of observations post of an intervention, I might end up with inconsistent standard errors. For the sake of consistent estimates, I base my analysis on clustered standard errors as proposed by Bertrand et al. (2002). Alternative remedies might be bootstrapping or collapsing serially correlated data into two observations prior to and post of the exogenous change.

Complementarily, I account for covariates on a micro as well as on a macro level. First, I have to control for variables unequally affecting the outcome variable in the treatment and control group, and thereby undermining or even violating the common-trend assumption. Secondly, I might control for further covariates impinging on the outcome variable in order to increase the efficiency of the estimates as long as the number of observations is not reduced due to missing values. Individual specific covariates are exclusively efficiency enhancing as the treatment materializes on a state level. Omitted variables, not undermining the common-trend assumption, do not violate the consistency of the estimates, however, all covariates accounted for have to be exogenous with respect to the treatment. In order to preclude feedback effects from the treatment on covariates, I provide specifications accounting for and dispensing with covariates below. In particular, I control for educational expenditures per capita on a macro level originating from United States Census Bureau (2015). Government expenditures, especially educational investments, might elevate the quality of the school system, and thereby pave the way for further educational investments. Additionally, I control for average incomes per capita originating from the United States Bureau of Economic Analysis (2017). Further, I include state income inequality made available by Sommeiller and Price (2014). On a micro level, I exclusively account for a gender dummy which is one for male students and 0 otherwise. However, as shown in the descriptives, educational expenditures, state income per capita as well as the state Gini coefficients are endogenous and hence affected by the treatment. Therefore, the specifications with covariates exclusively serve as a robustness check.

With respect to the control group, I rely on all US states which were not exposed to any oil boom. In particular, the control group is composed of all US states excluding Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. The following map visualizes the control group as part of the US graphically.

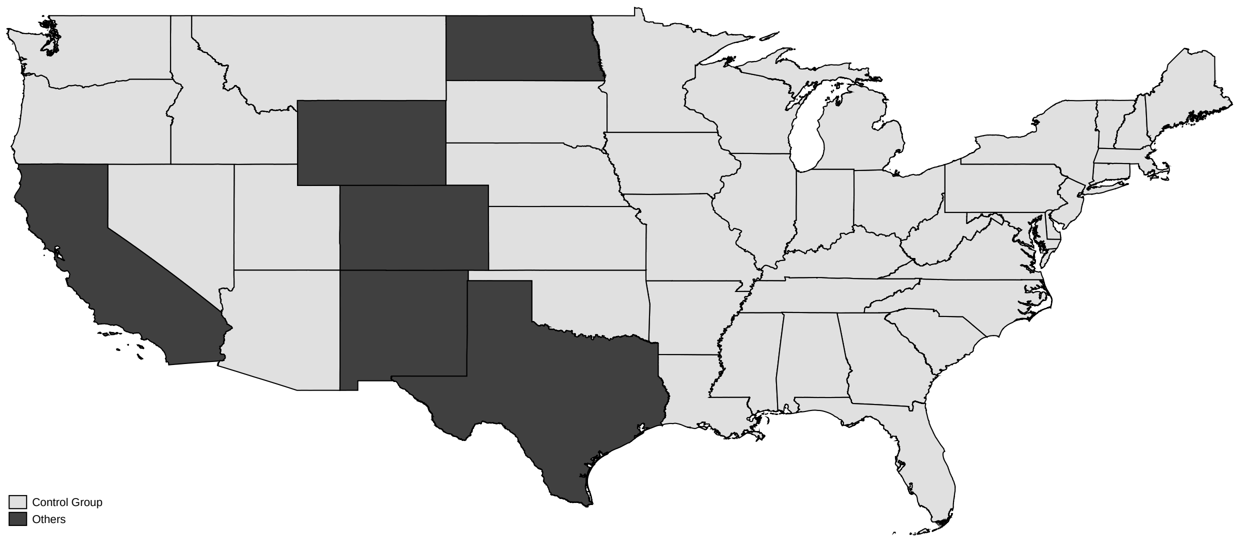


Figure 4.7: Control Group

Formally, the identification based on a differences-in-differences setup rests on four assumptions, the common-trend assumption, the single treatment assumption, the stable unit treatment value assumption (SUTVA) and quasi-randomization. Below, I discuss and validate each assumption point by point in light of the Alaska oil boom.[13]

Common Trend Assumption

First, I assume a parallel trend in the years of schooling in Alaska and the control group in a counterfactual scenario in which the treatment group would not have been exposed to any oil boom. In an effort to validate the common trend assumption, I provide placebo difference-in-differences estimates for the pretreatment period in table 4.2. In particular, prior to the oil boom, I should not detect any major deviations in the years of schooling between Alaska and the control group. In fact, the estimates of the coefficients attached to the interaction of the regional and time dummy variables are insignificant. Complementarily, I visualized trends in educational attainment and expenditures for the pretreatment period in figure 4.3 in the descriptive section above. Namely, in the panel on the left-hand side, I show educational trends for local residents living in the same state 5 years ago while in the panel on the right hand side I display educational trends of residents living even in the same house 5 years ago. Consistently, both panels in figure 4.3 point at parallel pretreatment trends in line with the main identifying assumption. Below, I validate that the main estimates of the effect of the Alaska oil boom on educational investments are insensitive to the composition of the control group conditional on parallel pretreatment trends as well.

[13] Roller and Steinberg (2017) evaluate similar assumptions in light of a school intervention.

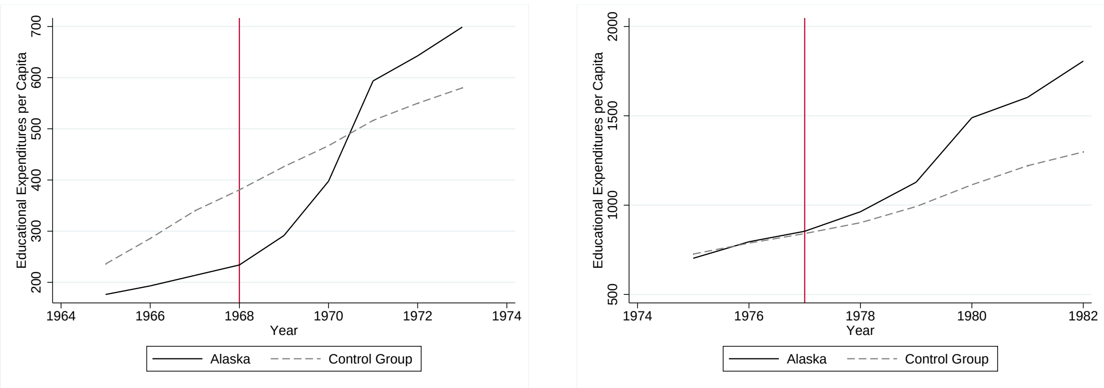
	(1) Schooling DiD	(2) Schooling DiD	(3) Schooling DiD	(4) Schooling DiD	(5) Schooling DiD	(6) Schooling DID	(7) Schooling DiD	(8) Schooling DiD
Alaska	0.243**	0.251**	0.255**	0.258**	0.264***	0.269***	0.274***	0.279***
	(0.103)	(0.103)	(0.103)	(0.102)	(0.102)	(0.102)	(0.102)	(0.102)
Time60	1.788***							
	(0.0288)							
Alaska × Time60	-0.246							
	(0.192)							
Time61		1.801***						
		(0.0292)						
Alaska × Time61		-0.270						
		(0.196)						
Time62			1.814***					
			(0.0297)					
Alaska × Time62			-0.281					
			(0.199)					
Time63				1.823***				
				(0.0302)				
Alaska × Time63				-0.289				
				(0.202)				
Time64					1.832***			
					(0.0308)			
Alaska× Time64					-0.307			
					(0.207)			
Time65						1.842***		
						(0.0314)		
Alaska× Time65						-0.325		
						(0.211)		
Time66							1.851***	
							(0.0320)	
Alaska × Time66							-0.342	
							(0.216)	
Time67								1.860***
								(0.0327)
Alaska × Time67								-0.360
								(0.221)
Constant	11.79***	11.80***	11.81***	11.82***	11.84***	11.85***	11.86***	11.87***
	(0.0119)	(0.0119)	(0.0118)	(0.0118)	(0.0119)	(0.0119)	(0.0119)	(0.0119)
N	5794	5794	5794	5794	5794	5794	5794	5794
R^2	0.473	0.472	0.471	0.467	0.463	0.459	0.454	0.449

Notes: The table displays placebo differences-in-differences estimates for the pretreatment period based on the years of schooling. Treatment Group: Alaska. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.2: Placebo Difference-in-Differences Estimates

As I make use of educational expenditures as an outcome variable as well, figure 4.8 shows parallel pretreatment trends for educational expenditures per capita prior to the oil boom in 1968 (panel on the left-hand side) and prior to the completion of the pipeline along with the implementation of the Alaska Permanent Fund in 1977 (panel on the right hand side). Post of both the oil boom as well as the implementation of the Alaska Permanent Fund, however, educational expenditures per capita deviated between the treatment and control group which indicates that expenditures are responsive to the treatment.

(a) Pretreatment 1969 (b) Pretreatment 1977



Notes: The figures depict trends in educational expenditures per capita in Alaska and control group for the pretreatment periods prior to 1968 and 1977, respectively. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Data source: United States Census Bureau (2015).

Figure 4.8: Common Trend Relative Educational Expenditures

In order to sum up, both figure 4.3 with respect to educational attainment and figure 4.8 with respect to educational expenditures point at roughly parallel pretreatment trends.

Single Treatment Assumption

Second, I postulate that, coinciding with the oil windfall, Alaska and the control group were not exposed to additional shocks or interventions which unequally affected the evolution of years of schooling between Alaska and the control group. Multiple coinciding interventions would make it harder to separate the causal impacts. Hence, multiple shocks or interventions coinciding with each other and undermining the common trend assumption have to be precluded. As the educational trends in Alaska were affected through numerous channels in the course of the oil boom as pointed out in the descriptives, I do not pretend to point identify the effect of the oil boom on human capital development. Rather, I aim at isolating major changes in human capital trends of student cohorts exposed to the oil boom. In fact, the 1960's set the stage for an educational expansion, however, this expansion materialized in both the treatment and control group, and hence does not undermine the identification. Figure 4.3 suggests that the deviation in 1968 is mainly driven by a shift in educational outcome variables in the treatment rather than the control group. In order to disentangle the impact of sequential rather than simultaneous treatments, I separately account for the oil boom starting in 1969, and the implementation of the Alaska Permanent Fund which led to unconditional transfers since 1982.

Stable Unit Treatment Value Assumption

Third, the stable unit treatment value assumption has to be satisfied, which implies that the number of potential outcomes coincides with the number of treatment values. One implication of the stable unit treatment values assumption is the absence of externalities, i.e. spillover effects from treated units on untreated units have to be precluded. In particular, the resource windfall gains attracted numerous people from other US states. In line with the stable unit treatment value assumption (SUTVA), I exclude interstate migrants moving between US states 5 years ahead of the respective census. Complementarily, I examine changes in the years of schooling of inhabitants born in Alaska, who still live in Alaska and did not change the place of residence within the past 5 years in table 4.8 below. This serves as a remedy in order to preclude self-selection effects into the treatment group through migration which might change the composition of the treatment and control group.

Quasi-Randomization

As pointed out previously, since Alaska is not a representative sample of the US population, I identify the average treatment effect on the treated (ATET) rather than the average treatment effect (ATE). Clearly, inhabitants in Alaska might differ from inhabitants in other US states both because the socio-demographic structure is different and the educational systems exhibit further disparities. In fact, US states differ slightly in educational systems, e.g. the compulsory years of schooling. However, as long as compulsory education does not change coinciding with the oil boom, the identification is not undermined. Rather, differences in the school systems are just reflected in different levels in educational attainment rather than changes in these levels. However, controlling for socio-demographic characteristics might lead to a measure closer to ATE. A further implication of a quasi-randomized experiment is the absence of self-selection effects, as pointed above. Self-selection effects might originate from migrants moving into or out of Alaska or the control group. However, I preclude interstate mobility by excluding interstate and international migrants that might change the composition of the treatment or control group.

After validating the identifying assumptions, I make use of the difference-in-differences setup in order to derive estimates for the impact of the Alaska oil boom on educational investments in the following section.

4.3.3 Results

Demand Side

In order to examine the impact of the Alaska oil boom on educational investments, I compare long run changes in the years of schooling in Alaska with the corresponding changes in a control group made up of several US states not exposed to any oil boom in the respective time period. In the first place, I provide separate estimates for the coefficients of the baseline model 4.21 while dispensing with and accounting for further covariates. Dispensing with covariates does not undermine the consistency of the estimates due to the common-trend assumption. However, accounting for covariates might undermine the identification as long as covariates are not exogenous with respect to the treatment. Therefore, I provide separate specifications dispensing with and accounting for covariates. The latter serves as a robustness check as most of the covariates, i.e. income inequality, GDP per Capita and educational expenditures are affected by the oil boom as well.

Before I proceed with the estimates of model 4.21, I display Kernel density estimates for the completed years of schooling above grade 8 in figure 4.9.

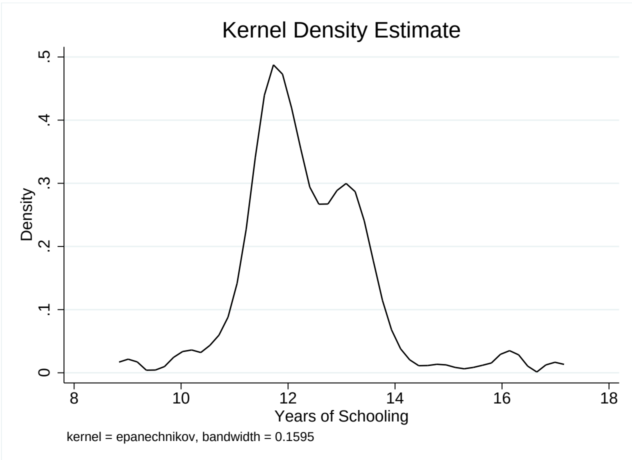


Figure 4.9: Kernel Density Estimate: Years of Schooling

	(1) Schooling DiD	(2) Schooling DiD	(3) Schooling DiD	(4) Schooling DiD	(5) College Ratio DiD	(6) College Ratio DiD	(7) College Ratio DiD	(8) College Ratio DiD
Sample?	All	1940-2000	1950-2000	1960-1980	All	1940-2000	1950-2000	1960-1980
Treat	0.281***	0.206***	0.228***	0.325***	0.0413***	0.0255***	0.0270***	0.0470***
	(0.0241)	(0.0328)	(0.0370)	(0.0408)	(0.00363)	(0.00566)	(0.00677)	(0.00763)
Time69	1.872***	-0.555***	-0.721***	0.330***	0.245***	-0.117***	-0.168***	0.0752***
	(0.0312)	(0.0131)	(0.0159)	(0.00920)	(0.00666)	(0.00267)	(0.00345)	(0.00210)
Treat × Time69	-0.372***	-0.295***	-0.317***	-0.278***	-0.0799***	-0.0636***	-0.0651***	-0.0601***
	(0.0312)	(0.0231)	(0.0216)	(0.0152)	(0.00666)	(0.00430)	(0.00374)	(0.00263)
Graduate Year		0.0611***	0.0731***	0.00124		0.0116***	0.0153***	-0.00124***
		(0.000492)	(0.000773)	(0.00140)		(0.0000899)	(0.000128)	(0.000285)
Constant	11.88***	-106.9***	-130.4***	10.49***	0.201***	-22.44***	-29.62***	2.717***
	(0.0241)	(0.973)	(1.544)	(2.759)	(0.00363)	(0.176)	(0.257)	(0.562)
N	5794	2565	2115	855	5335	2565	2115	855
R^2	0.444	0.592	0.523	0.248	0.355	0.486	0.467	0.206

Notes: The table displays differences-in-differences estimates (DiD) of the Alaska oil boom on educational attainment (years of schooling and college ratio) while dispensing with covariates. Treatment Group: Alaska. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Clustered standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.3: Difference-in-Differences Estimates of the Alaska Oil Boom on Educational Attainment without Covariates

	(1) Schooling DiD	(2) Schooling DiD	(3) Schooling DiD	(4) Schooling DiD	(5) College Ratio DiD	(6) College Ratio DiD	(7) College Ratio DiD	(8) College Ratio DiD
Alaska	0.368***	-0.00712	-0.0669	-0.161*	0.0436***	-0.0334**	-0.0477**	-0.0450***
	(0.0372)	(0.0607)	(0.0863)	(0.0821)	(0.00795)	(0.0142)	(0.0199)	(0.0165)
Time69	-0.323***	-0.275***	-0.307***	-0.0751**	-0.120***	-0.0877***	-0.0959***	-0.0283***
	(0.0153)	(0.0396)	(0.0516)	(0.0292)	(0.00384)	(0.00964)	(0.0114)	(0.00664)
Treat × Time69	-0.135***	-0.295***	-0.286***	-0.590***	-0.0700***	-0.0760***	-0.0729***	-0.158***
	(0.0153)	(0.0218)	(0.0261)	(0.0685)	(0.00383)	(0.00390)	(0.00508)	(0.0145)
Male	0.193***	0.124***	0.124***	0.0934***	-0.00282***	-0.00100*	-0.00102*	-0.00102*
	(0.00839)	(0.00929)	(0.00957)	(0.00988)	(0.000269)	(0.000549)	(0.000577)	(0.000511)
State Income per Capita		0.250***	0.335***	0.722***		0.0589***	0.0778***	0.157***
		(0.0335)	(0.0797)	(0.130)		(0.00761)	(0.0188)	(0.0275)
Gini			-1.777	-0.0551			-0.391	0.0172
			(1.319)	(0.767)			(0.328)	(0.198)
Teacher-Student-Ratio				24.90***				5.676***
				(4.830)				(1.063)
Educational Expenditures				-0.0155				-0.00252
				(0.0229)				(0.00489)
Graduate Year				-0.0638***				-0.0139***
				(0.0119)				(0.00259)
Constant	12.45***	13.00***	13.71***	136.6***	0.264***	0.325***	0.482***	27.29***
	(0.0350)	(0.0478)	(0.537)	(23.13)	(0.00806)	(0.00894)	(0.133)	(5.022)
N	2813019	668372	627212	580422	2941817	240388	225784	205120
R^2	0.00796	0.00396	0.00464	0.0104	0.116	0.119	0.140	0.302

Notes: The table reports differences-in-differences estimates (DiD) of the Alaska oil boom on educational attainment (years of schooling and college ratio) while accounting for extended covariates. Treatment Group: Alaska. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Total expenditures as well as the average income are put in log-terms. Clustered standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.4: Difference-in-Differences Estimates of the Alaska Oil Boom on Educational Attainment with Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Schooling	Schooling	Schooling	Schooling	College Ratio	College Ratio	College Ratio	College Ratio
	DiD	DiD	DiD	DiD	DiD	DiD	DiD	DiD
Sample?	1964-1972	1965-1974	1966-1976	1967-1978	1964-1972	1965-1974	1966-1976	1967-1978
Alaska	0.306***	0.286***	0.262***	0.191***	0.0483***	0.0392***	0.0320***	0.0140*
	(0.0430)	(0.0433)	(0.0432)	(0.0418)	(0.00832)	(0.00838)	(0.00837)	(0.00813)
Time69	0.0978***	0.0292*	0.0711***	0.226***	0.0249***	0.00563	0.0119***	0.0472***
	(0.0125)	(0.0157)	(0.0115)	(0.0111)	(0.00326)	(0.00353)	(0.00300)	(0.00277)
Alaska × Time69	-0.0875***	-0.204***	-0.216***	-0.155***	-0.0208***	-0.0425***	-0.0467***	-0.0292***
	(0.00823)	(0.0113)	(0.0144)	(0.0155)	(0.00149)	(0.00193)	(0.00272)	(0.00311)
Graduate Year	0.0327***	0.0576***	0.0514***	0.0144***	0.00563***	0.0125***	0.0111***	0.00156***
	(0.00386)	(0.00508)	(0.00405)	(0.00262)	(0.000902)	(0.00101)	(0.000906)	(0.000548)
Constant	-51.22***	-100.3***	-88.01***	-15.28***	-10.78***	-24.22***	-21.58***	-2.784**
	(7.606)	(10.01)	(7.976)	(5.168)	(1.776)	(1.983)	(1.785)	(1.081)
N	315	360	405	450	315	360	405	450
R^2	0.152	0.223	0.253	0.107	0.154	0.234	0.250	0.0750

Notes: The table reports differences-in-differences estimates (DiD) of the Alaska oil boom on educational attainment (years of schooling and college ratio). Treatment Group: Alaska. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. All US states which were not exposed to an oil boom in the respective period. The sample is made up of students which were born and still live in the respective state. Robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.5: Difference-in-Differences Estimates of the Alaska Oil Boom on Educational Attainment for Different Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Schooling	Schooling	Schooling	Schooling	College Ratio	College Ratio	College Ratio	College Ratio
	DiD	DiD	DiD	DiD	DiD	DiD	DiD	DiD
Sample?	All	1978-1995	1979-1990	1980-1986	All	1978-1995	1979-1990	1980-1986
Alaska	0.291***	0.0900**	0.0654*	0.0383	0.0379***	-0.00388	-0.00812	-0.0154*
	(0.0240)	(0.0363)	(0.0360)	(0.0366)	(0.00376)	(0.00804)	(0.00824)	(0.00847)
Time82	2.144***	-0.169***	0.809***	0.365***	0.329***	-0.0333***	0.215***	0.0960***
	(0.0290)	(0.0268)	(0.0231)	(0.0205)	(0.00614)	(0.00592)	(0.00621)	(0.00578)
Alaska × Time82	-0.506***	-0.352***	-0.328***	-0.211***	-0.0998***	-0.0741***	-0.0784***	-0.0611***
	(0.0290)	(0.0157)	(0.0163)	(0.0168)	(0.00614)	(0.00354)	(0.00365)	(0.00424)
Graduate Year		0.106***	-0.0928***	0.0586***		0.0256***	-0.0235***	0.0198***
		(0.00281)	(0.00295)	(0.00656)		(0.000468)	(0.000723)	(0.00165)
Constant	12.05***	-196.1***	197.0***	-102.9***	0.218***	-50.31***	46.91***	-38.97***
	(0.0240)	(5.581)	(5.833)	(13.00)	(0.00376)	(0.931)	(1.431)	(3.279)
N	5794	720	450	225	5335	720	450	225
R^2	0.354	0.346	0.337	0.460	0.396	0.321	0.404	0.537

Notes: The table reports differences-in-differences estimates (DiD) of the implementation of the Alaska Permanent Fund on educational attainment (years of schooling and college ratio) while dispensing with covariates. Treatment Group: Alaska. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Clustered standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.6: Difference-in-Differences Estimates of the Alaska Oil Boom on Educational Attainment with Adapted Timing

	(1) Schooling DiD	(2) Schooling DiD	(3) Schooling DiD	(4) Schooling DiD	(5) College Ratio DiD	(6) College Ratio DiD	(7) College Ratio DiD	(8) College Ratio DiD
Sample?	All	1978-1995	1980-1990	1980-1986	All	1978-1995	1980-1990	1980-1986
Alaska	0.320***	0.0140	-0.615***	-0.553***	0.0166*	-0.00774	-0.148***	-0.138***
	(0.0373)	(0.0601)	(0.0861)	(0.112)	(0.00836)	(0.0155)	(0.0169)	(0.0214)
Time82	-0.817***	0.340***	0.507***	0.511***	-0.156***	0.114***	0.145***	0.145***
	(0.0175)	(0.0361)	(0.0269)	(0.0281)	(0.00468)	(0.00959)	(0.00643)	(0.00661)
Alaska × Time82	-0.299***	-0.304***	-0.440***	-0.415***	-0.0613***	-0.0830***	-0.129***	-0.124***
	(0.0176)	(0.0194)	(0.0548)	(0.0579)	(0.00467)	(0.00422)	(0.0137)	(0.0146)
Male	0.186***	0.124***	0.0940***	0.0939***	-0.00382***	-0.00104*	-0.00168***	-0.00172***
	(0.00826)	(0.00925)	(0.00982)	(0.00982)	(0.000322)	(0.000581)	(0.000431)	(0.000436)
GDP per Capita		-0.0345	0.750***	0.720***		-0.0388***	0.156***	0.151***
		(0.0344)	(0.115)	(0.117)		(0.00830)	(0.0233)	(0.0237)
Gini			-1.002*	-1.336**			-0.232	-0.288*
			(0.572)	(0.631)			(0.157)	(0.168)
Teacher-Student-Ratio			24.14***	24.28***			5.461***	5.496***
			(4.888)	(4.864)			(1.085)	(1.090)
Graduate Year			-0.0878***	-0.0828***			-0.0206***	-0.0198***
			(0.00897)	(0.0102)			(0.00188)	(0.00211)
Educational Expenditures				-0.0210				-0.00367
				(0.0212)				(0.00444)
Constant	12.63***	13.30***	184.3***	174.7***	0.291***	0.433***	40.58***	38.99***
	(0.0354)	(0.0695)	(17.37)	(19.87)	(0.00851)	(0.0158)	(3.626)	(4.087)
N	2813019	668372	580422	580422	2941817	240388	205120	205120
R^2	0.0403	0.00447	0.0145	0.0146	0.271	0.162	0.505	0.507

Notes: The table reports differences-in-differences estimates (DiD) of the implementation of the Alaska Permanent Fund payments on educational attainment (years of schooling and college ratio) while dispensing with covariates. Treatment Group: Alaska. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Clustered standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.7: Difference-in-Differences Estimates of the Alaska Oil Boom on Educational Attainment with Adapted Timing and Covariates

Table 4.3 reports difference-in-differences estimates of the Alaska Oil Boom on the average years of schooling while dispensing with covariates. The specifications reported in columns (1) - (4) refer to the years of schooling, while specifications reported in columns (5) - (8) account for the share of graduates who completed at least one year of college by graduation year. As the results should be insensitive to slight shifts in the sample, I report estimates for different sample periods as well, i.e. the estimates shown in columns (2) and (6) are based on a limited sample period spanning the years from 1940 to 2000, the specifications in columns (3) and (7) refer to the sample period from 1950 to 2000 and the specifications in columns (4) and (8) to the sample period from 1960 to 1980. Conspicuously and consistently, the oil boom appears to dampen educational investments through all specifications according to the coefficient attached to the interaction of the treatment and the time dummy variable. With respect to the years of schooling, the decline in educational attainment compared to the control group ranges between 0.278 and 0.372, while with respect to the college ratio the decline ranges between 0.0601 and 0.0799, each significant at the 1 percent level. Apparently, even in the long sample ranging until 2000, resource booms unleash negative effects on educational investments. This might be due to the Alaska Permanent Fund which smoothes unconditional transfers as a consequence of the resource boom. This result is qualitatively in line with the prediction of Gylfason (2001) suggesting a crowding out of human capital as a consequence of resource booms.

Complementarily, I derive difference-in-differences estimates while accounting for covariates in table 4.4 as a robustness check. Again, table 4.4 reports the effect of the oil boom on educational investments in terms of the outcome variables years of schooling (columns (1) - (4)) and the college ratio (columns (5)-(8)). In line with the previous results, according to the estimates in table 4.4, the oil boom set the stage for a shortfall of educational investments compared to the control group which was not exposed to any oil boom. The result consistently holds with respect to both educational indicators, the average years of schooling as well as the share of college graduates by graduation year.

Regarding the former, the decline in the years of schooling post of the oil boom ranges between 0.135 and 0.590, while with respect to the latter the decline ranges between 0.0700 and 0.158.

Apparently, the main coefficients remain qualitatively unchanged when controlling for individual and state specific covariates. In general, I include covariates for the sake of efficiency, however, as long as covariates are affected by the treatment, accounting for these covariates might contaminate the identification. As pointed out in the descriptive section, state specific covariates, i.e. state income per capita, educational expenditures per capita as well as income inequality might be affected by the oil boom. Controlling for these covariates might therefore contaminate the identification of causal effects. Hence, I explicitly separated setups accounting for covariates (table 4.4) and dispensing with covariates (table 4.3). Omitted variables do not affect the consistency of the estimates due to the common-trend assumption. The supposition that outcome variables might have a unit root, does not impinge on the consistency of the estimates either, as I rely on clustered standard errors as proposed by Bertrand et al. (2002).

As pointed out above, conditional on parallel pretreatment trends, the estimates should be insensitive to shifts in the composition of the control group. In order to validate this main assumption, I provide several placebo tests in tables 4.13 to 4.16 in the appendix. In particular, I run the same procedures as above with each US state separately serving as a control group. Conspicuously, the results are mainly in line with the baseline results. Namely, the oil boom set the stage for a retardation of human capital development. Hence, the baseline results are not driven by the composition of the control group conditional on common pretreatment trends. Complementarily, I provide difference-in-differences estimates for the effect of the tax reform, i.e. the abolition of all state income taxes, on income inequality measured in Gini coefficients in table 4.12. The distributional effects of the tax reform are crucial as they reflect transient or even structural changes in the returns to skills. Apparently, the abrogation of progressive taxes in 1980 promoted a tremendous increase in income inequality in terms of Gini coefficients in line with the descriptives provided in the panel on the right hand side of figure 4.4. In light of the distributional effects, the educational effects of the oil boom are even more astonishing. Namely, even in light of a fierce but transient increase in the returns to skills, human capital investments saw a deceleration.

I order to ascertain whether the tax reform precludes a shortfall of educational investments in response to the oil boom, I adapt the timing of the baseline specification. Thus far, I exclusively referred to the oil boom in 1968 which set the stage for an enormous income windfall. However, the payments of the Alaska Permanent Fund started in 1982 directly after the tax reform. Hence, in table 4.6, I test for the shift in educational attainment post of the implementation of the Alaska Permanent Fund payments in 1982. Again, the specifications differ with respect to the underlying sample, i.e. the specifications in columns (1) and (5) rely on the whole sample, the specifications in columns (2) and (6) are based on graduation years between 1978 - 1995, the specification in columns (3) and (7) refer to graduation years between 1979 and 1990 and the specifications in columns (4) and (8) rely on students graduating between 1980 and 1986. In line with the previous results, the income windfalls imposed in 1982 corresponded with a shortfall in educational investments compared to the control group through all underlying samples. This even holds when I account for compounding reforms in the sample 1978 - 1995 comprising the tax reform in 1980 and the payments of the Alaska Permanent Fund starting in 1982. Hence, the increase in the returns to skills due to the tax reform 1980 does not compensate for the shortfall of educational investments in response to the income windfall in 1982. The robustness checks in table 4.7 which are augmented by covariates are qualitatively in line with this result.

Thus far, I excluded migrants changing the state of residence 5 years before the respective census, in order to preclude self-selection effects into the treatment group. However, as I retraced back the year of graduation based on the individual years of schooling, the school starting age and the individual age, excluding migration patterns within 5 years before the decennial census might not fully control for migration patterns. In order to test whether the baseline results are driven by changes in the composition of the treatment or control group, I additionally rely on local residents which were born and still live in the respective state. In fact this might exclude residents which completed the education in one state but continued working in another state. However, as the theoretical predictions particularly pointed at educational responses of students which qualify for resource windfall gains, the latter problem becomes less severe. Table 4.8 reports difference-in-differences estimates for the effect of the oil boom on educational attainment of local residents which were born and still live in the respective state while participating in the census. In essence, the results consistently point at a shortfall of educational investments compared to the control group post of the oil boom. This shortfall is qualitatively insensitive to slight shifts in the sample and in line with the baseline specifications above. Comparing the estimates in table 4.8 for individuals which were born and still live in Alaska with the same estimates in table 4.5 for individuals which did not change the state of residence within 5 years shows that the effect for the former is even stronger for the respective time periods.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Schooling	Schooling	Schooling	Schooling	College Ratio	College Ratio	College Ratio	College Ratio
	DiD	DiD	DiD	DiD	DiD	DiD	DiD	DiD
Sample?	1964-1972	1965-1974	1966-1976	1967-1978	1964-1972	1965-1974	1966-1976	1967-1978
Alaska	-0.569***	-0.526***	-0.429***	-0.499***	-0.119***	-0.110***	-0.0880***	-0.131***
	(0.0473)	(0.0468)	(0.0457)	(0.0446)	(0.00929)	(0.00909)	(0.00894)	(0.00910)
Time69	0.219***	0.0585***	0.0817***	0.232***	0.0539***	0.0136***	0.0164***	0.0499***
	(0.0232)	(0.0187)	(0.0150)	(0.0163)	(0.00457)	(0.00386)	(0.00338)	(0.00450)
Alaska × Time69	-0.210***	-0.258***	-0.341***	-0.240***	-0.0508***	-0.0770***	-0.0893***	-0.0437***
	(0.0145)	(0.0135)	(0.0152)	(0.0199)	(0.00321)	(0.00301)	(0.00333)	(0.00527)
Graduate Year	-0.0383***	0.0254***	0.0404***	0.0143***	-0.00950***	0.00667***	0.00956***	0.00276***
	(0.00736)	(0.00465)	(0.00292)	(0.00275)	(0.00148)	(0.000987)	(0.000637)	(0.000621)
Constant	88.40***	-37.01***	-66.48***	-15.21***	18.96***	-12.85***	-18.54***	-5.183***
	(14.49)	(9.165)	(5.754)	(5.420)	(2.906)	(1.944)	(1.254)	(1.226)
N	322	368	414	460	322	368	414	460
R^2	0.112	0.155	0.246	0.198	0.133	0.203	0.278	0.211

Notes: The table reports differences-in-differences estimates (DiD) of the Alaska oil boom on educational attainment (years of schooling and college ratio).Treatment Group: Alaska. Control Group: All US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. All US states which were not exposed to an oil boom in the respective period. The sample is made up of students which were born and still live in the respective state. Robust standard errors in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.8: Difference-in-Differences Estimates of the Alaska Oil Boom on Educational Attainment among local Residents

Rather than examining the educational effects of the oil boom on the demand side, the following section sheds light on the supply side.

Supply Side

Thus far, I exclusively referred to years of schooling on the demand side, though controlling for fiscal and educational expenditures on the supply side. In order to ascertain the change in educational expenditures as a consequence of the oil boom, I rely on further difference-in-differences estimates of the Alaska Oil boom on educational expenditures per capita. In a first step, figure 4.10 displays Kernel density estimates of educational expenditures per capita approximating a Gaussian normal distribution.

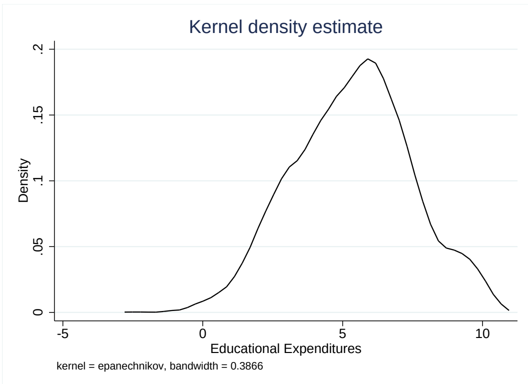


Figure 4.10: Kernel Density Estimate: Educational Expenditures

Again, in order to isolate the impact of the oil boom on educational expenditures, I have to rely on a common-trend assumption. However, in light of figure 4.6 pre-treatment trends are parallel exclusively for educational expenditures per capita. Hence, table 4.9 depicts the short run as well as the long run effects of the Alaska Oil Boom on educational expenditures per capita. The short run effects only capture changes in educational expenditures 4 to 7 years post of the oil boom in 1969 in columns (2) - (3) and post oft the completion of the pipeline 1977 which induced a fierce increase in fiscal capacity in columns (5) - (6), respectively. Complementarily, the long run effects are reported in column (1) with respect to the Alaska Oil Boom and in column (4) with respect to the completion of the pipeline.

Complementarily, the specifications in table 4.10 rely on the same structure while accounting for covariates. With respect to covariates, Hanushek (1986) as well as Hanushek and Rivkin (1996) specifically relied on the US between 1890 and 1990 in order to explain the rise in educational expenditures. The authors decompose the time series 1890-1990 into three main transitions. Namely, *The Great Expansion* spanning the period from 1890 to 1940, the *Baby Boom* between 1940 and 1970 and the *The Great Intensification* spanning the period between 1970 and 1990. The "decomposition of the spending growth shows that it resulted from a combination of falling pupil-staff-ratios, increasing real wages to teachers, and rising expenditures out of the classroom." (Hanushek and Rivkin (1996), p. 35) In addition, Morgan et al. (2001) highlight the importance of student enrollment in explaining, among other educational outcomes, educational expenditures. Moreover, they point at costs arising from employees in the educational sector as a major contributor to educational expenditures.[14] In light of the literature, I control for the teacher-student ratio, the state income per capita and Gini coefficients. Further, I control for the population size and interest payments. Again, as state income per capita and Gini coefficients are endogenous with respect to the treatment, the estimates controlling for covariates exclusively serve as a robustness check.

In line with the descriptives in figure 4.6, the estimates in tables 4.9 and 4.10 show a transient, significant increase in educational expenditures post of the oil boom and a structural decline in educational expenditures in the long run. This result is reflected in figure 4.6 as well. Contrasting the results on the supply and demand side of educational attainment, it becomes apparent that post of the oil boom, further fiscal capacity was in fact spilled into educational expenditures. However, further educational expendi-

[14]Fernandez and Rogerson (1997) conclude that trends in educational expenditures correspond with trends in per capita income while the number of students appears to dampen educational expenditures per capita. In addition, Busemeyer (2007) specified an econometric model which mainly draws upon the GDP per capita, tertiary enrollment, tax revenues and the share of conservatives in the parliament as covariates in a cross country study.

tures on the supply side corresponded with a decline in the years of schooling on the demand side. In particular, in light of the descriptive statistics, the decline in educational investments precedes the decrease in educational expenditures. This suggests, that the decline in educational expenditures is at least partially due to the decline in the average years of schooling compared to the control group. Alternatively, it might be possible that the general fund to which oil companies contributed partially crowded out educational expenditures.

	(1)	(2)	(3)	(4)	(5)	(6)
	Expenditures	Expenditures	Expenditures	Expenditures	Expenditures	Expenditures
	DiD	DiD	DiD	DiD	DiD	DiD
Sample?	All	1963-1973	1965-1976	All	1963-1973	1965-1976
Alaska	1.354***	0.860***	0.755***	1.491***	1.127***	1.071***
	(0.125)	(0.113)	(0.129)	(0.183)	(0.111)	(0.140)
Time69	2.786***	0.689***	0.640***			
	(0.0688)	(0.142)	(0.147)			
Alaska × Time69	-0.399**	0.246	0.350*			
	(0.161)	(0.214)	(0.197)			
Time77				2.619***	0.438***	0.396**
				(0.0669)	(0.146)	(0.158)
Alaska × Time77				-0.578***	0.172	0.266
				(0.194)	(0.184)	(0.192)
Constant	3.581***	4.417***	4.559***	4.070***	5.480***	5.590***
	(0.0550)	(0.0971)	(0.118)	(0.0499)	(0.103)	(0.132)
N	2636	473	473	2636	430	430
R^2	0.397	0.0591	0.0509	0.378	0.0368	0.0317

Notes: The table displays differences-in-differences estimates of the Alaska oil boom on educational expenditures per capita. Treatment Group: Alaska. Control Group: US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Robust standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.9: Difference-in-Differences Estimates Educational Expenditures without Covariates

	(1) Expenditures DiD	(2) Expenditures DiD	(3) Expenditures DiD	(4) Expenditures DiD	(5) Expenditures DiD	(6) Expenditures DiD
Sample?	All	1963-1973	1963-1976	All	1963-1973	1963-1976
Alaska	-1.140***	-1.142***	-1.105***	-1.259***	-1.165***	-1.239***
	(0.0918)	(0.117)	(0.115)	(0.0839)	(0.113)	(0.129)
Time69	0.241***	0.156**	0.185***			
	(0.0616)	(0.0687)	(0.0669)			
Alaska × Time69	-0.144	0.121	0.00161			
	(0.0923)	(0.111)	(0.113)			
Time77				-0.184***	0.0786	0.0304
				(0.0708)	(0.0830)	(0.0876)
Alaska × Time77				-0.277***	0.236*	0.333***
				(0.105)	(0.128)	(0.122)
Teacher - Pupils - Ratio	-29.02***	-24.08***	-25.07***	-27.68***	-38.56***	-40.08***
	(3.682)	(7.129)	(6.676)	(3.641)	(6.534)	(6.037)
Population	-1.070***	-1.042***	-1.038***	-1.063***	-1.080***	-1.113***
	(0.0212)	(0.0292)	(0.0273)	(0.0209)	(0.0357)	(0.0376)
GDP per Capita	0.277***	0.406***	0.381***	0.471***	0.0893	0.0152
	(0.0576)	(0.103)	(0.0913)	(0.0641)	(0.112)	(0.127)
Interest	0.610***	0.607***	0.607***	0.618***	0.600***	0.607***
	(0.0143)	(0.0203)	(0.0185)	(0.0146)	(0.0234)	(0.0249)
Gini	-0.634	-0.0386	0.788	-1.023	1.723	1.193
	(0.771)	(1.558)	(1.452)	(0.748)	(2.121)	(1.839)
Constant	16.00***	14.95***	14.58***	15.82***	16.29***	17.26***
	(0.485)	(1.067)	(0.964)	(0.510)	(1.315)	(1.166)
N	1092	378	462	1092	420	420
R^2	0.845	0.869	0.865	0.845	0.820	0.807

Notes: The table displays differences-in-differences estimates of the Alaska oil boom on educational expenditures per capita under consideration of covariates. The time dummy variable is 1 post of the respective year and 0 otherwise. The treatment dummy variable is 1 for Alaska and 0 for the control group. Treatment Group: Alaska. Control Group: US states besides of Alaska, North Dakota, Texas, California, New Mexico, Colorado and Wyoming. Robust standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.10: Difference-in-Differences Estimates Educational Expenditures without Covariates

In the following section, I check the sensitivity of the results with respect to an external and synthetic control group and I derive distributional effects in the course of a changes-in-changes procedure.

4.4 Robustness Checks

4.4.1 Control Group

In the previous sections I based my analysis on an internal control group within the US composed of states which were not exposed to any oil boom in the respective period. Further, I verified that, conditional on parallel pretreatment trends, the identification is insensitive to an internal shift in the control group. However, as the treatment group is segregated from the US directly adjacent to the Canadian boarder, it is pending to show that the identification is insensitive to an external shift in the control group as well. The latter is particularly relevant due to the segregation of Alaska in North America pointing to Canada as a natural control group.

In the following section, I test whether the results are in fact driven by the specific composition of the control group within the US. This is particularly relevant in light of the fact that Canada and Alaska are much more similar in terms of the geographic and population structures. Even though the identification is based on the assumption of a common trend in the outcome variable between the treatment and control group in a counterfactual scenario without any oil boom, and hence explicitly allows for disparities between the treatment and control group, the estimates might be biased if the effects of the intervention are unequally mediated through certain covariates (confoundedness). For instance, coinciding with the resource boom in the 1960's, an educational expansion might be mediated through population density. Namely, in a less densely populated state, an educational expansion might materialize with retardation due to the lack in educational institutions. However, as pointed out previously, the University of Alaska is spread throughout the entire state serving students throughout 10 local campuses and 3 urban campuses in Fairbanks and Juneau. Hence, the educational institutions do not serve as an impediment for human capital development.

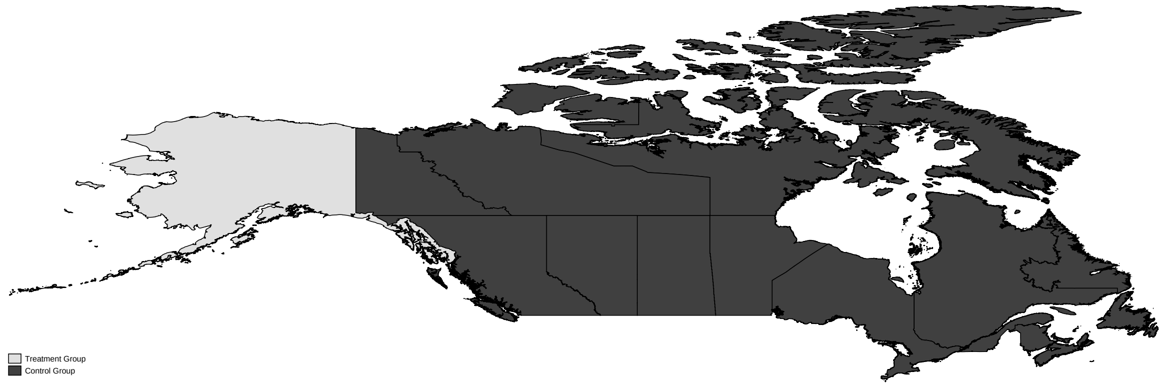


Figure 4.11: Map Canada

In order to test the robustness of the results, I formulate alternative control groups composed of each Canadian States in light of oil reserves in several Canadian provinces. The alternative control groups are displayed in figure 4.11. Again, relying on parallel pretreatment trends, the results depicted in table 4.11 show that the Alaska oil boom elicited a deceleration of human capital development consistently for each Canadian state serving as a separate control group. Consistently with the previous section, the analysis excludes migrants moving in or out of Alaska within 5 previous years, in order to preclude self-selection and sample selection problems. Further, the international educational indicator exclusively differentiates between primary, secondary and college education and is less precise compared to the estimates in the previous section. Hence, I can conclude that the baseline results are not driven by the specific composition of the internal control group. Rather, the results are insensitive to the formulation of an external control group as well.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Education	Education	Education	Education	Education	Education	Education	Education	Education	Education
	DiD	DiD	DiD	DiD	DiD	DiD	DiD	DiD	DiD	DiD
Control Group ?	Newfoundland	Prince Edward	Nova Scotia	New Brunswick	Quebec	Ontario	Manitoba	Saskatchewan	Alberta	British Columbia
Treat	4.237***	2.961***	3.176***	3.573***	3.124***	2.520***	3.362***	3.463***	2.499***	2.051***
	(0.0428)	(0.0709)	(0.0380)	(0.0402)	(0.0293)	(0.0288)	(0.0365)	(0.0372)	(0.0329)	(0.0312)
Time69	-0.0108	-0.906***	-0.425***	-0.256***	0.0238*	-0.592***	-0.579***	-0.756***	-0.838***	-0.922***
	(0.0472)	(0.0879)	(0.0389)	(0.0426)	(0.0143)	(0.0120)	(0.0351)	(0.0365)	(0.0240)	(0.0209)
Treat × Time69	-2.685***	-1.789***	-2.271***	-2.439***	-2.720***	-2.104***	-2.116***	-1.940***	-1.858***	-1.773***
	(0.0586)	(0.0945)	(0.0521)	(0.0549)	(0.0375)	(0.0367)	(0.0493)	(0.0504)	(0.0422)	(0.0405)
Constant	6.104***	7.380***	7.165***	6.768***	7.217***	7.821***	6.979***	6.878***	7.842***	8.290***
	(0.0327)	(0.0653)	(0.0262)	(0.0292)	(0.00985)	(0.00836)	(0.0240)	(0.0250)	(0.0178)	(0.0145)
N	146971	116066	175639	161024	685777	953618	192424	183233	316336	378515
R^2	0.0661	0.0489	0.0423	0.0511	0.0112	0.00909	0.0479	0.0559	0.0245	0.0184

Notes: The table displays differences-in-differences estimates of the Alaska oil boom on educational attainment based on an external control group. Treatment Group: Alaska. Control Group: Respective Canadian state. Robust standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.11: Difference-in-Differences Sensitivity Check

4.4.2 Synthetic Control Method

Thus far, I constructed the control group based on a sample of untreated states, a composition which was legitimized by parallel pretreatment trends. In addition, I provided several placebo-tests in an effort to validate the assumption that conditional on parallel pretreatment trends, the estimates are insensitive to changes in the composition of the control group. However, "even if aggregate data are employed, there remains uncertainty about the ability of the control group to reproduce the counterfactual outcome trajectory that the affected units would have experienced in the absence of the intervention or event of interest." (Abadie et al. (2010), p. 493) A recent approach proposed by Abadie and Gardeazabal (2003), Abadie et al. (2010) and Abadie et al. (2015) suggests a synthetic control group which is constructed based on a weighted combination of control units.

Formally, I was interested in the ATE defined as the difference between the potential outcome of the treated and the potential outcome of the untreated:

$$\pi = Y_{1,t}^{I} - Y_{1,t}^{N} \tag{4.22}$$

The synthetic control method is based on a weighted combination of untreated units. If weights are denoted as w_j, the treatment effect can be estimated as follows:

$$\hat{\pi} = Y_{1,t}^{I} - \sum_{j=2}^{T+1} w_j Y_{jt} \tag{4.23}$$

with $w_2 + ... + w_{J+1} = 1$. Empirically, I make use of the entire pretreatment period in order to derive a weighted composition of the control group. In the panel on the left I build a synthetic control group while educational attainment is exclusively predicted by state GDP per capita, while in the panel on the right hand side a synthetic control group is constructed based on a prediction of educational attainment by the state GDP per capita, state Gini coefficients, educational expenditures and the teacher-students ratio.

(a) Synthetic Control based on log(GDP per capita)

(b) Synthetic Control based on log(GDP per capita), EduExpenditures, Gini coefficients

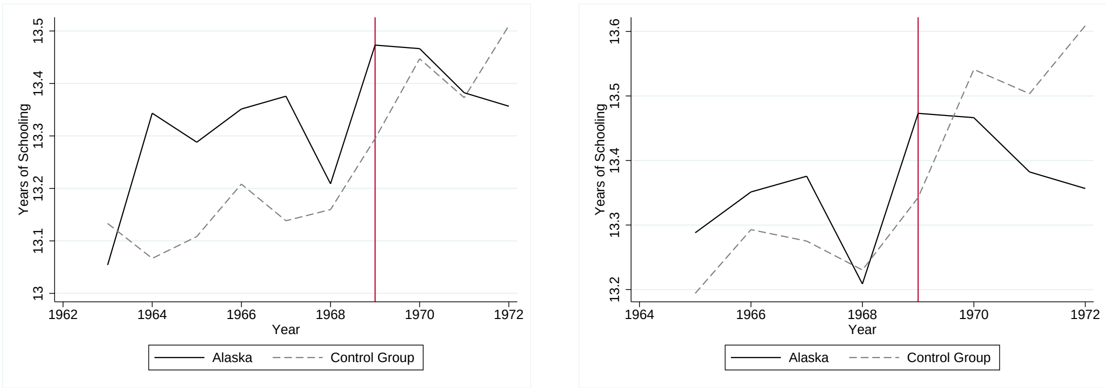


Figure 4.12: Synthetic Control Group

Contrasting figure 4.12 and figure 4.3 suggests that even in light of a synthetic control group, average educational achievement in the treatment group fell short of educational attainment in the control group post of the oil boom, in line with the previous findings.

4.4.3 Changes-in-Changes

In the previous sections, I estimated the average treatment effect on the treated. However, in order to examine whether the result is actually driven by a decline in educational attainment in the lower or the upper tail of the distribution, I complement my difference-in-differences setup with a changes-in-changes model proposed by Athey and Imbens (2006).[15] The latter compares the evolution of educational attainment in the treatment group with the evolution of educational attainment in the control group for each percentile of the educational distribution. While making use of the notation set out in the previous section, the effect at the p^{th} percentile is defined as the difference between the p^{th} percentile of the potential distributional outcome of the treated and

[15] Roller and Steinberg (2017) ascertain the distributional effects in the course of preponed school tracking in Germany.

the potential distributional outcome of the untreated:

$$\Delta_{g,t}^{CiC}(p) = F_{Y_{g,t}^{I}}^{-1}(p) - F_{Y_{g,t}^{N}}^{-1}(p) \tag{4.24}$$

Unlike the potential distributional outcome of the treated, $F_{Y_{1,1}^{I}}$, the potential distributional untreated outcome , $F_{Y_{1,1}^{N}}$, is unobservable. According to the changes-in-changes model, I can estimate the counterfactual distribution in the following way:

$$\Delta_{1,1}^{CiC}(p) = F_{Y_{1,1}^{I}}^{-1}(p) - F_{Y_{0,1}^{I}}^{-1}\left(F_{Y_{0,0}^{I}}\left(F_{Y_{1,0}^{N}}^{-1}(p)\right)\right) \tag{4.25}$$

After determining the counterfactual distribution, I can derive quantile treatment effects with respect to the oil boom in the 1960's (panel on the left hand side of figure 4.13) and the implementation of the Alaska Permanent Fund payments in 1982 (panel on the right hand side of figure 4.13) below. Conspicuously, the decline in educational attainment after the implementation of the Alaska Permanent Fund payments in 1982 disproportionately affected students between the 4th and 8th percentile of educational attainment, while the decline with respect to the initial oil boom is much more moderate and equally distributed.

(a) Changes-in-Changes 1969 (b) Changes-in-Changes 1982

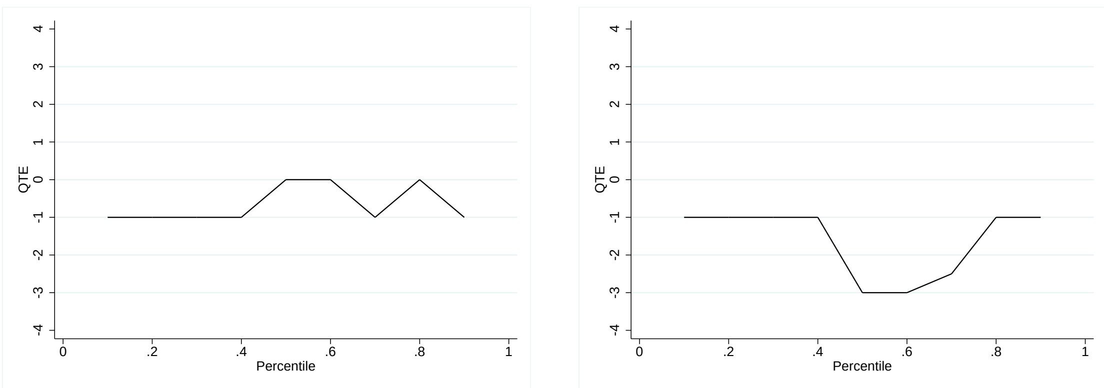


Figure 4.13: Changes-in-Changes Estimates

4.5 Conclusion

Introductorily, I basically raised three questions: How can the relationship between natural resource shocks and human capital responses be theoretically explained? Do resource booms give rise to a crowding out or a crowding in effect with respect to human capital formation? Which policy recommendations can be invoked for resource booming economies? In order to tackle these questions, I combined a theoretical analysis with an empirical investigation.

Theoretically, I showed that a resource boom translating into a Dutch disease might be detrimental to educational investments measured in the years of schooling. A Dutch disease crowds out the tradable sector which is relatively skilled labor intensive in favor of the non-tradable sector which is relatively unskilled labor intensive. In light of lower returns to skills due to the Dutch disease, individuals might invest less in education at the present. Moreover, unconditional resource transfers might lower labor supply, and hence the returns to skills as well. Conversely, windfall gains feeding into additional educational expenditures might be conducive to human capital development as long as educational costs are reduced.

Empirically, I set out a differences-in-differences framework while making use of the the Alaska oil boom as an exogenous variation. In line with the theoretical predictions, the income windfall led to a shortfall in educational attainment compared to a control group composed of several US states. For instance, between 1969 and 1980 graduates from Alaska experienced a shortfall in the years of schooling compared to the control group of 0.278. These results are robust to internal as well as external shifts in the composition of the control group.

In line with Gylfason (2001), this chapter showed that income windfalls might lead to educational shortfalls. In order to turn the curse into a blessing, the government might contemplate to lower educational costs rather than providing unconditional resource transfers.

4.6 Appendix: Distributional Effects in the Course of the Oil Boom

	(1) Gini DiD	(2) Gini DiD	(3) Gini DiD	(4) Gini DiD	(5) Gini DiD	(6) Gini DiD	(7) Gini DiD
Alaska	0.0148***	0.00344	0.00258	0.00277	0.00207	0.00103	0.00792**
	(0.00250)	(0.00259)	(0.00285)	(0.00313)	(0.00335)	(0.00346)	(0.00348)
Time80	0.0513***						
	(0.00143)						
Alaska × Time80	0.0517***						
	(0.00143)						
Time81		0.0523***					
		(0.00144)					
Alaska × Time81		0.0696***					
		(0.00144)					
Time82			0.0529***				
			(0.00147)				
Alaska × Time82			0.0765***				
			(0.00147)				
Time83				0.0540***			
				(0.00167)			
Alaska × Time83				0.0832***			
				(0.00167)			
Time84					0.0560***		
					(0.00193)		
Alaska × Time84					0.0927***		
					(0.00193)		
Time85						0.0581***	
						(0.00213)	
Alaska × Time85						0.105***	
						(0.00213)	
Time86							0.0599***
							(0.00223)
Alaska × Time86							0.104***
							(0.00223)
Constant	0.484***	0.486***	0.489***	0.491***	0.494***	0.496***	0.499***
	(0.00250)	(0.00259)	(0.00285)	(0.00313)	(0.00335)	(0.00346)	(0.00348)
N	752	752	752	752	752	752	752
R^2	0.214	0.299	0.368	0.434	0.508	0.576	0.615

Notes: The table displays differences-in-differences estimates of the Alaska oil boom on Gini coefficients. The control group is made of all US states which were not exposed to an oil boom in the respective period. Educational Expenditures, State Income and the Population Size are put in log terms. Robust standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.12: Difference-in-Differences Gini Coefficients

4.7 Appendix: Placebo Difference-in-Differences

	(1) Education Alabama	(2) Education Arizona	(3) Education Arkansas	(4) Education California	(5) Education Colorado	(6) Education Connecticut	(7) Education Delaware	(8) Education Columbia	(9) Education Florida	(10) Education Georgia
Alaska	1.839***	-0.0214	1.850***	-0.0725*	-0.210***	0.144***	0.371***	0.349***	0.290***	1.683***
	(0.0399)	(0.0397)	(0.0414)	(0.0378)	(0.0391)	(0.0389)	(0.0459)	(0.0446)	(0.0382)	(0.0393)
Time	-1.145***	-1.874***	-1.118***	-1.785***	-1.743***	-1.849***	-1.903***	-2.263***	-1.426***	-0.790***
	(0.0187)	(0.0192)	(0.0246)	(0.00602)	(0.0177)	(0.0184)	(0.0446)	(0.0458)	(0.0101)	(0.0155)
Alaska × Time	-0.816***	-0.0870	-0.843***	-0.176***	-0.218***	-0.112**	-0.0582	0.302***	-0.535***	-1.171***
	(0.0569)	(0.0571)	(0.0591)	(0.0541)	(0.0566)	(0.0568)	(0.0699)	(0.0707)	(0.0547)	(0.0559)
Constant	10.23***	12.09***	10.22***	12.15***	12.28***	11.93***	11.70***	11.72***	11.78***	10.39***
	(0.0132)	(0.0125)	(0.0174)	(0.00364)	(0.0106)	(0.00995)	(0.0262)	(0.0240)	(0.00632)	(0.0115)
N	304421	218122	183615	1981531	239109	247459	63476	71619	715074	442242
R^2	0.0184	0.0378	0.0218	0.0369	0.0358	0.0407	0.0394	0.0482	0.0254	0.00887

Notes: The table displays placebo differences-in-differences estimates of the Alaska oil boom on educational investments. Treatment Group: Alaska. Control Group: Respective State. The graduation years are retraced based on the age, the years of schooling, the census year and the average school starting age. Robust standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.13: Placebo Tests Control Group 1

	(1) Education Hawaii	(2) Education Idaho	(3) Education Illinois	(4) Education Indiana	(5) Education Iowa	(6) Education Kansas	(7) Education Kentucky	(8) Education Louisiana	(9) Education Maine	(10) Education Maryland	(11) Education Massachusetts	(12) Education Michigan
Alaska	0.572***	0.0390	0.414***	0.499***	0.134***	0.0530	1.826***	1.880***	0.409***	0.402***	0.193***	0.437***
	(0.0456)	(0.0414)	(0.0380)	(0.0383)	(0.0386)	(0.0389)	(0.0405)	(0.0401)	(0.0406)	(0.0390)	(0.0382)	(0.0380)
Time	-1.451***	-2.595***	-1.804***	-2.013***	-2.399***	-2.238***	-1.077***	-1.126***	-2.192***	-1.595***	-1.650***	-2.010***
	(0.0383)	(0.0321)	(0.00927)	(0.0128)	(0.0175)	(0.0195)	(0.0205)	(0.0191)	(0.0293)	(0.0164)	(0.0129)	(0.00987)
Alaska $\times$Time	-0.510***	0.634***	-0.156***	0.0519	0.438***	0.277***	-0.884***	-0.835***	0.232***	-0.366***	-0.311***	0.0495
	(0.0660)	(0.0626)	(0.0546)	(0.0553)	(0.0565)	(0.0572)	(0.0575)	(0.0570)	(0.0612)	(0.0562)	(0.0553)	(0.0547)
Constant	11.50***	12.03***	11.66***	11.57***	11.94***	12.02***	10.25***	10.19***	11.66***	11.67***	11.88***	11.64***
	(0.0257)	(0.0173)	(0.00523)	(0.00701)	(0.00838)	(0.00998)	(0.0150)	(0.0140)	(0.0152)	(0.0103)	(0.00661)	(0.00550)
N	83417	87854	895663	439835	244755	206004	265438	310728	107201	321790	481031	745715
R^2	0.0263	0.0642	0.0380	0.0491	0.0677	0.0578	0.0172	0.0175	0.0538	0.0283	0.0338	0.0477

Notes: The table displays placebo differences-in-differences estimates of the Alaska oil boom on educational investments. Treatment Group: Alaska. Control Group: Respective State. The graduation years are retraced based on the age, the years of schooling, the census year and the average school starting age. Robust standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.14: Placebo Tests Control Group 2

	(1) Education Minnesota	(2) Education Mississippi	(3) Education Missouri	(4) Education Montana	(5) Education Nebraska	(6) Education Nevada	(7) Education New Hampshire	(8) Education New Jersey	(9) Education New Mexico	(10) Education New York	(11) Education North Carolina	(12) Education North Dakota
Alaska	0.0307	2.147***	0.671***	0.0196	0.163***	-0.150***	0.0482	0.381***	0.365***	1.579***	0.474***	0.638***
	(0.0385)	(0.0417)	(0.0386)	(0.0422)	(0.0396)	(0.0414)	(0.0415)	(0.0382)	(0.0379)	(0.0391)	(0.0379)	(0.0395)
Time	-2.077***	-1.339***	-1.723***	-2.491***	-2.195***	-1.772***	-1.936***	-1.654***	-1.794***	-0.856***	-2.002***	-1.829***
	(0.0150)	(0.0248)	(0.0143)	(0.0358)	(0.0244)	(0.0298)	(0.0328)	(0.0121)	(0.00758)	(0.0148)	(0.00908)	(0.0188)
Alaska × Time	0.116**	-0.622***	-0.238***	0.530***	0.234***	-0.188***	-0.0249	-0.307***	-0.167***	-1.104***	0.0407	-0.132**
	(0.0558)	(0.0592)	(0.0556)	(0.0646)	(0.0590)	(0.0615)	(0.0630)	(0.0551)	(0.0543)	(0.0558)	(0.0395)	(0.0570)
Constant	12.04***	9.925***	11.40***	12.05***	11.91***	12.22***	12.02***	11.69***	11.71***	10.49***	11.60***	11.43***
	(0.00830)	(0.0181)	(0.00866)	(0.0191)	(0.0123)	(0.0173)	(0.0175)	(0.00667)	(0.00410)	(0.0107)	(0.00491)	(0.0119)
N	331821	200587	392422	80129	140874	86125	87314	552823	1396516	461881	873526	246465
R^2	0.0484	0.0280	0.0349	0.0590	0.0542	0.0412	0.0430	0.0328	0.0383	0.00975	0.0486	0.0378

Notes: The table displays placebo differences-in-differences estimates of the Alaska oil boom on educational attainment. Treatment Group: Alaska. Control Group: Respective State. The graduation years are retraced based on the age, the years of schooling, the census year and the average school starting age. Robust standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.15: Placebo Tests Control Group 3

	(1) Education Ohio	(2) Education Oklahoma	(3) Education Pennsylvania	(4) Education South Dakota	(5) Education Tennessee	(6) Education Texas	(7) Education Utah	(8) Education Vermont	(9) Education Virginia	(10) Education West Virginia	(11) Education Wisconsin	(12) Education Wyoming
Alaska	-0.136***	0.645***	0.787***	1.978***	0.250***	1.625***	-0.251***	0.109**	1.014***	-0.209***	1.450***	0.338***
	(0.0388)	(0.0380)	(0.0422)	(0.0412)	(0.0435)	(0.0396)	(0.0399)	(0.0448)	(0.0392)	(0.0384)	(0.0417)	(0.0385)
Time	-2.075***	-1.848***	-1.507***	-0.950***	-2.597***	-0.999***	-2.501***	-2.278***	-1.134***	-1.997***	-1.882***	-1.941***
	(0.0179)	(0.00909)	(0.0341)	(0.0225)	(0.0395)	(0.0173)	(0.0240)	(0.0457)	(0.0159)	(0.0139)	(0.0269)	(0.0141)
Alaska × Time	0.114**	-0.113**	-0.454***	-1.011***	0.636***	-0.962***	0.540***	0.317***	-0.826***	0.0362	-0.0788	-0.0197
	(0.0566)	(0.0545)	(0.0637)	(0.0583)	(0.0667)	(0.0565)	(0.0589)	(0.0706)	(0.0558)	(0.0555)	(0.0601)	(0.0556)
Constant	12.21***	11.43***	11.29***	10.09***	11.82***	10.45***	12.32***	11.96***	11.06***	12.28***	10.62***	11.73***
	(0.00931)	(0.00493)	(0.0191)	(0.0167)	(0.0217)	(0.0124)	(0.0134)	(0.0243)	(0.0111)	(0.0376)	(0.0179)	(0.00816)
N	222306	925657	93154	237590	72786	345539	134248	58853	396712	351795	150774	378350
R^2	0.0529	0.0422	0.0304	0.0159	0.0612	0.0137	0.0582	0.0492	0.0141	0.0488	0.0432	0.0437

Notes: The table displays placebo differences-in-differences estimates of the Alaska oil boom on educational attainment. Treatment Group: Alaska. Control Group: Respective State. The graduation years are retraced based on the age, the years of schooling, the census year and the average school starting age. Robust standard errors in parentheses.* $p < .1$, ** $p < .05$, *** $p < .01$.

Table 4.16: Placebo Tests Control Group 4

5

Conclusion

"The conventional view concerning the role of natural resources in economic development has been that resource endowment is most critical in the early low-income stage of the development process."

– Auty (1993), p. 1.

This dissertation was devoted to the relationship between natural resource booms, the selectivity of factor mobility and human capital formation. Accordingly, I raised the following research questions in the introductory chapter: Do resource booms lay the ground for brain drain or brain gain effects? Are selective migration patterns mediated through distributional effects? Do the selectivity patterns of migration materialize consistently in international and regional contexts? How can the relationship between resource abundance and human capital formation be explained theoretically? Are quasi-experimental setups appropriate for the analysis of educational investments in response to resource booms?

In order to tackle these questions, I formulated 3 essays. **Chapter 2** was devoted to the selectivity effects of international migration patterns as a consequence of resource booms. Theoretically, selective migration effects emerge as a consequence of a deindustrialisation in response to the real appreciation. The bust of the tradable sector makes skilled labor relatively worse off while unskilled labor is better off. These distributional effects of a Dutch disease materialize in nominal terms as well as in real terms due to the Stolper-Samuelson theorem. If the subsequent decline in skilled labor income falls short of initial resource transfers, the Dutch disease increases the probability of brain drain effects. However, the theoretical setup was referring to labor income inequality rather than total income inequality. Even though the returns to skills decline, total income inequality might still see an increase if the political elite appropriates significant shares of resource windfall gains. Hence, the net inequality effects are ambiguous. Empirically, I relied on static and dynamic panel models as well as a simultaneous equation model in order to test the theoretical predictions. Consistently through all model specifications, resource booms foster brain drain effects in the long run. In order to preclude brain drain effects, the Dutch disease might be cured or even prevented in the first place. In this regard, the competitiveness of the tradable sector might be strengthened through public educational investments in the long run. Further, an increase in the savings rate in the economy might prevent or lower the appreciation of the exchange rate (Matsen and Torvik (2005)). Alternatively or complementarily, resource revenues might be invested into a financial fund set up abroad, in order to smooth the inflow of resource windfall gains (Stiglitz (2004)). Rather than curing the Dutch disease in the beginning, brain drain effects in particular might be lowered in the end if a resource transfer is accompanied by tax cuts in a proportional or progressive tax system. The predictions raised in this chapter might be relevant for the analysis of foreign aid as well. As long as income windfalls originating from foreign aid are substantial enough in order to translate into a Dutch disease, a foreign aid gain might lead to a brain drain in the long run.

While Chapter 2 referred to international migration patterns, **Chapter 3** was devoted to interstate mobility patterns within the US in response to natural resource abundance. Theoretically, a resource boom lowers the relative educational background of prospective immigrants, as unskilled labor derives a stronger utility gain from unconditional resource transfers. Empirically, I rely on static and dynamic panel models which consistently point at negative selectivity effects of internal immigration as a consequence of resource booms. In order to internalize counterfactual trends in the selectivity of immigration, I further relied on a selectivity measure which was defined as the difference in the selectivity of migrants moving into oil abundant states and the average selectivity of migrants moving across non-oil abundant states. These robustness checks based on counterfactual trends are inevitable, as long as migrant selection follows some path dependencies. Path dependencies became in fact apparent in light of dynamic panel models set out in Chapter 2 for international migration patterns and in

Chapter 3, though modest, for regional migration patterns. Clearly, the baseline results are not affected by internalizing counterfactual trends. Complementarily, I made use of a non-parametric setup proposed by Douglas and Wall (1993), Douglas (1997) and Douglas and Wall (2000), which relates the quality of life to the relative amount of net migration and serves as a means to take into account the multilateral character of migration decisions. Even accounting for multilateral migration decisions, the empirical results are in line with the theoretical conjectures.

Rather than relating resource booms to the human capital of migrants, **Chapter 4** was devoted to changes in educational investments among local residents as a consequence of the Alaska oil boom. Theoretically, I pointed out that unconditional resource transfers might lead to a decline in labor supply, and hence might disincentivize educational investments. Moreover, in an open economy, a Dutch disease increases the opportunity costs of acquiring education as low-skilled wages go up and reduces the returns of educational investments as high-skilled wages go down. If individuals anticipate the decline in the returns to skills in the future, this might lead to a decay in educational investments at the present as well. Empirically, I relied on a difference-in-difference setup, comparing the evolution of the years of schooling among local residents in Alaska with the evolution of the years of schooling in a control group composed of several US states right after the oil boom while focussing on local residents. The results suggest a shortfall of educational investments in Alaska compared to a control group in response to the oil windfall in the 1960's. The results are robust to the definition of a synthetic control group as well as to an external control group in Canada which is much more similar in terms of the geographic structure and population density. Moreover, the results are qualitatively insensitive to the definition of local residents. Even in an extreme scenario which accounts for residents born and still living in Alaska, the results remain qualitatively unaffected. In light of the results of Chapter 3 and 4, a government encountering resource windfalls might contemplate to improve the quality of the school system or lower educational costs rather than easing the household budget constraint through resource transfers.

The role of educational investments for economic prosperity has been highlighted for several decades since the seminal contributions of Schultz (1961) and Becker (1962). However, the skill composition of a society is not only affected by educational investments of local residents but also by the selectivity of migration. This dissertation related natural resource booms, selective migration and education in the course of 3 essays. The essays support the view that natural resource abundance serves as a curse rather than a blessing. In particular, resource windfalls might crowd out human capital through both a decline in educational investments and through brain drain effects.

In the beginning of this conclusion, I referred to Auty (1993) pointing at the stage of economic development which determines whether resource abundance materializes as a curse or a blessing. However, this dissertation shows that elements of a resource curse might even materialize in developed countries.

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