Master Thesis

The Effect of Regime Change on Poverty in Kyrgyzstan: Evidence from Reconstructed Household Income

Malte Ladewig*

supervised by Petra Thiemann

June 30, 2020

Abstract

In the first years of their independence from the Soviet Union, the political landscapes in Kyrgyzstan and Uzbekistan were both characterized by autocratic regimes. While Kyrgyzstan eventually freed itself from the governments firm retention of power, Uzbekistan's president remained in charge up to his death in 2016. Exploiting the fact that the border between the two countries only materialized after independence and thus provides for a comparable treatment and control group on either side of it, this thesis uses a difference-in-differences model to estimate the effect that the regime change in Kyrgizstan had on poverty. The household's income data that is used for this purpose is retrieved from matching expenditure aggregates to the quantiles of income distributions for the respective country and year. Surprisingly, and in contradiction with most of the existing literature, the results show increasing effects of democratization on poverty rates in Kyrgyzstan.

*MSc Economics | Department of Economics | Personal No.: 19941030-8853.

Contents

List of Tables

List of Figures

List of Abbreviation

DiD	Difference-in-Differences
FGT	Foster-Greer-Thorbecke
LiTS	"Life in Transition" survey
PCA	Principal component analysis
PMK	People's Movement of Kyrgyzstan
PSU	Primary Sampling Unit

1 Introduction

The fall of the soviet union enabled the former Soviet republics to embark on their own journeys from centralised foreign rule to self-determined state organisation. As similar as political structures were under the Soviet regime, as distinct were the paths that countries followed after they gained independence. While Uzbekistan, for instance, was ruled by the same authoritarian leader until his death in 2016, neighbouring country Kyrgyzstan underwent two revolutions, both followed by regime changes in 2005 and 2010 (Temirkulov, 2010). As data from PovcalNet indicate, the turbulent political times also reveal themselves in the poverty trends of the countries. Being very stable in pre-independence times, the national shares of population living below the global poverty line of $1.90 spiked with very different intensities for the former member states after the fall of the soviet union. Especially Kyrgyzstan showed a remarkable poverty alleviation success, from having the second highest poverty rate of all former soviet republics in 1997 to having almost entirely eradicated extreme poverty in 2015. Over the same time, its neighbouring country Uzbekistan was less successful and records the highest share of extreme poverty among the former soviet republics in its population.

Since both countries had similar political starting positions under the soviet foreign rule and yet developed so distinctly thereafter, the question appears how poverty trends were affected by the fact that Kyrgyzstan shook off the authoritarian regime in 2010 and underwent a democratization process while Uzbekistan remained under firm authoritarian rule.

The main obstacle in answering this question is the unavailability of good data to investigate into the roots of poverty and derive important policy implications. This problem does not only exist for the case of former soviet countries, but is frequently encountered in poverty related research in many other development countries (McKenzie, 2005). Even in cases where household survey data is available, it often seems impossible to retrieve reliable poverty estimates from the income and expenditure information captured. This would require very detailed accounting of the different components which is often not feasible, the more so in larger households where income and expenditure flows are not as easy to understand. Other complications arise from the frequent occurrence of subsistence production that has a distorting effect on estimations.

These and other complications give the impression that the reconstruction of income data based on surveys leads to large measurement errors and is hardly worth the large costs that are attached to collecting the required data and do the laborious calculations (Deaton, 1997, p.29). What is therefore needed is a way to estimate incomes even without precise recordings of all the detailed indicator components, as this would make large numbers of survey data from developing countries accessible for poverty research (McKenzie, 2005).

The here applied methodology builds on an approach by Hruschka, Gerkey, and Hadley (2015) that differs from the standard procedures of simply aggregating income components. All that is needed for this method to work are three types of information: (1) a relative, country-specific wealth ranking, (2) the Gini coefficient and (3) the mean income. With realistic assumptions about the distributional shape, incomes can be estimated by matching a household's position in the wealth ranking to its counterpart in the income distribution.

With the household income recovered, a difference-in-differences (DiD) model can be constructed to estimate the impact of the Kyrgyz shift to a more democratic regime, where Uzbekistan serves as a control unit. It was only in 1991 when the border between Uzbekistan and Kyrgyzstan materialized and even later when it started to impose restrictions on the free movement of people, goods and services from one country to the other (Megoran, 2012). A result can be found in the fact that even today, populations around the border are still of mixed ethnic identities (Akiner, 2016). Restricting the sample to these regions therefore makes the groups more comparable and strengthens the identification of causality in the model. With the crucial assumptions for validity of the DiD model in place, the estimation uncovers increasing effects of regime change on poverty rates in Kyrgyzstan.

The thesis proceeds as follows. The second part provides an overview of the political developments of Kyrgyzstan and Uzbekistan since their independence. While the latter has been autocratically ruled from the start until today, the former has undergone two revolutions and now seems to settle in more democratic structures. The third part briefly outlines the data used for the rest of the analysis. The main source is the *Life in Transition Survey* (LiTS), which is enlarged with macro data from the PovcalNet data base. The fourth part will sketch three different grounds on which to determine poverty rates. The first one is income, where the so called Foster-Greer-Thorbecke (FGT) poverty measures are commonly used. These will also be applied in the model estimation at a later stage. The second ground is based on assets and utilities and is often used in accounts of multidimensional poverty that work with deprivations of goods and services instead of monetary equivalents. By using a principal component analysis (PCA), a relative wealth index can be constructed for each country, but it does not allow cross-country comparisons of households. The third ground has expenditure as its determinant for poverty instances. Since representative expenditure data is difficult to construct, introduces large measurement errors and requires comprehensive survey data, aggregates will be used to create a relative country ranking instead. This will then be applied as a foundation to recover household incomes from income distribution matching. In the fifth part, the now retrieved household poverty will be used in a DiD model to estimate the effect that the democratization in Kyrgyzstan had on poverty instances in the country, where Uzbekistan will serve as the comparison unit.

2 Historical context

Even if it can be argued that the breakdown of the soviet union does not count as a real natural experiment because it misses randomness in its exposure of "freedom" to the former member countries, it nevertheless created a situation in which they came from comparable political conditions and were eventually able to pave their own paths of self-governance for the first time after decades of foreign dictation. The windings and curves that these paths took diverged for the different countries, as can be seen in the examples of Kyrgyzstan and Uzbekistan. Krgyzstans first president after the breakdown was Askar Akaev, who remained in power for the following 15 years. What first was recognized as the central Asian *island of democracy* turned into a authoritarian style government, characterized by nepotism and corruption (Graney, 2019). Amendments to the constitution with the purpose of extending presidential power were passed in 1996, 1998 and 2000. Especially the large scale personal enrichment of the ruling elites as well as the increasing attempts to repress the opposition and media gave rise to the formation of protests among the population (Temirkulov, 2010). Finally, after the parliamentary elections in February 2005 assigned 69 of the 75 seats to Akaev's party and allowed his son, daughter and sister-in-law into parliament, the *Tulip Revolution* in Kyrgyzstan lead to the overthrow of the regime. The protests were lead by the *People's Movement of Kyrgyzstan* (PMK) and had their epicentre in the region Jalalabad close to the Uzbek border, from where they spread to the rest of the country and eventually forced Akaev to flee abroad. He was succeeded by the former leader of the PMK, Kurmanbek Bakiyev, who managed to attain control after some months of instability and competing revolutionary forces (Temirkulov, 2010). However, the change in government did not bring the desired institutional improvements. Instead, state nepotism was still present, with family members of Bakiyev installed in many strategically and economically important positions in the country. Fire sales of state-owned companies into the hands of ruling elites and persecution of media and opposition was a common practice. In addition, unpopular decisions in the dealing with the economic crisis in 2008 further boosted discontent in the population. Increases in taxes on public services lead to price increases of 400% for heating and 170% for electricity, upsetting particularly the poor parts of society (Temirkulov, 2010). When the Bakiyev regime elapsed on an ultimatum set by the opposition to cut back taxes, end nepotism and return privatized companies, mass protests broke out throughout the country. The unrest even aggravated when the regime responded with violence and arrests of oppositional leaders, and eventually forced Bakiyev into exile and thus made him follow the same fate as Akaev five years earlier.

An important difference between the Tulip Revolution in 2005 and the regime overthrow in 2010 is that former was organized and lead by the PMK. Some therefore see it rather as an elite induced coup than a revolution. In contrast, the regime overthrow in 2010 occurred as an immediate response of the people of Kyrgyzstan to the regime forces (Temirkulov, 2010). While the Tulip revolution disappointed the high hopes for a more lawful state (Juraev, 2008), the regime change in 2010 seems to have finally ended nepotism and government abuse of power in Kyrgyzstan. Even though some reports about fraud persisted, the first past-conflict presidential elections in 2011 were at the same time the first ones in the republic in which the incumbent president willingly made space for his successor (Akiner, 2016).

As opposed to Kyrgyzstan, Uzbekistan has been resilient to any form of regime change. From the country's independence in 1991 up to his death in 2016, president Karimov fiercely held on to power in an autocrat-style government. While protest movements lead to two regime changes within five years in Kyrgyzstan, the start of similar developments in Uzbekistan were brutally stifled by the regime (Murtazashvili, 2012). All form of op-

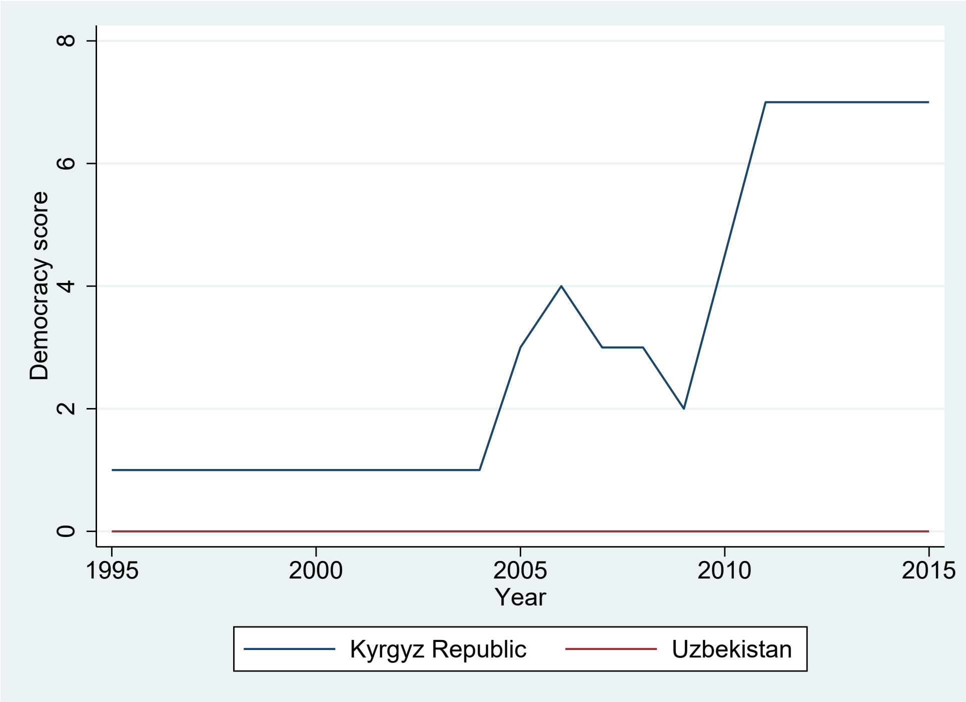


Figure 1: Democracy scores for Uzbekistan and Kyrgyzstan over time

position to the government was surpressed right from the start (Melvin, 2004).

The post-independence history of Kyrgyzstan and Uzbekistan, two neighbouring countries, shows that both followed distinct paths, the former shaking off nepotism, corruption and the abuse of governmental power in 2010 while the latter has been trapped in president Karimov's stable but authoritarian leadership right from the nations birth. The apparent gap also shows in the POLITY project's democracy scores as displayed in figure 1, imputed as a weighted score on a scale from zero to ten from citizen's institutionalized abilities to express their political preferences, from the institutional constraints to the government and from civil liberties in society. Up to the year 2005, Kyrgyzstan and Uzbekistan have constant, almost identical and very low democracy scores of one and zero respectively. While Uzbekistan's democracy score does not change until 2015, the curve for Kyrgyzstan shows a temporary upward spike with the Tulip revolution in 2005 but quickly starts to decline again in 2007. Coinciding with the second revolution in 2010, it then peaks to a score of seven where it stabilized since then.

The different paths of state development bring up the question how the fundamental political change in one country affected the poorest in society as compared to the poor living in stable political conditions on the other side of the border. Exploiting the historic situation that both countries started in very similar circumstances but then diverged in their paths with the setting in of the revolutionary events in Kyrgyzstan in 2010, a *differences-in-differences* (DiD) model will be used in the later sections to estimate the effect this had on poverty in Kyrgyzstan. Before that, the following section continues by introducing the data that is used for this purpose.

3 Data

To estimate the effect of the Kyrgyz revolution on poverty rates, micro data and macro data will be combined. The micro data originates from the *Life in Transition* household surveys (LiTS), conducted by the *European Bank for Reconstruction and Development*. The goal of the surveys was to gain a better understanding of living conditions in the transitional economies of the former Soviet block. They were conducted in three nationally representative waves in the years 2006, 2010 and 2016. The first wave in 2006 covered about 29000 households in 29 countries. The second wave was extended to 34 countries and amounted to a total of about 39000 surveyed households. The third and latest wave encompassed 51000 households from 34 different countries. The surveys were conducted in a two-stage stratified clustered sampling process. In the first stage, primary sampling units (PSU) were determined from local territorial units with the probability of being picked proportional to their size. The PSU were stratified by geographic region and rural/urban to make the survey maximally representative. In the second stage, a number of addresses were chosen for the interviews from these PSU.
The questionnaires that were presented to the household members differed slighty between the years, but also had many overlaps. Besides questions on political attitudes and employment activities of the participants, the most interesting parts for this work's purpose are the ones on household expenditure, access to utilities such as water or electricity and asset ownership. To create pooled cross-sectional data, the surveys from all three years were combined into one data set. Table 1 lists the variables of each survey year and their means. Expenditure variables in the 2006 survey are measured in USD, while those for the years 2010 and 2016 represent local currrencies. Utilities and assets are coded into indicator variables and thus give the share of population that accesses them.

In addition to the micro data from the LiTS, macro data on the country-level was added from the *PovcalNet* analysis tool of the World Bank. In particular, the database provided

Table 1: Means of selected variables from LiTS survey

	2006		2010		2016	
	KGZ	UZB	KGZ	UZB	KGZ	UZB
Panel A: Expenditure						
Food, beverages and tabacco	31.76	25.33	2277.25	101697.69	3192.42	250372.93
Clothing and footwear	26.62	14.45	608.63	10355.54	589.37	38920.29
Transport	9.43	5.95	679.28	24732.19	.	.
Transport and communication	.	.	.	.	950.41	60799.48
Education	2.19	1.46	257.70	4524.85	386.16	22539.17
Health	1.84	2.50	148.71	6084.29	349.38	38278.17
Durable goods	2.12	1.58	174.66	3790.83	433.75	33007.30
Furnishing	1.26	1.05	.	.	.	.
Utilities	.	.	324.11	26566.13	724.77	52980.41
Panel B: Asset ownership						
Bank account	0.02	0.05	0.00	0.02	.	.
Mobile phone	0.20	0.16	0.92	0.79	.	.
Telephone (incl mobile)	.	.	.	.	0.98	0.99
Computer	0.05	0.02	0.11	0.08	0.37	0.33
Internet	0.01	0.01	0.05	0.02	0.54	0.22
Car	0.28	0.24	0.33	0.28	0.48	0.39
Secondary residence	0.10	0.08	0.05	0.03	.	.
Debit card	.	.	0.00	0.04	.	.
Credit card	0.01	0.02	0.01	0.01	.	.
Bicycle	.	.	.	.	0.34	0.52
Motorcycle	.	.	.	.	0.03	0.03
Colour TV set	.	.	.	.	0.96	0.97
Washing mashine	.	.	.	.	0.78	0.40
Panel C: Utilities						
Pipeline tap water	0.55	0.47	0.65	0.68	0.76	0.60
Electricity	0.99	0.99	1.00	1.00	0.99	1.00
Fixed telephone line	0.27	0.26	0.30	0.33	0.22	0.35
Public central heating	0.20	0.14	0.14	0.08	0.15	0.29
Pipeline gas	0.25	0.75	0.22	0.93	0.23	0.61
Observations	1000	999	1016	1500	1500	1506

gini coefficients and mean incomes for the LiTS countries over different years. As the analysis proceeds, these will be used to recover incomes for the survey households, which will then allow poverty estimation. All incomes are reported in 2011 USD PPP from the *2011 International Comparison Program.* PovcalNet also entails data on the poverty rate as well as the poverty gap and the squared poverty gap for each country, which will be further explained in the following section.

4 How to measure poverty

In order to find underlying characteristics of poverty trends and possible parameters explaining them, some way of categorization between poor and non-poor households must be made. How these are distinguished depends on the definition of poverty one chooses to adopt. There is a large body of literature on different ways of measuring poverty, each of them having different strengths and weaknesses depending on the context in which they are used. Before elaborating on the methods used here to impute poverty rates from the LiTS data, this section discusses three different groups of poverty estimation: income-based, asset-based and expenditure-based measures.

4.1 Income based poverty measures

Income based methods where a household is poor if its income undercuts a predetermined poverty line are the most common of the measures. The simplest of them is referred to as *poverty headcount*, where the only distinction is made between being underneath or above the line. The World Bank's global poverty line currently lies at \$ 1.90 in 2011 prices, while it is also common to calculate local poverty lines that are adjusted to each countries specific circumstances. Even though poverty headcount seems very convenient for reasons of simplicity, it fails to account for the *extent* of the shortfall underneath the threshold. A country with many households just below the line would not be distinguishable from a country where the gap is wider.

This weakness can be overcome by allowing poverty shortfalls to enter the measure, as done by Foster, Greer, and Thorbecke (1984). Their index is often referred to as the

Foster-Greer-Thorbecke (FGT) poverty score and can be expressed as

$$FGT_\alpha = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^\alpha . \tag{1}$$

The FGT poverty measure normalizes the poverty gap by setting the shortfall of a household's income y_i from the poverty line z in proportion to the latter. A country's poverty can then be estimated by summing over the number of households below the threshold q and dividing through the total number of households n. The exponent α allows to adjust the weight that poverty shortfalls take (Foster, Greer, and Thorbecke, 2010). The case $\alpha = 0$, for instance, reduces equation (1) to

$$FGT_0 = \frac{q}{N} \tag{2}$$

and thus returns the *poverty headcount* as stated above, i.e. the proportion of people living below a certain poverty line. To include poverty shortfalls, the parameter can be set to $\alpha = 1$, such that equation (1) calculates the *poverty gap* in taking the from

$$FGT_1 = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right) . \tag{3}$$

Instead of only counting the number of households below the poverty line, equation (3) allows the *extent* of poverty into the measure by expressing it as the average ratio of the poverty shortfall to the poverty line. An intuitive way of interpreting equation (3) is that it reconstructs the hypothetical amount of income that is lacking to alleviate every poor person to the poverty threshold, which is given by $\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)$ (Ravallion and Atkinson, 1994, p.38). However, it does not tell anything about the distribution among the poor in society, since it only reproduces the average poverty gap. Poverty distributions can differ a lot from each other but still have the same average poverty incidence. By squaring equation (3) (or setting $\alpha = 2$), the FGT measure can be adjusted to also include aspects of inequality and poverty severity into the measure, since larger poverty shortfalls are weighted to a higher extent than smaller shortfalls. The FGT_2 index will then be calculated as

$$FGT_2 = \frac{1}{n}\sum_{i=1}^{q}\left(\frac{z-y_i}{z}\right)^2 . \tag{4}$$

In general, it holds that the higher the chosen parameter α is, the more emphasize is put on the bottom of the income distribution. Ultimately, as $\alpha \to \infty$ only the poorest of households is taken into account (Foster, Greer, and Thorbecke, 2010).
For the above measures to be applicable, it is obviously required that income data are available. Especially in less economically developed countries, it is often difficult to access precise data on household incomes for various reasons, such as lacking tax reports, a large share of self-employment, subsistence production or mistrust towards interviewers in household surveys (Rutstein and Johnson, 2004; Sahn and Stifel, 2003). Of the LiTS waves, only one carries information on self-estimated household income. As will be shown in the succeeding parts of this work, it is nevertheless possible to retrieve income estimates even in the absence of income data. Furthermore, it has been argued that poverty has more to it than only a low income (Sen, 2000, e.g.). These complications gave rise to the so called wealth indices that usually determine poverty based on assets and deprivations instead of income.

4.2 Principal component analysis and asset based indices

The construction of asset based wealth indices, as done for instance in Alkire and Santos (2010) or Smits and Steendijk (2015), is an alternative to the usage of income levels to determine poverty rates. To construct such an index, information is needed on a household's access to a range of goods and services that are related to its wealth (Rutstein and Johnson, 2004). The assets are then assigned with weights, so that they can be combined to compute an individual household poverty score. A useful method to do so is the *principal component analysis* (PCA).
A PCA uses a number of correlated variables to summarize the essential information of the data in a new set of variables (Abdi and Williams, 2010). In this case, the overall aim is to compromise the information from different poverty indicators in a way that allows to rank households according to their poverty status. In doing this, new variables are created, called *principal components*. Principal components are linear combination of the original variables and are obtained from the singular value decomposition of a normalized matrix of the initial data. More generally, the n normalized variables a_i that are chosen

to be included in the PCA for household i can be expressed as

$$\begin{aligned} a_{1i} &= v_{11} \times A_{1i} + v_{12} \times A_{2i} + ... + v_{1n} \times A_{ni} \\ &... \\ a_{ni} &= v_{n1} \times A_{1i} + v_{n2} \times A_{2i} + ... + v_{nn} \times A_{ni} \end{aligned} \tag{5}$$

where the respective variable has a linear relation to the principal components A weighted by the coefficients v (Filmer and Pritchett, 2001). While the a_i are known since they have been part of the initial data, the right-hand side expressions are unobserved and to be uncovered by the PCA. Because the system of equations has too many unknowns to be estimated without further assumptions, it is necessary to impose the restrictions that the components A_n are orthogonal to each other and that the sum of squares of the weights v_n add up to one (Filmer and Scott, 2008). With these restrictions, the principal components and weights can be estimated from (5), where the first principal component A_{1i} is that with the highest captured variance, A_{2i} the one with the highest remaining variance *after* A_{1i} has been determined, and so on.

Inverting the system of equations (5) gives

$$\begin{aligned} A_{1i} &= b_{11} \times a_{1i} + b_{21} \times a_{2i} + ... + b_{n1} \times a_{ni} \\ &... \\ A_{ni} &= b_{1n} \times a_{1i} + b_{2n} \times a_{2i} + ... + b_{nn} \times a_{ni}. \end{aligned} \tag{6}$$

where the b are the factor scores that show the relationship between the normalized wealth indicating variables and the principal components. The first principal component A_{1i} with the highest variance can then be used as an index that ranks households by their poverty status.

As table 1 shows, the LiTS surveys documented a number of household assets and utility accesses. By using a PCA in the way explained above, an index can be created to rank households relative to the other households.

Several steps should be taken into account when creating an asset based poverty index in order to ensure that each of the included indicator variables has a strong enough relationship with wealth (Hjelm, Mathiassen, Miller, and Wadhwa, 2017).

Since the objective is to reconstruct household income, all variables included in the PCA should have a strong enough relationship with it. There are several steps to ensure that this requirement holds. A first step to test the suitability of income indicators is to check for enough variation. If there is only very little, it will not be able to explain incomes because households cannot be ranked from poor to rich on basis of the indicator. Table 1 displays the share of population with access to utilities and asset ownership captured in the LiTS. *Electricity*, for instance, is a variable that does not vary much in the data. As good as the entire population has access to electricity in all three waves, which is why it will not help to distinguish households by their wealth and should be discarded from the PCA when constructing a wealth index.

A contrary relationship can be seen for the ownerships of a *bank account*, *credit card* and *debit card*, which are either not reported in the respective survey wave (indicated as "." in table 1) or only possessed by a negligibly small share of population. Similar to the case of electricity, this makes it impossible to interpret the ownership of the asset as a sign of wealth, and they should be excluded from the analysis in consequence. The variables *computer* in 2006, *internet* in 2006 and 2011, as well as *secondary residences* in 2010 should be discarded for the same reasoning. *Colour TV set* and *motorcycle* only appear in the third wave of the survey but both do not show enough variation to be useful either, just as *Telephone* for 2016.

Once all the non-varying variables have been identified, the intercorrelations between the indicators should be examined in a second step. Table 2 shows the correlation matrix for the different assets and utilities from table 1 in Kyrgyzstan 2016. If one of the chosen

Table 2: Correlations between wealth indicator variables, Kyrgyzstan 2016

	Tap water	Tel. line	Heating	Gas	Comp.	Wash. mashine	Car	Bicycle	Internet
Tap water	1.00								
Tel. line	0.23	1.00							
Heating	0.22	0.34	1.00						
Gas	0.28	0.38	0.46	1.00					
Comp.	0.19	0.24	0.31	0.31	1.00				
Wash. mashine	0.14	0.16	0.17	0.14	0.31	1.00			
Car	0.09	0.10	0.07	0.05	0.30	0.30	1.00		
Bicycle	0.04	0.03	0.00	0.06	0.16	0.21	0.28	1.00	
Internet	0.20	0.10	0.26	0.17	0.45	0.21	0.21	0.16	1.00

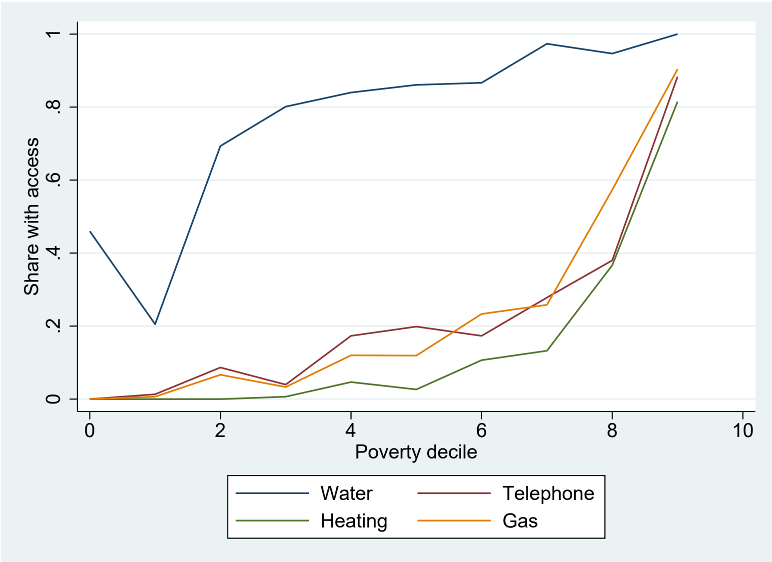
indicators shows only very weak correlation close to zero with the others, it can be interpreted as a sign that it does not have strong predictive power for wealth. If, in contrast, the correlation is very strong such that it approaches one, it could indicate that two variables in reality explain the same thing and one should be discarded. As the correlation coefficients for Kyrgyzstan in 2016 in table 2 reveal, none of the asset or utility variables has remarkably low correlations to all the other indicators. It therefore is not necessary to omit it any of them form the PCA.

A third and important step follows once the index is already constructed in a graphical analysis. Figure 2 depicts the relations between the remaining wealth variables and the wealth deciles created from the first component of the PCA for Kyrgyzstan in the year 2016. If the asset and utility variables are good predictors for the constructed index, they should show an increasing relationship with it (Rutstein and Johnson, 2004). Even though graph 2a and 2b both do not show strictly increasing lines, the general trend is clearly visible that the share of the population that accesses the respective categorial variables increases with wealth. The preceding two steps therefore identified the right indicators to be discarded from the PCA.

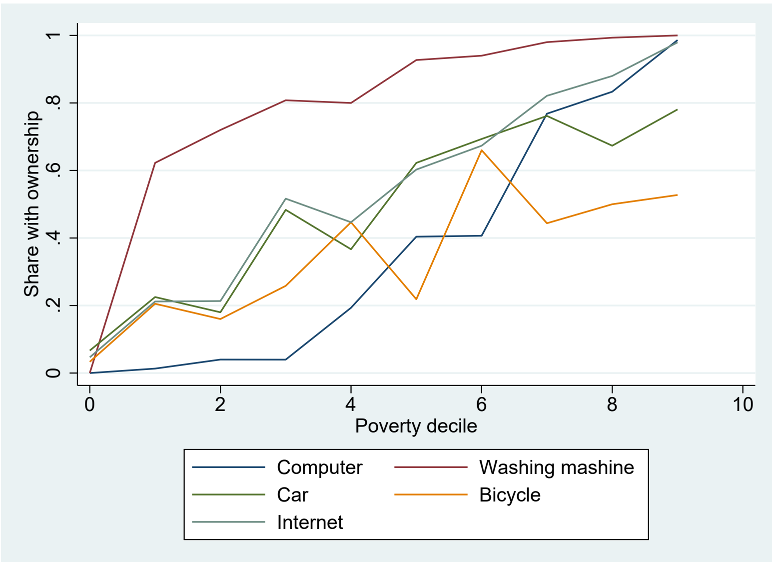
Given the first two steps have been executed and there are no undesired relations shown in the third step, the indicators for the construction of the wealth index are determined and the PCA can be run to obtain household scores.

The PCA on assets and utilites thus enables the creation of a relative wealth index that allows to rank households according to their wealth for a specific country and year. However, it does not provide results that can be compared across countries or years for two reasons. Firstly, the *Life in Transition* questionnaire does not encompass the same questions for each wave. If one wanted to create an index where scores can be compared across survey waves as done in Rutstein and Staveteig (2014), the factor components used for the analysis should be identical. Otherwise, the resulting score from one survey wave measures a different wealth concept than the score of the other. It still allows to create an ordinal ranking from poorest to wealthiest among households of the *same* country and survey wave, but no cardinal comparability across indices. A way around this issue would be to only include overlapping questions that appear in all three waves of the survey. This however reduces the used information for the analysis substantially due to the varying survey questionnaire design and therefore makes results less precise.

Even if it was possible to overcome the first problem, it is still doubtful whether the PCA would allow comparisons. As Ferguson, Tandon, Gakidou, and Murray (2003) note, a bundle of assets in one country can relate to a different socio-economic status in another



(a) Utilities



(b) Assets

Figure 2: Wealth indicators for Kyrgyzstan 2016

for a variety of reasons, such as cultural norms, environmental conditions or even market distortions that lead to different price relations. All these factors can have an impact on the distribution of an asset, with the results that its implications as an indicator for wealth shifts.

It follows that a PCA on assets and utilities cannot help to use the *Life in Transition* survey in order to compare poverty over time and across countries. At best, it can produce a relative index that allows to rank households according to their status.

4.3 Expenditure based poverty measures

Besides income and assets, another frequently used method to estimate poverty rates is based on expenditure data. Similar to income related measures and in contrast to the asset based indices, expenditure data has the convenience that it can be expressed as a simple monetary value. In addition, it is usually not as fluctuating as income because households tend to smoothen their consumption over time (Deaton, 1997). This means that households tend to save more in times of affluence and dissave during scarcity, such that consumption levels are to some degree balanced. Often, houshold survey's questionnaires include sections on the value of consumption that a household spent on certain good categories. The ones reported in the LiTS can be found in panel A of table 1.

When comparing expenditure between different households, it is crucial to adjust the measures to the size of each household. Economies of scale imply that the per capita amount spent on different goods decreases with the number of people in a household for the reason that a part of the goods is shared among its members. Simply dividing the overall expenditure by the number of people living in the household will underestimate wealth of households with many members. Two households with the same expenditure but different household sizes should be weighted differently in their wealth estimates (Atkinson, Rainwater, and Smeeding, 1995). Several methods exist to account for this particularity. For the purpose of this analysis, the OECD-modified equivalence scale is applied which uses a weight constructed as the sum of 1 representing the first adult, 0.5 for every additional adult in the household and 0.3 for every child. Per capita expenditure of household i then is defined as

$$Equalized\ household\ expenditure_i = \frac{Household\ expenditure_i}{1 + 0.5 \times Adults_i + 0.3 \times Children_i}. \tag{7}$$

The usual way to obtain wealth estimates from expenditure data is by aggregating the different categories and comparing the total of them. As Deaton and Zaidi (2002) note, there are a few considerations to be taken into account that can complicate this process to a large degree. For once, it is important to include the value of home-produced and consumed goods. Especially in developing countries, the production of food can make a difference in assessing the wealth of households, since those for who subsistence farming is an important factor evidently spend less money on food.

Before aggregating the different expenditure categories and comparing the household equivalent sums, another important step is to critically assess the components as some of them have properties that impede comparability. *Rent* is one of these categories. While some households own the dwellings they live in, others have to pay rent on a regular basis which can constitute a large share of the overall expenditure. To account for this possible distortion, a hypothetical rent equivalent should be added to the expenditure aggregates of those who live in their own dwelling (Ackland, Braithwaite, Foley, Garner, Grootaert, Milanovic, Oh, Sipos, Tsirounian, and Ying, 1996).

Other categories that are sometimes considered problematic in the aggregate are *durable goods* and *health* (Alam, Murthi, Yemtsov, Murrugarra, Dudwick, Hamilton, and Tiongson, 2005, p.42). While other expenditure components are typically closely related to the current economic situation of a household, investments in durable goods can be problematic because they last for a long time once taken and therefore rather represent long-term wealth, while the other spendings occur in a more regular manner. Aggregates may therefore turn into an incorrect wealth indicator if durable goods are included.

A different reasoning lies behind the exclusion of health. Expenditure of this kind is often not a choice based on the current economic status but a necessity due to wealth-independent conditions. It is thus doubtful whether or not the poor really spend less on health than the better off (Rutstein and Johnson, 2004; Deaton and Zaidi, 2002).

Unfortunately, the LiTS survey neither records hypothetical rents throughout the waves nor does it list values of subsistence production in food or other products. In addition, expenditure data should be weighted with a price index that balances out differences in the acquisition costs for different countries (Deaton and Zaidi, 2002). None of this kind is given in the survey data, which makes the imputation of absolute poverty rates from expenditure aggregation imprecise and prone to errors.

In presence of these caveats, the LiTS does not entail sufficient data to impute reliable and cross-country comparable poverty rates from expenditure aggregation alone. However, similar to the asset-based index, the aggregates should become much more precise indicators of wealth when only compared within a country for a certain year. In that case, many of the above mentioned distortions that arise from country or time specific differences are minimized, such as price relations or culturally-determined consumer preferences. The fact that the available expenditure categories are not exhaustive then becomes less problematic, since the absolute amounts spent for each category are more comparable across households. The aggregated expenditure in equivalent units for household i is then calculated as specified in equation (7), were $\textit{Household expenditure}_i$ in the numerator is the sum of the q expenditure components x, $\sum_{i=1}^{q} x_i$, and the outcome can be ranked against other household's wealth.

4.4 From relative wealth estimates to income

The sections 4.2 and 4.3 use two different ways to construct a relative ranking of households according to their wealth, but neither allow to compare households from different countries or survey waves without imposing oversimplifying assumptions.

In the following, a method is used that works with these relative rankings and matches the households to the respective percentiles in an exogenously given income distribution. The levels of income for the households that are assigned in this manner are expressed in purchasing power parity (PPP), which makes them comparable even over different countries and years. Before turning to this, however, it is necessary to distinguish between the two relative wealth rankings from above, as the choice of the ranking is determinant for the correct assignment of incomes.

So far, the term *wealth* has been used interchangeably for both, the asset-based index as well as expenditure aggregates without further consideration. As a comparison of the calculated indices shows, the two really measure different things. Table 3 shows the correlation coefficients for an asset-based index constructed in a PCA, an expenditure-based index constructed also in a PCA, and an aggregated expenditure measure. Not surprisingly, it does not make much of a difference whether expenditure components are aggregated or fed into a PCA. The resulting ranks are strongly correlated with coefficients very close to one.

The more important result from table 3, however, is that the asset-based index does not correlate much with the measures constructed from expenditure components. The coefficients here are scattered around 0.4 in all years. This finding is in line with the vast

Table 3: Correlations between asset-based index and expenditure aggregates, Kyrgyzstan

	Asset index	Expenditure index	Expenditure aggregated
2006			
Asset index	1.00		
Expenditure index	0.39	1.00	
Expenditure aggregated	0.42	0.95	1.00
2010			
Asset index	1.00		
Expenditure index	0.38	1.00	
Expenditure aggregated	0.36	0.99	1.00
2016			
Asset index	1.00		
Expenditure index	0.40	1.00	
Expenditure aggregated	0.38	0.98	1.00

majority of the literature that suggests that asset-based poverty rankings are difficult to reconcile with findings from income or expenditure based measures of poverty (Sahn and Stifel, 2003; Howe, Hargreaves, Gabrysch, and Huttly, 2009; Rutstein and Johnson, 2004). A likely explanation for this is that assets depict a long-run wealth status, since they are accumulated over a longer period of time, while income and expenditure are more fluctuant (Filmer and Pritchett, 1999). Even though long-term poverty in form of asset and utility deprivations can give important insides for policy questions that expenditure might not be able to supply, the goal here is to create comparability of the data by recovering income estimates and calculating the FGT measures introduced in section 4.1 on a household level.

In theory, a household's expenditure is equal to it's income adjusted for either the amount that is saved in case expenditure remains below the income, or dissaved in case it surpasses it (Deaton and Zaidi, 2002, p.13). This introduces some degree of imprecision to the income estimates depending on the extent of consumption smoothing in a society. However, income and expenditure are not as detached as often assumed when long enough time periods are regarded (Deaton and Zaidi, 2002, p.14). Most of the consumption smoothing occurs over the period of a few months. In many developing countries where agriculture is the main source of income for households, seasons can also make up for a gap between expenditure and income. Since the matching is on *annual* mean incomes, much of the consumption smoothing can be captured. Expenditure therefore can be expected to be more congruent with income than assets or utilities which themselves are better in explaining wealth in the longer run.

A problem that arises in the matching procedure is that countries usually do not have data on detailed income distributions available that would allow to assign precise incomes to the percentiles from the household ranking. Following Hruschka, Gerkey, and Hadley (2015), it is still possible to estimated incomes even without these information based on three parameters. Firstly, there must be a *relative wealth index* that enables comparison between individuals within a country. This has been developed in the above subsections. Secondly, the *Gini coefficient* for the respective country and year must be known. In combination with the third required parameter, the *mean income* of the country, and an assumption on the distributional shape of income, the Gini can be used to reconstruct the income distribution, which is then matched on the relative ranks of the wealth index. With this approach, it is possible to use the relative, country-specific index and translate it into a standardized income measure. The country-level data for the Gini and the mean income are taken from the *PovcalNet* database.

An essential question when estimating poverty rates in this way is how to determine a suitable assumption for the shape of the income distribution. Empirically, income distributions have shown to be positively skewed in most cases, with a heavy tail as incomes increase (Cowell, 2015, p.18). Pen (1971) illustrates it vividly in his famous *dwarf parade* analogy, where participants of the parade are ordered from short to tall and walk past over a certain time interval. In the example we would witness that the person with the mean height walks by some considerable time after the median person, and that the last participants to pass will shoot up high compared to the rest.

From the dwarf parade, it is easy to see that the normal distribution would not make a good fit due to its symmetric shape. Mean and median are equal, and there is no tail to accomodate the very high incomes. An alternative is a lognormal distribution. Given a normally distributed variable y, the variable x follows a lognormal distribution if it holds that

$$y = log(x). \tag{8}$$

The cumulative distribution function (cdf) of x is then defined as

$$F_X(x;\mu,\sigma) = \frac{1}{2}\text{erfc}\left[-\frac{lnx-\mu}{\sigma\sqrt{2}}\right] \tag{9}$$

where μ is the mean of y, σ the standard deviation of y and $erfc$ the *complementary error function* (Mitzenmacher, 2003).

Lognormal distributions are frequently used to depict income, since they are positively skewed and convenient to operate (Cowell, 2015, p.84). Most importantly, they have often fit well to empirical evidence. E.g. Lopez and Serven (2006) find it impossible to reject the null that income is not lognormally distributed in their analysis of more than 800 observations. Similarly, Pinkovskiy and Sala-i Martin (2009) find better fit for the lognormal distribution when compared to a gamma or a Weibull distribution, two commonly used alternatives.

Assuming a lognormal distribution, the Gini coefficient is given as

$$G_{\text{lognormal}} = 2\phi\frac{\sigma}{\sqrt{2}} - 1, \tag{10}$$

with ϕ being the cdf of the standard normal distribution with a mean of zero and standard deviation of one (Harttgen and Vollmer, 2013). Solving equation (10) for σ yields

$$\sigma = \sqrt{2}\phi^{-1}\left(\frac{G+1}{2}\right), \tag{11}$$

where ϕ^{-1} denotes the inverse of the standard normal distribution. If the mean income is known, σ can be used to calculate μ as

$$\mu = log(\text{mean income}) - \frac{\sigma^2}{2}. \tag{12}$$

With μ and σ from equations (11) and (12), it is then possible to construct the inverse lognormal cumulative distribution function (icdf) as

$$x(p) = e^{\mu+\sigma u(p)} \tag{13}$$

where $u(p)$ is the inverse of the standard normal distribution at percentile p.

Even though the lognormal distribution appears to be a generally good fit, it has some weaknesses to reconcile the top incomes in the tail (Cowell, 2015, p.87). For this reason, incomes of the rich are more commonly applied onto a *pareto distribution* (Jenkins, 2017; Cowell, 2015). Even though it has a superior fit to the upper incomes, it is eventually characterised by a cut off as one moves further to the left in the distribution. This can be seen from the cdf of the pareto distribution, which can be expressed as

$$F_X(x; \alpha, x_t) = y = 1 - \left(\frac{x}{\bar{x}}\right)^{-\alpha}, \qquad \bar{x} < x. \tag{14}$$

In the above equation, α is the shape parameter while x_t determines the threshold for the cut off. According to Cowell (2015, p.156), the Gini coefficient for the pareto distribution is defined as

$$G_{\text{pareto}} = \frac{1}{2\alpha - 1}, \tag{15}$$

which can be solved for the shape parameter α to obtain

$$\alpha = \frac{1 + G}{2 \times G}. \tag{16}$$

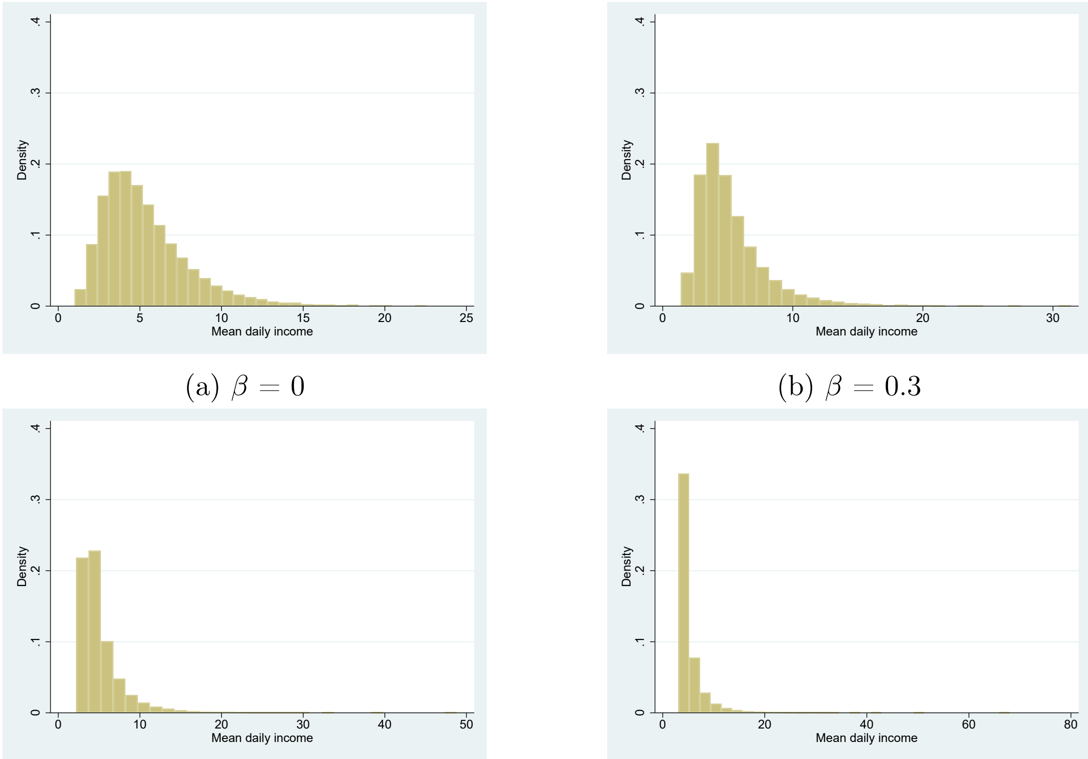
Following Hruschka, Gerkey, and Hadley (2015), the threshold parameter $\bar{x}$ can be defined as a deviation from the mean income from

$$\bar{x} = \left[1 - \left(\frac{1}{\alpha}\right)\right] \times \text{meanincome}, \tag{17}$$

such that the threshold decreases with higher values for the shape parameter α.
Similar to the case of the lognormal distribution above, it is possible to invert the cdf from equation (14) by simply solving for income x, which will yield

$$x = \bar{x}(1 - y)^{-\frac{1}{\alpha}}, \qquad \bar{x} < x. \tag{18}$$

As equations (16) and (17) show, α and $\bar{x}$ can be recovered in case the mean income and the Gini are known. The inverse cdf in equation (18) then allows to assign an income level to a certain position y in the distribution. The same holds for the lognormal distribution, as shown in equations (9)-(13). As the density plots in figure 3a for lognormal and figure 3d for pareto depict, the latter has a higher degree of skewness than the former does. Determining the assumed income distribution with the best possible fit for the matching



(a) $\beta = 0$ (b) $\beta = 0.3$ (c) $\beta = 0.7$ (d) $\beta = 1$

Figure 3: Density plots for different values of β for Kyrgyzstan 2016

procedure is crucial. The more it deviates from the real distribution, the more imprecise will be the income estimates for the households (Harttgen and Vollmer, 2013).

To adjust the assumed distribution more flexibly to the PovcalNet data, the pareto and the lognormal distribution can be combined by using weighted geometric means (Hruschka, Gerkey, and Hadley, 2015), such that

$$\text{Income}_{\beta} = \text{Income}_{Pareto}^{\beta} \times \text{Income}_{Lognormal}^{1-\beta}, \qquad 0 \leq \beta \leq 1. \tag{19}$$

Equation (19) allows for a range of intermediate distributions between the lognormal and pareto. The higher the parameter β, the closer the distribution approaches the pareto distribution. Figure 3 shows how the density plots change with the value of β, where $\beta = 0$ implies a lognormal distribution and $\beta = 1$ a pareto distribution.

To find the value for β that produces the best fit, the matched household poverty data for each of the possible distributions from equation (19) is averaged over country and year, and then compared to the original PovcalNet data. The one with the smallest difference is then selected as best. Table 4 shows the PovcalNet estimates in comparison to the ones from the matching procedure described above. As the numbers reveal, differences between the original data and the respective best fitting distributions are very small, indicating that the latter do a good job in reproducing poverty rates. It should be noted that the estimates in the table do not all come from the same distributions for a given country and year, but that the optimal fit for one FGT measure of interest does not necessarily coincide with that of another FGT measure.

When the best available approximate distributions of income is identified, every household has a matched income as well as estimates for the different FGT poverty measures assigned to itself. Most importantly, and in contrast to the asset index, the income measure allows for comparisons across countries and years that were not feasible before. In

Table 4: Comparison between estimated poverty rates and PovcalNet poverty rates

	2006		2010		2016	
	PovcalNet	Matched	PovcalNet	Matched	PovcalNet	Matched
Armenia						
Poverty headcount	0.0322	0.0350	0.0190	0.0167	0.0178	0.0185
Poverty gap	0.0057	0.0056	0.0029	0.0032	0.0029	0.0029
Squared poverty gap	0.0016	0.0014	0.0008	0.0007	0.0008	0.0007
Belarus						
Poverty headcount	0.0011	0.0000	0.0000	0.0000	0.0000	0.0000
Poverty gap	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000
Squared poverty gap	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000
Estonia						
Poverty headcount	0.0076	0.0000	0.0074	0.0000	0.0047	0.0000
Poverty gap	0.0045	0.0000	0.0042	0.0000	0.0031	0.0000
Squared poverty gap	0.0036	0.0000	0.0028	0.0000	0.0027	0.0000
Kazakhstan						
Poverty headcount	0.0062	0.0060	0.0013	0.0000	0.0002	0.0000
Poverty gap	0.0010	0.0013	0.0002	0.0000	0.0000	0.0000
Squared poverty gap	0.0003	0.0003	0.0000	0.0000	0.0000	0.0000
Kyrgyz Republic						
Poverty headcount	0.0987	0.0990	0.0407	0.0416	0.0137	0.0150
Poverty gap	0.0177	0.0191	0.0109	0.0094	0.0024	0.0029
Squared poverty gap	0.0050	0.0056	0.0058	0.0027	0.0008	0.0006
Lithuania						
Poverty headcount	0.0152	0.0000	0.0150	0.0000	0.0139	0.0000
Poverty gap	0.0072	0.0000	0.0101	0.0000	0.0071	0.0000
Squared poverty gap	0.0046	0.0000	0.0084	0.0000	0.0059	0.0000
Latvia						
Poverty headcount	0.0146	0.0010	0.0174	0.0000	0.0064	0.0000
Poverty gap	0.0083	0.0000	0.0075	0.0000	0.0028	0.0000
Squared poverty gap	0.0061	0.0000	0.0053	0.0000	0.0019	0.0000
Moldova						
Poverty headcount	0.0241	0.0206	0.0053	0.0042	0.0016	0.0000
Poverty gap	0.0059	0.0054	0.0011	0.0009	0.0004	0.0000
Squared poverty gap	0.0025	0.0016	0.0004	0.0002	0.0002	0.0000
Russia						
Poverty headcount	0.0030	0.0030	0.0006	0.0012	0.0002	0.0000
Poverty gap	0.0006	0.0004	0.0001	0.0000	0.0001	0.0000
Squared poverty gap	0.0002	0.0002	0.0000	0.0000	0.0000	0.0000
Ukraine						
Poverty headcount	0.0013	0.0011	0.0000	0.0000	0.0005	0.0000
Poverty gap	0.0001	0.0001	0.0000	0.0000	0.0000	0.0000
Squared poverty gap	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Uzbekistan						
Poverty headcount	0.5346	0.5105	0.2927	0.3100	0.1401	0.1441
Poverty gap	0.1760	0.1396	0.0825	0.0850	0.0375	0.0370
Squared poverty gap	0.0803	0.0644	0.0348	0.0329	0.0149	0.0162

the section to follow, this newly accessible piece of information will be used to estimate differences in the poverty trends between Kyrgyzstan and Uzbekistan.

5 Difference-in-Differences model

The DiD estimation strategy builds on a counterfactual framework in which changes in the trend of the dependent variable, in this case poverty, are only attributed to the occurence of an event that affects a part of the population in the data, the so called *treatment group*, while the trend of the *control group*, i.e. the non-affected population part, remains unaffected.

The intuition behind DiD can be explained in a framework of potential outcomes (Angrist and Pischke, 2009, p.228). In the given context of Uzbekistan and Kyrgyzstan, the essential assumption here is that in absence of the democratization shock in Kyrgyzstan, both countries poverty trends could have been described as

$$E[y_{0ict}|c,t] = \gamma_c + \lambda_t, \tag{20}$$

where y_{0ict} is household's i poverty status in measure of interest, c indicates the country and t the time. This simply says that in the potential outcome without regime change, both countries poverty trends could be described linearly as a sum of a country specific trend γ and a country common time trend λ. While the left-hand side of equation (20) is observed for Uzbekistan, it remains a counterfactual and thus unobserved for Kyrgyzstan. With the difference between a country's treated and untreated outcome being $E[y_{1ict} - y_{0ict}|c,t] = \delta$ where either y_{1ict} or y_{0ict} is unobserved, and D_{ct} being a dummy for democratization in country c and time$t$, y_{ict} can be written as

$$y_{ict} = \gamma_c + \lambda_t + \delta D_{ct} + \epsilon_{ict}. \tag{21}$$

Given that $E[\epsilon_i|c,t] = 0$, this expression can be used to write each country's difference in poverty rates before and after as

$$\begin{aligned} &E[y_{ict}|c = UZB, t = past2010] - E[y_{ict}|c = UZB, t = pre2010] \\ &\quad = \lambda_{past2010} - \lambda_{pre2010} \end{aligned} \tag{22}$$

and

$$
\begin{aligned}
&E[y_{ict}|c = KGZ, t = past2010] - E[y_{ict}|c = KGZ, t = pre2010] \\
&\quad = \lambda_{past2010} - \lambda_{pre2010} + \delta.
\end{aligned}
\tag{23}
$$

Subtracting equation (22) from (23) yields the difference-in-differences, which is simply given by δ since the other terms cancel out. This also is the parameter of interest to determine the effect that the democratization in Kyrgyzstan had on poverty rates.

The crucial assumption for this potential outcome framework to produce the wanted DiD estimate δ as the effect of Kyrgyzstan's 2010 revolution on poverty rates is that the countries principally follow common trends as stated in equation (20). The assumption can be tested if the data has more than just the two time periods pre and after treatment. A graph of the poverty levels of the two countries can reveal if they indeed had common trends prior to the setting in of treatment, which should be the only reason why Kyrgyzstan deviated from this common trend.

Even though the LiTS comes in only three waves and therefore does not have enough points in time to depict a time trend, the PovcalNet data base provides for longer time series. Figure 4 shows poverty headcount rates for the years that have data for both countries. Even though the level of poverty is about twice as high in Uzbekistan in 2003, both countries follow parallel downward sloping trends up to 2010.[1] In 2010, Kyrgyzstan's poverty rates start stagnating and continue to do so after a small kink in 2011, while Uzbekistan's poverty rates continue to follow the very stable trend from before.

A counterargument against the validity of the common path assumption could be that Kyrgyz poverty rates only started to stagnate because they reached a considerably low level that made further reduction infeasible. Even though it is true that poverty rates cannot turn negative, they certainly can go to zero as the PovcalNet data for other countries shows in table 4. In 2009, the poverty rate for Kyrgyzstan was still above 2% and even increased to a level of 4% in 2010. Thus, figure 4 is a strong indicator that the common path assumption is met and that a causal interpretation of the 2010 events in Kyrgyzstan is possible.

Given that the common path assumption is fulfilled, δ can be estimated in an OLS

[1]Data for 2009 is not listed in the PovcalNet database. The available years that were used for the construction of the graph are 2003, 2005, 2008, 2010, 2011, 2012, 2013 and 2015.

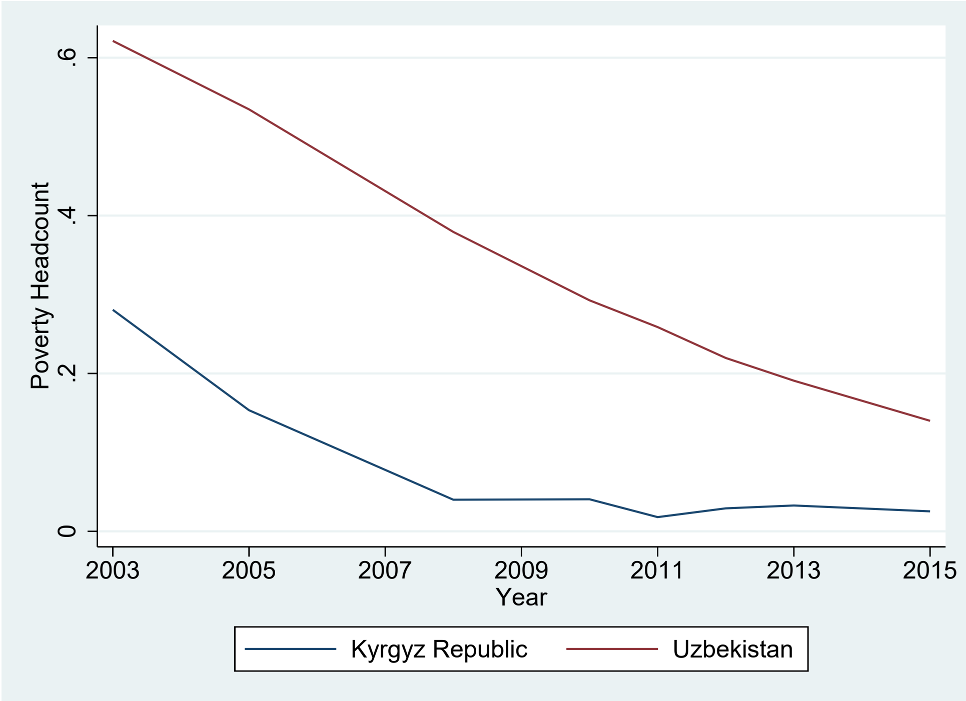


Figure 4: Time trends for poverty headcount in Uzbekistan and Kyrgyzstan

regression where the model is specified as

$$y_{ict} = \alpha + \gamma \, KGZ_c + \lambda \, year2016_t + \delta \, (KGZ_c \times year2016_t) + X_i'\beta + \epsilon_{ict}, \qquad (24)$$

with KGZ_c taking the value one if the country c is Kyrgyzstan and $year2016_t$ being a dummy indicating observations for 2016, which here identifies as the period after the treatment set in. X_i' is a vector of control variables on the household level.

In the ideal DiD framework, the only difference between the treatment and the control group is the treatment status. δ then inevitably reproduces the treatment effect (Duflo, Glennerster, and Kremer, 2006). Perfect comparability, however, is not attainable outside of an experimental setting without true randomization between the groups. Even though Kyrgyzstan and Uzbekistan are neighbouring countries, their populations are likely to vary in a number of characteristics. This can pose a challenge to the DiD if the differences in country characteristics vary over time. Including controls X_i' into the model (24) aims to increase comparability between treatment and control group over time (Wooldridge, 2009, p.452) and to reduce standard errors. Table 5 lists the population means for some of them, as well as their differences. In columns (1)-(3) that cover the entire country, four of the six displayed characteristics are highly significant in their differences in means. The comparison looks more promising when restricted to the regions at the border between Uzbekistan and Kyrgyzstan. While household size, number of children and number of adults per households are insignificant here, the difference in the share of sample population living in rural areas is much larger and highly significant, as well as the difference in average education levels.

Table 5: Mean comparisons between control and treatment group, 2006

	Full sample			Border regions		
	(1) UZB	(2) KGZ	(3) Diff	(4) UZB	(5) KGZ	(6) Diff
Rural	0.641	0.640	-0.001	0.501	0.714	0.213***
	(0.480)	(0.480)	(0.021)	(0.501)	(0.453)	(0.038)
No of children	1.419	1.140	-0.279***	1.318	1.489	0.172
	(1.307)	(1.266)	(0.058)	(1.294)	(1.378)	(0.106)
No of adults	3.702	3.162	-0.540***	3.515	3.457	-0.058
	(1.876)	(1.466)	(0.075)	(1.794)	(1.396)	(0.130)
Household size	5.121	4.302	-0.819***	4.833	4.946	0.114
	(2.326)	(2.001)	(0.097)	(2.281)	(1.890)	(0.169)
Education	3.421	3.482	0.061	3.474	3.304	-0.170**
	(0.812)	(0.963)	(0.040)	(0.880)	(0.894)	(0.071)
Christian	0.044	0.131	0.087***	0.097	0.029	-0.069***
	(0.205)	(0.338)	(0.012)	(0.297)	(0.167)	(0.020)

Standard errors in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

6 Results and discussion

Tables 6 as well as 7 and 8 in the appendix show regression outputs with FGT_0 (poverty headcount), FGT_1 (poverty gap) and FGT_2 (squared poverty gap) respectively as dependent variable. As explained in section 4.1, all three have different interpretations to them and can thus contribute their own valuable insights to the question how poverty was affected by the Kyrgyz revolution in 2010.

As noted by Bertrand, Duflo, and Mullainathan (2004), DiD estimation commonly understates standard errors for reasons of serial correlation. In essence, the OLS estimation assumes that errors are uncorrelated over time, i.e. that the variance-covariance matrix is diagonal. Poverty rates, however, are likely to be correlated over time for a specific group, which would imply that the variance-covariance matrix is not diagonal but block-diagonal. To account for serial correlation, standard errors of the estimates are clustered at the PSU level.

Column (1) of table 6 depicts the estimates of the Kyrgyz 2010 events. The coefficient for

Table 6: DiD estimation results for FGT_0

	(1)	(2)	(3)
KGZ	-0.415***	-0.423***	-0.447***
	(0.020)	(0.021)	(0.034)
year2016	-0.372***	-0.367***	-0.393***
	(0.022)	(0.022)	(0.040)
KGZ × year2016	0.287***	0.289***	0.313***
	(0.024)	(0.024)	(0.041)
Education		-0.003	-0.013
		(0.009)	(0.015)
Christian		0.089*	0.072
		(0.043)	(0.073)
Children		0.000	0.000
		(0.006)	(0.009)
Rural		0.012	0.021
		(0.019)	(0.034)
Constant	0.515***	0.513***	0.569***
	(0.018)	(0.043)	(0.070)
Observations	5005	5005	2283
R^2	0.19	0.19	0.22
Border regions only	No	No	Yes

Clustered standard errors at PSU level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

KGZ shows that in 2006, the share of people below the poverty line was 41.5 percentage points lower in Kyrgyzstan than in Uzbekistan. This fits into the picture obtained from graph 4. The treatment effect is given by *KGZ* × *year2016* and shows that the regime change in Kyrgyzstan had a strongly positive, highly significant effect on the share of people living below $1.90 a day with a coefficient of 0.287.

For column (2), control variables on the household level are added to the regression to account for potential differences between treatment and control group. It is crucial that the included variables are not themselves outcomes of the treatment, for otherwise they are so called *bad controls* and will lead to biased estimates (Angrist and Pischke, 2009, p.47). The asset and utility variables from table 1, for instance, are likely candidates for bad controls, since they are expected to be affected by the change in government. As column (2) shows, the inclusion of control variables does only slightly change the coefficient of the estimated treatment effect, and it is still significant at the 0.001 level.

In addition to the control variables, column (3) reduces the sample to the regions that are located around both sides of the Kyrgyz-Uzbek border. Before Uzbekistan and Kyrgyzstan gained independence and two self-governed nations were created, the border between the two countries was hardly recognizable. As Megoran (2004) notes, Soviet authorities never clearly demarcated the border that nowadays divides the Ferghana valley into a Kyrgyz and an Uzbek part. In consequence, the building of infrastructure such as gas, irrigation and transportation did not separate between either side of the valley. Free movement of people and closely connected economic structures resided in a high degree of intertwingularity across the states (Akiner, 2016). Even after independence, it was not until 1999 that the border manifested as an impediment in the daily life of the people (Megoran, 2004). As a result, today's populations on either side of the border are of mixed ethnicities (Akiner, 2016). [2] Reducing the sample to those regions that are close to the Kyrgyz-Uzbek border should therefore strengthen the robustness of the results, since it enables to control for many unobservable differences in the characteristics of the households that could vary over time and otherwise make the estimates vulnerable to bias. As compared to results in columns (1) and (2), the estimated treatment effect in column (3) is still highly significant but slightly higher at 0.313. While the dummy for Christian religion is significant in column (2), it now turned insignificant, which supports the assumption that there is less variation in characteristics between control and treatment group in column (3).

Tables 7 and 8 show regression results with poverty depth (FGT_1) and poverty severity (FGT_2) as dependent variables. Similar to the results for FGT_0, both show highly significant and positive coefficients for $KGZ \times year2016$. Thus, not only had the revolution in Kyrgyzstan an increasing effect on the share of people living in absolute poverty, but it also affected the extent of poverty in society as well as the severity of it in the same direction.

A major concern for the validity of the results is that even after reducing the sample to the border regions and adding household control variables, there are time-varying characteristic differences that are not controlled for in the regression. Especially migration can be an issue, since the Kyrgyz conflict in 2010 that lead to the overthrow of the regime had its epicentre along the Uzbek border in the south-west of the country. Supporters of the interim government who were mostly of Uzbek ethnicity were clashing with predominantly Kyrgyz proponents of president Bakyiev, causing reportedly 100.000 people to flee to the other side of the border. Even though the conflict only lasted for about a week and

[2] According to Akiner (2016), the Kyrgyz region Osh that is located closs to the Uzbek border accomodated 27 % of ethnic Uzbeks in 2010.

Table 7: DiD estimation results for FGT_1

	(1)	(2)	(3)
KGZ	-0.121***	-0.122***	-0.124***
	(0.008)	(0.008)	(0.012)
year2016	-0.103***	-0.102***	-0.099***
	(0.010)	(0.010)	(0.014)
KGZ × year2016	0.087***	0.086***	0.081***
	(0.010)	(0.010)	(0.014)
Education		-0.004	-0.002
		(0.004)	(0.006)
Christian		0.006	-0.010
		(0.018)	(0.026)
Children		-0.001	-0.002
		(0.002)	(0.003)
Rural		-0.000	0.009
		(0.007)	(0.012)
Constant	0.140***	0.153***	0.147***
	(0.008)	(0.017)	(0.023)
Observations	5005	5005	2283
R^2	0.11	0.11	0.11
Border regions only	No	No	Yes

Clustered standard errors at PSU level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: DiD estimation results for FGT_2

	(1)	(2)	(3)
KGZ	-0.060***	-0.060***	-0.061***
	(0.005)	(0.005)	(0.007)
year2016	-0.049***	-0.049***	-0.047***
	(0.005)	(0.005)	(0.008)
KGZ × year2016	0.044***	0.044***	0.041***
	(0.005)	(0.005)	(0.008)
Education		-0.001	0.000
		(0.002)	(0.003)
Christian		-0.001	-0.015
		(0.010)	(0.012)
Children		-0.001	-0.001
		(0.001)	(0.002)
Rural		-0.001	0.004
		(0.004)	(0.007)
Constant	0.065***	0.071***	0.065***s
	(0.004)	(0.010)	(0.013)
Observations	5005	5005	2283
R^2	0.08	0.08	0.08
Border regions only	No	No	Yes

Clustered standard errors at PSU level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the vast majority of them returned shortly after it was settled (Akiner, 2016), there could still be some selection bias if for instance wealthier refugees did not return to Kyrgyzstan in the aftermath of the riots. This would lead to time-varying changes between treatment and control group and could explain the positive effect of the regime change in 2010 on poverty rates. A possible way to account for this uncertainty is to combine the DiD model with propensity score matching for better comparability between treatment and control group, as for instance done in Galiani, Gertler, and Schargrodsky (2005). Based on a number of observable characteristics, treated households can then be matched to untreated ones that have the same characteristics. Unfortunately, good matching results require sufficient household information to find similar counterparts. The LiTS does not list enough of these characteristics to allow a matching procedure without omitting important variables.

The conflict in 2010 is also source of a further concern about the validity, which is that the short outbreak of violence drove people into poverty and thus explains the positive coefficient for the DiD estimation. If this was true, the effect would expectedly be higher when restricting the sample to the conflict zone in the border region as opposed to running the regression on entire countries. While this is the case for the regression on poverty headcount in table 6, tables 7 and 8 show the opposite for the poverty gap and the squared poverty gap. If the conflict had a long-lasting impact on the south-western regions of Kyrgyzstan and in absence of other confounding factors, it should not only show in the amount of people living below the poverty line but also in the severity and the depth of poverty. It is therefore unlikely that the increasing effect of the Kyrgyz regime change can solely be explained with the tensions connected to the revolution.

7 Conclusion

The analysis above makes two main contributions that should be emphasized. The first contribution relates to the usage of household survey data for poverty estimation without reliable income information. The absence of adequate income data can be a serious obstacle when estimating poverty trends and the factors affecting it. A high number of surveys conducted in developing countries, including the LiTS that was analysed above, only account insufficiently for expenditure components, such that it becomes a great challenge to estimate a household's poverty status. Making these surveys available would therefore unclose a large amount of data resources that were previously inaccessible and could incentivize important research in the field of poverty alleviation. The strategy used in this analysis is a promising solution for the issue, as it only needs (1) a number of expenditure variables to construct a relative household ranking, (2) the mean income for a given country year and (3) the respective Gini coefficient. However, further research needs to be done on the precision of the results that it can produce. Potential bias can occur from applying a misrepresentative income distribution shape, from wrong assumptions used for the construction of the relative wealth index or from measurement errors in the survey design.

The second contribution of this work builds on the first one and makes use of the imputed income data to gain a better understanding of poverty implications from the Kyrgyz regime change in 2010. The Kyrgyz-Uzbek border offers an excellent opportunity to study this effect due to its late manifestation and the comparability of the two populations on either side of it. The DiD estimations showed that the transition from an autocratic and corrupt government to a more democratic one in Kyrgyzstan had increasing effects on all three FGT poverty measures that were tested. This comes as a surprising result, since much of the literature in recent years connects good institutions with economic prosperity (Acemoglu and Robinson, 2012, e.g.). The apparent contradiction with previous findings makes it even more interesting for further research to examine the channels through which the effect in Kyrgyzstan works more precisely. It should nevertheless be pointed out that the fall of the soviet union created a unique historical context that only enabled for the estimation of the DiD model in the first place. The generalizability of these results should therefore be regarded with cautiousness.

References

ABDI, H., AND L. J. WILLIAMS (2010): "Principal component analysis," *Wiley Interdisciplinary Reviews: Computational Statistics*, 2(4), 433–459.

ACEMOGLU, D., AND J. A. ROBINSON (2012): *Why nations fail: The origins of power, prosperity, and poverty.* Crown Publishers, New York, 1st ed. edn.

ACKLAND, R., J. BRAITHWAITE, M. FOLEY, T. GARNER, C. GROOTAERT, B. MILANOVIC, G.-T. OH, S. SIPOS, S. TSIROUNIAN, AND Y. YING (1996): "Household expenditure and income data for transitional economies (HEIDE): Data cleaning and imputation: Appendix 1 of RAD project "Poverty and Targeting of Social Assistance in Eastern Europe and the Former Soviet Union"," .

AKINER, S. (2016): *Kyrgyzstan 2010: Conflict and context*, Silk Road paper. The Central Asia-Caucasus Institute, Paul H. Nitze School of Advanced International Studies and The Silk Road Studies Program, Institute for Security and Development Policy, Washington, D.C. and Stockholm-Nacka.

ALAM, A., M. MURTHI, R. YEMTSOV, E. MURRUGARRA, N. DUDWICK, E. HAMILTON, AND E. TIONGSON (2005): *Growth, Poverty and Inequality : Eastern Europe and the Former Soviet Union.* The World Bank, Washington, DC.

ALKIRE, S., AND M. E. SANTOS (2010): "Acute Multidimensional Poverty: A New Index for Developing Countries," *SSRN Electronic Journal.*

ANGRIST, J. D., AND J.-S. PISCHKE (2009): *Mostly harmless econometrics: An empiricist's companion.* Princeton Univ. Press, Princeton, NJ.

ATKINSON, A. B., L. RAINWATER, AND T. M. SMEEDING (1995): *Income Distribution in OECD Countries: Evidence from the Luxembourg Income Study.* Organisation for Economic Co-operation and Development, Paris.

BERTRAND, M., E. DUFLO, AND S. MULLAINATHAN (2004): "How Much Should We Trust Differences-In-Differences Estimates?," *The Quarterly Journal of Economics*, 119(1), 249–275.

COWELL, F. A. (ed.) (2015): *Measuring inequality.* Oxford University Press, Oxford.

Deaton, A., and S. Zaidi (2002): *Guidelines for Constructing Consumption Aggregates for Welfare Analysis*, vol. No. 135 of *LSMS Working Paper*.

Deaton, A. S. (1997): *The Analysis of Household Surveys : A Microeconometric Approach to Development Policy*. The World Bank, Washington, D.C.

Duflo, E., R. Glennerster, and M. Kremer (2006): "Using Randomization in Development Economics Research: A Toolkit," *National Bureau of Economic Research*.

Ferguson, B. D., A. Tandon, E. Gakidou, and C. J. Murray (2003): "Estimating permanent income using indicator variables," *Health systems performance assessment: debates, methods and empiricism. Geneva: World Health Organization*, pp. 747–760.

Filmer, D., and L. H. Pritchett (1999): "The Effect of Household Wealth on Educational Attainment: Evidence from 35 Countries," *Population and Development Review*, 25(1), 85–120.

——— (2001): "Estimating Wealth Effects Without Expenditure Data—Or Tears: An Application To Educational Enrollments In States Of India," *Demography*, 38(1), 115–132.

Filmer, D., and K. Scott (2008): *Assessing Asset Indices*. The World Bank.

Foster, J., J. Greer, and E. Thorbecke (1984): "A Class of Decomposable Poverty Measures," *Econometrica*, 52(3), 761–766.

——— (2010): "The Foster–Greer–Thorbecke (FGT) poverty measures: 25 years later," *The Journal of Economic Inequality*, 8(4), 491–524.

Galiani, S., P. Gertler, and E. Schargrodsky (2005): "Water for Life: The Impact of the Privatization of Water Services on Child Mortality," *Journal of Political Economy*, 113(1), 83–120.

Graney, K. (ed.) (2019): *Russia, the former Soviet republics, and Europe since 1989: Transformation and tragedy*. Oxford University Press, New York, NY.

Harttgen, K., and S. Vollmer (2013): "Using an asset index to simulate household income," *Economics Letters*, 121(2), 257–262.

Hjelm, L., A. Mathiassen, D. Miller, and A. Wadhwa (2017): *Creation of a Wealth Index: VAM Guidance Paper.*

Howe, L. D., J. R. Hargreaves, S. Gabrysch, and S. R. A. Huttly (2009): "Is the wealth index a proxy for consumption expenditure? A systematic review," *Journal of Epidemiology & Community Health*, 63(11), 871–877.

Hruschka, D. J., D. Gerkey, and C. Hadley (2015): "Estimating the absolute wealth of households," *Bulletin of the World Health Organization*, 93(7), 483–490.

Jenkins, S. P. (2017): "Pareto Models, Top Incomes and Recent Trends in UK Income Inequality," *Economica*, 84(334), 261–289.

Juraev, S. (2008): "Kyrgyz democracy? The Tulip Revolution and beyond," *Central Asian Survey*, 27(3-4), 253–264.

Lopez, H., and L. Serven (2006): *A Normal Relationship ? Poverty, Growth, And Inequality.* The World Bank.

McKenzie, D. J. (2005): "Measuring inequality with asset indicators," *Journal of Population Economics*, 18(2), 229–260.

Megoran, N. (2004): "The critical geopolitics of the Uzbekistan–Kyrgyzstan Ferghana Valley boundary dispute, 1999–2000," *Political Geography*, 23(6), 731–764.

——— (2012): "Rethinking the Study of International Boundaries: A Biography of the Kyrgyzstan–Uzbekistan Boundary," *Annals of the Association of American Geographers*, 102(2), 464–481.

Melvin, N. J. (2004): "Authoritarian Pathways in Central Asia: A Comparison of Kazakhstan, the Kyrgyz Republic and Uzbekistan," in *Democracy and pluralism in Muslim Eurasia*, ed. by Y. Ro'i, Cummings Center series. Frank Cass, London and New York.

Mitzenmacher, M. (2003): "A Brief History of Generative Models for Power Law and Lognormal Distributions," *Internet Mathematics*, 1(2), 226–251.

Murtazashvili, J. (2012): "Coloured by revolution: the political economy of autocratic stability in Uzbekistan," *Democratization*, 19(1), 78–97.

Pen, J. (1971): *Income distribution : facts, theories, policies*. Praeger, New York.

Pinkovskiy, M., and X. Sala-i Martin (2009): *Parametric Estimations of the World Distribution of Income*. National Bureau of Economic Research.

Ravallion, M., and A. Atkinson (1994): *Poverty Comparisons*, Distribution section. Harwood Academic Publishers.

Rutstein, S. O., and K. Johnson (2004): "The DHS wealth index," *DHS Comparative Reports*, (6).

Rutstein, S. O., and S. Staveteig (2014): "Making the Demographic and Health Surveys Wealth Index comparable," *DHS Methodological Reports*, (9).

Sahn, D. E., and D. Stifel (2003): "Exploring Alternative Measures of Welfare in the Absence of Expenditure Data," *Review of Income and Wealth*, 49(4), 463–489.

Sen, A. (2000): "A Decade of Human Development," *Journal of Human Development*, 1(1), 17–23.

Smits, J., and R. Steendijk (2015): "The International Wealth Index (IWI)," *Social Indicators Research*, 122(1), 65–85.

Temirkulov, A. (2010): "Kyrgyz "revolutions" in 2005 and 2010: comparative analysis of mass mobilization," *Nationalities Papers*, 38(5), 589–600.

Wooldridge, J. M. (2009): *Introductory econometrics: A modern approach*. South-Western CENGAGE Learning, 4 edn.