# Sanctions and Counter-Sanctions: What Did They Do?

Gayane Barseghyan\*

American University of Armenia

#### Abstract

Taking the multilateral sanctions program launched against Russia in 2014 as a case study, this paper investigates the economic effects of sanctions and counter-sanctions on a target economy. A synthetic control method for comparative case studies is employed to construct counterfactuals. The estimation results demonstrate that in Russia following sanctions and counter-sanctions real GDP per capita, FDI net inflows and income inequality fell, while the ban on agricultural and food imports introduced by Russia boosted the domestic agricultural sector, resulting in higher agricultural productivity and farm worker incomes. Various placebo studies confirm the significance of obtained estimates. Results are robust to random donor samples.

**Keywords:** sanctions, counter-sanctions, synthetic control method. **JEL Classifications:** C33, F51, O50.

<sup>\*</sup>Gayane Barseghyan, https://orcid.org/0000-0001-7685-9485. American University of Armenia. Email: gbarseghyan@aua.am. I would like to thank Zareh Asatryan, Gurgen Aslanyan, Zuzana Fungáčová for valuable comments and suggestions, as well as the participants in a seminar at the Bank of Finland (BOFIT) and at the Armenian Economic Association's 8<sup>th</sup> annual meeting. I also thank Gregory Moore for proofreading. The paper reflects the views of the author and not necessarily those of the Bank of Finland or the American University of Armenia. The usual disclaimer applies.



#### 1 Introduction

International sanctions are increasingly relied upon as tools for inducing policy changes in a target country by raising the costs to the target country for pursuing policies found unsavory by the sanctioning countries. There is a rich body of examples of international sanctions throughout the 20cth century (see e.g. Hufbauer et al., 2007).

In this paper, I estimate the economic effects of sanctions and counter-sanctions on a target economy, using as a case study the multilateral sanctions program launched against Russia in 2014. The special interest arises from the fact that it involves economic and financial sanctions implemented by a large number of advanced countries and includes protective counter-sanctions undertaken by the target country.

While earlier papers studying macroeconomic effects of Russian sanctions use time-series analysis techniques, I estimate the causal effects of Russian sanctions and counter-sanctions with the synthetic control method (SCM) for comparative case studies (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Abadie et al., 2015). This transparent, data-driven approach, which allows direct estimation of the causal effects of an intervention, has been used in many applications (e.g. Acemoglu et al., 2016; Billmeier and Nannicini, 2013; Cavallo et al., 2013; Campos et al., 2019; and Puzzello and Gomis-Porqueras, 2018). The SCM has several advantages over other approaches (Abadie et al., 2015). Billmeier and Nannicini (2013, p. 987) note that "while panel models control only for confounding factors that are time invariant (fixed effect) or share a common trend (difference-in-differences)," the SCM accounts for time-varying unobservable confounding factors. Using the SCM, counterfactuals (synthetic control units) are constructed as a convex combination of unaffected units and the causal impact of the intervention is estimated as the difference in postintervention periods between actual outcome variables and synthetic counterparts (provided a good pre-intervention fit is obtained).

The SCM has been applied by Mirkina (2018) in examining the effects of sanctions on foreign direct investments for a large set of target countries, and Gharehgozli (2017) in assessing the impact of sanctions on Iran's GDP. Taking into account the "smart" nature of sanctions and counter-sanctions imposed by Russia, I consider a broader spectrum of possible impacts of sanctions, including the impact of sanctions on GDP per capita and foreign direct investment, as well as the effects on agriculture value added and income inequality. Two measures of agriculture value added are considered to assess whether counter-sanctions imposed on imports of food products from sanctioning countries caused sectoral and productivity changes in the Russian economy. Income inequality is considered as counter-sanctions potentially enhance earnings of agricultural laborers, while smart sanctions lower the incomes of the Russian elite. This work differs from the empirical studies of Neuenkirch and



Neumeier (2016) and Afesorgbor and Mahadevan (2016) on the distributional consequences of sanctions by providing an evidence from a single country and given the particular combination of sanctions and counter-sanctions involved in the Russian case makes it possible to suggest a mechanism through which income inequality is affected. Thus, the investigation of the effects on agriculture value added per worker serves also this purpose.

In estimating the effects of sanctions and counter-sanctions, I address the following question: What would be the levels of the outcome variables in Russia had no sanctions or counter-sanctions been in force since 2014?

The estimation results show that the agriculture value added in GDP in actual Russia for the period 2014–2017 is on average higher by 0.54 percentage points annually compared to the counterfactual. This suggests that import substitution took place as a result of the counter-sanctions in the form of bans on agri-food imports introduced by Russia. The estimates reveal that sanctions and countersanctions since 2014 have reduced FDI net inflows as a percentage of GDP on average by 2 percentage points a year. For real GDP per capita, it is important to account for the decline in oil prices that began in the fourth quarter of 2014. To disentangle these effects, I construct a counterfactual that closely mimics the Russian economy in terms of oil rents to estimate the causal effects of sanctions and counter-sanctions. The estimates suggest that there was on average a \$1,337 loss of per capita GDP per year over the 2014–2017 period, i.e. 5% of annual average GDP of synthetic Russia in this period. The largest drop is estimated for 2015, which is also the only significant estimate based on the lead-specific p-values. Income inequality, measured by the Gini coefficient, is found to be lower on average by 1 percentage point per year compared to the counterfactual over the 2014–2016 period. This result can be explained by the adverse effects of smart sanctions on top income earners and improvements at the other end of the income distribution due to counter-sanctions leading to expansion of agricultrual sector. The argument is further supported by the finding that agriculture value added per worker increased by about \$3,900 per year on average during 2014–2017, reflecting both improvements in productivity and living standards of agricultural laborers.

The robustness of the results is confirmed by performing placebo studies as suggested in Abadie et al. (2010) and Cavallo et al. (2013). The robustness of results to random donor pools is assessed in accordance with the approach of Campos et al. (2019).

The rest of the paper is organized as follows. Section 2 provides a brief overview of the sanctions introduced in 2014 and reviews the relevant literature. Section 3 presents the empirical methodology and the data. Section 4 reports and discusses the results. Section 5 concludes.



#### 2 Literature review

International sanctions can inflict long-lasting harm on the target economy. Neuenkirch and Neumeier (2015), assessing the impact of UN and US economic sanctions on GDP growth for 1976–2012, find that UN sanctions decrease a target country's annual real per capita GDP growth rate by more than 2 percentage points. Moreover, the negative impact lasts for 10 years, accounting for an aggregate decline in GDP per capita of 25.5%. US sanctions are found to have a smaller impact, decreasing the target country's GDP growth by 0.75–1 percentage point, with the adverse effects lasting for seven years and producing an aggregate decline of 13.4%.

Here, I study the economic effects of a multilateral sanctions program combined with counter-sanctions undertaken by the target country. I use as a case study the multilateral sanctions program imposed on Russia in 2014. The geopolitical tensions between Russia and Ukraine over the Crimea precipitated a diplomatic crisis between Russia and roughly 40 countries, including the EU-28 and the US. The sanctions undertaken by the international community included diplomatic and economic sanctions. Diplomatic sanctions, e.g. suspension of partnership talks, were introduced in March-April 2014. Sanctions in the forms of asset freezes and travel bans were imposed on individual and entities in March 2014. This was followed by imposition of economic sanctions in July and September 2014 that targeted Russia's energy, defense, and financial sectors. In particular, access to Western capital markets was banned for Russia's six major banks.

Russia responded with its own set of counter-sanctions. In March 2014, the existence of an undisclosed blacklist of Western officials and politicians was announced. In August 2014, an agricultural and food import ban was imposed on sanctioning countries.

These sanctions and counter-sanctions have subsequently been extended since 2014, broadly remaining within the mentioned types. For a detailed timeline of events and sanctions, see e.g. Crozet and Hinz (2016), Dreger et al. (2016), Korhonen et al. (2018), or Russel (2018). Korhonen et al. (2018) provide a brief review of the history of sanctions against Russia and counter-sanctions, as well as an assessment of the impacts on the Russian economy and the economies of other countries involved.

Various estimates of the impacts of sanctions and counter-sanctions on the Russian economy have been offered (e.g. Reuters, 2014, 2017; Russell, 2018). Alexei Kudrin, an adviser to president Vladimir Putin and a former finance minister, suggested that the cost of sanctions in 2017 was 0.5% of Russian GDP, noting that this was less than the initial decline from the 1% of GDP experienced in the first years of sanctions (Reuters, 2017). Based on their own counterfactual analysis, the IMF (2019) reports that sanctions explain 0.2 percentage points of the shortfall of Russia's growth rate in the period 2014–2018 from the growth expectation of the



October 2013 WEO. The IMF (2015) also reported an estimated reduction of Russian real GDP in the short-run of around 1–1.5% while over the medium run with prolonged sanctions the cumulative output loss was predicted to be as high as 9% of GDP (the duration of the short and medium-run is not spelled out in the report).

A number of relevant studies on the effects of Russia sanctions deserve mention.

Applying the event-study methodology, Stone (2016) estimates the effects of economic sanctions on Russian securities prices. He finds that news of sanctions decreased returns and increased the variance of returns of Russian securities in the sanctioned sectors relative to non-sanctioned ones. However, no significant difference was established within a sector for sanctioned and non-sanctioned firms. The paper concludes that sanctions are effective in imposing economic costs on Russia and three channels of transmission of the sanctions effects are suggested: lower expected profits, higher uncertainty, and negative wealth effects.

Ahn and Ludema (2019) develop a theoretical model where the government can choose to "shield" strategically important firms from negative effects induced by smart sanctions. They then examine the impact of smart sanctions on the firm performance using firm- and individual-level data for US-EU sanctions episodes against Russia beginning in 2014. They find significant losses for sanctioned firms compared to non-sanctioned firms, and that strategic firms outperform sanctioned non-strategic firms. The authors point out that this last finding is evidence of an unintended allocation of damage to taxpayers that demonstrates the cronyism of the prevailing regime.

Using bilateral flow data, Belin and Hanousek (2019) study the effectiveness of sanctions imposed on exports and imports. Their paper finds a much stronger decline in European and American food imports than in exports of extraction equipment. The authors also attribute variations in sanction effectiveness to enforcement differences.

Peeva (2019) assesses the political impact of sanctions on Russian elections to investigate how sanctions affected the targeted regime. She points out that Putin's vote share increased by 1.54 percentage points in the 2018 presidential election relative to the 2012 election at polling stations geographically proximate to sanctioned firms.

The first group of papers, reviewed above, find that Russia sanctions, while adversely affecting targeted entities economically, also had unintended political effects.

The macroeconomic effects of Russia sanctions are considered in the following group of papers.

Dreger et al. (2016) take on the impact of economic sanctions and oil prices on exchange rate of Russias ruble using daily data covering the period January 1, 2014 to March 31, 2015. Based on impulse response analysis and variance decomposition in a cointegrated VAR model, they find that the greater part of ruble depreciation is related to the drop of oil prices, while conditional volatility is driven by unanticipated



sanctions.

Tuzova and Qayum (2016) obtain similar results in a VAR model. Using quarterly data from 1999Q1 to 2015Q1, they find a significant impact from changes in oil prices. For sanctions remaining in place until the end of 2017, they find an average 19% reduction of real GDP on the quarter-to-quarter basis for the forecast period.

Applying a structural vector autoregression model, Kholodilin and Netsunajev (2019) investigate the real effects of the sanctions on the Russian and euro-area economies with quarterly data for the period 1997Q1–2018Q1. Using an aggregate index that measures the intensity of economic sanctions in the spirit of Dreger et al. (2016), they obtain weak evidence for the decline of growth rates in Russia and in the euro-area. Although the effects are small, depreciation pressures in the wake of sanctions are identified.

Finally, Crozet and Hinz (2016) examine the trade effects of Russia sanctions and counter-sanctions from both the macro and micro perspectives. Using monthly data in a general equilibrium trade model, they estimate significant trade losses for both Russia and the sanctioning countries. For the sanctioning countries, most losses are incurred for products not targeted by Russian counter-measures, i.e. self-inflicted losses described by the authors as "friendly fire." Taking French firm-level customs data, they identify the source of the friendly fire, i.e. the decline in imports, to be increased country risk rather than a change in Russian consumer preferences with respect to French products.

Unlike the above studies, I use a panel dataset for the period 2000–2017 and construct counterfactuals employing the SCM, a transparent statistical methodology to perform data-driven comparative case studies. The SCM has been used previously in two sanctions studies. Mirkina (2018) considers data from 1970 to 2010 to study the effects of sanctions on foreign direct investment in many countries sanctioned during that time period. Gharehgozli (2017) assesses the effects of intensification of sanctions on Iran's GDP during 2011–2014.

Taking into account the smart nature of sanctions and counter-sanctions imposed by Russia, I look at a broader spectrum of possible impacts of sanctions than any of the above-mentioned studies, including those focused on the macroeconomic effects of sanctions on Russia. Along with the impacts of sanctions on the GDP per capita and foreign direct investment, I examine the effects on agriculture value added and income inequality. Two indicators of agriculture value added are considered in assessing sectoral and productivity changes in the Russian economy from the imposition of counter-sanctions, restricting imports of agri-food products from sanctioning countries. Income inequality is also considered, as sanctions target the Russian elite and counter-sanctions impact the domestic agricultural sector and, hence, the earnings of agricultural laborers. Note that there are earlier studies examining empirically the distributional consequences of sanctions. Neuenkirch and Neumeier (2016) find that US economic sanctions adversely affect people living in



poverty and Afesorgbor and Mahadevan (2016) obtain that economic sanctions tend to exacerbate income inequality in a target country.<sup>1</sup> This paper differs from those providing an evidence from a single country and given the types of sanctions and counter-sanctions in force makes it possible to suggest a mechanism through which inequality is affected. For this purpose, I also consider effects on agriculture value added per worker.

## 3 Empirical methodology and data

This section briefly presents the methodology and then discusses the data and details on selection of control countries into donor pools.

#### 3.1 Methodology

To estimate the evolution of the Russian economy in terms of specific outcome variables if it was not subject to sanctions and did not impose counter-sanctions itself, I use the SCM developed by Abadie and Gardeazabal (2003) and further extended in Abadie et al. (2010).

The effect of intervention (i.e. sanctions programs) at time period t for country i, is represented as:

$$\alpha_{it} = Y_{it}^I - Y_{it}^N, \qquad t \ge T_0,$$

where  $Y_{it}^I$  is the outcome variable at time period t for the country exposed to the intervention at time period  $T_0$  and  $Y_{it}^N$  is the outcome variable observed at time period t for country i had it not been exposed to intervention. Assuming that intervention had no impact before  $T_0$ , for all  $t < T_0$  the following holds  $Y_{it}^I = Y_{it}^N$ .

In order to estimate the effects of intervention,  $\hat{\alpha}_{it}$ , the  $Y_{it}^N$ , for  $t \geq T_0$  should be estimated. This is the unobserved variable, i.e. the counterfactual. As the estimation of the effect of intervention is performed with the SCM, the counterfactual is constructed as a convex combination of control countries not exposed to intervention, where the weights are chosen optimally. The optimal weights,  $w_j^*$ , are chosen to minimize the pre-intervention difference between the affected country and its synthetic counterpart in terms of covariates of the outcome variable (denoted by  $Z_i - (r \times 1)$  vector of observed covariates, which are not affected by the intervention). Assuming that there are N+1 countries and the affected country is denoted by i=1, the unbiased estimator of causal effect of the intervention, suggested by



<sup>&</sup>lt;sup>1</sup>For details on the theoretical considerations in the hypothesis formulations, see their papers.

Abadie et al. (2010), is given as:

$$\hat{\alpha}_{1t} = Y_{1t} - \sum_{j=2}^{N+1} w_j^* Y_{jt}, \qquad t \ge T_0$$

where the weights  $(w_j^* \ge 0, \sum_{j=2}^{N+1} w_j^* = 1)$  satisfy  $\sum_{j=2}^{N+1} w_j^* Z_j = Z_1$  and  $\sum_{j=2}^{N+1} w_j^* Y_{jt} = Y_{1t}$  for  $t < T_0$ . All related details on the SCM and proofs can be found in Abadie et al. (2010).

After applying this methodology to estimate the effects of sanctions, I perform number of robustness exercises. First, following Abadie et al. (2010) and Cavallo et al. (2013), I conduct placebo tests to assess the chances of observing effects of the same magnitude for the whole post-intervention period and for each post-intervention period if the intervention is assigned at random in the donor pool. I also follow Campos et al. (2019) by randomly selecting countries into donor pools to analyze how sensitive the results are to a particular donor pool choices.

Details on data and selection of control countries are presented in the next subsection.

#### 3.2 Data and control countries

Data

I use a panel dataset of countries covering the period 2000–2017, which, if not stated otherwise, comes from the World Bank World Development Indicators (WDI) database.

I study five outcome variables: real GDP per capita (PPP, 2011 international dollars), foreign direct investment (net inflows, % of GDP), agriculture, forestry, and fishing, value added (as percentage of GDP and per worker),<sup>2</sup> and income inequality measured by the Gini coefficient. In choosing the pre-sanctions characteristics for GDP per capita, I follow the corresponding literature (Abadie et al., 2015; Campos et al., 2019; and Cavallo et al., 2013). Thus, I use the following predictors of economic growth: per capita real GDP, inflation rate, shares of industry and agriculture in value added, gross capital formation, secondary education, trade openness, and GDP per capita growth. Along with these predictors, I also use an important characteristic of Russian economy, oil rents (% GDP). The last characteristic applies to all outcome variables. For the FDI predictors, I use the predictors that the relevant literature uses as main determinants of FDI (see e.g. Schneider and Frey (1985); Asiedu, 2006; Blonigen and Piger, 2014; Anderson et al., 2017; Mirkina, 2018). It includes FDI, real GDP per capita, trade openness, inflation rate, oil rents, and GDP per capita



 $<sup>^2</sup>$ For brevity, I refer to these indicators as agriculture share (value added, % of GDP) and agriculture value added per worker.

growth. For the outcome variables on two measures of agriculture value added, I use agriculture value added, GDP per capita and its growth rate, gross capital formation, trade openness, and oil rents. For income inequality outcome variable, I use Gini coefficients obtained from the Standardized World Income Inequality Data (SWIID) version 8.1 of Solt (2019).<sup>3</sup> The data are available for 2000–2016. The set of predictors, drawn following Roine et al. (2009), Afesorgbor and Mahadevan (2016), and Neuenkirch and Neumeier (2016), include GDP per capita, school enrollment (secondary), trade openness, tax revenues as a percentage of GDP, rural population as a percentage of total population, agriculture share, population growth, and Gini coefficient.

#### Control countries

I exclude from the analysis the affected countries, i.e. those that have imposed sanctions on Russia and then subject to Russian counter-sanctions. I also exclude from the analysis other countries subject to sanctions since 1975 (see e.g. Mirkina, 2018; Neuenkirch and Neumeier, 2015). After excluding countries because of data unavailability, 46 countries are left in the donor pool. Following Puzzello and Gomis-Porqueras (2018),<sup>4</sup> the baseline group of countries is also constructed such that the countries in terms of the average of their outcome variables in pre-intervention periods diverge from the ones for Russia within a specified range.<sup>5</sup>

## 4 Estimation results

Estimates of the causal impacts of the sanctions and counter-sanctions on five outcome variables for Russian economy, as well as the robustness analysis, are presented and discussed in this section.

#### 4.1 Estimated effects

Synthetic Russia is constructed as a convex combination of the countries in the donor pool such that it most closely resembles Russia in terms of the pre-sanctions values of the predictors of the outcome variables. Table 1 reports the estimation results. It

<sup>&</sup>lt;sup>5</sup>Divergence must be within 80%.



<sup>&</sup>lt;sup>3</sup>For the considered countries and time period, this dataset provides the largest coverage (e.g. WDI data were only available for five control countries and only up to 2015). Note that the Gini coefficient here is based on disposable income and the mean of reported 100 values for any given observation is used in the analysis.

<sup>&</sup>lt;sup>4</sup>They limit the control pool based on the outcome variable as "it summarizes the effects of its determinants" and the control pool is restricted because of the concerns regarding interpolation biases that may arise if the units in the control pool are too different in their economic characteristics (Abadie et al., 2010) or overfitting that may arise because of a large number of units (Abadie et al., 2015).

also reports the countries that have obtained positive weights in the synthetic Russia (weights in parentheses). In the baseline model for GDP per capita, synthetic Russia is composed of 43.5% Kazakhstan, 22.8% Trinidad and Tobago, 19.2% Korea, 13.9% Costa Rica, and 0.6% Bahamas.

Table A1 in the Appendix compares the pre-intervention characteristics of actual and synthetic Russia. The synthetic country matches most of the characteristics quite well and much better than the average in the donor pool, confirming that the average of the countries in the donor pool does not provide a suitable control group for Russia. For GDP per capita (Panel C, Table A1), note that synthetic Russia closely resembles actual Russia in terms of oil rents as a percentage of GDP, while the average for the control countries is much lower. In other words, the drop of oil prices in the fourth quarter of 2014 affects the GDP of synthetic Russia to a similar extent as that of actual Russia. Hence, synthetic Russia impacted by the oil price drop provides a reasonable estimate of GDP per capita in the absence of sanctions and counter-sanctions.

Given the obtained weights for the baseline models, Figure 1 depicts actual and counterfactual trends for the outcome variables (left column for each outcome variable). In all cases, the solid line represents actual Russia and the dashed line depicts the estimated synthetic counterfactual. The vertical line divides the pre-sanction period from its aftermath. Synthetic Russia for the considered outcome variables provides close fit in the pre-intervention period. This observation is bolstered by the values for the root mean square prediction error (RMSPE) and pre-sanction gaps reported in the Table 1.

It can be inferred from Figure 1 that the counterfactual reproduces actual data for agriculture share quite accurately. Divergence of the actual and counterfactual series after 2014 suggests that the share of the agriculture in the value added would have been lower without sanctions and counter-sanctions. The baseline estimate reported in Table 1 shows that the share of agriculture value added in GDP for the period 2014–2017 would have been on average lower by 0.54 percentage points per year in the absence of sanctions and counter-sanctions. Thus, the estimation results suggest that import substitution took place as a result of Russia's counter-sanction bans on agri-food imports.

Table 1: Estimation results

	Agriculture share		FDI		GDP per capita		Gini coefficient		Agriculture value added per worker	
	Baseline 17 coun- tries	All 46 coun- tries	Baseline 25 coun- tries	All 46 coun- tries	Baseline 27 coun- tries	All 46 coun- tries	Baseline 12 countries	All 15 coun- tries	Baseline 25 coun- tries	All 42 coun- tries
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Control countries with positive weights  Pre-interv Difference RMSPE	KAZ (45.3) KOR (19.8) LCA (9.9) OMN (6.6) ZAF (18.4) rention period 0.04 0.10	DOM (12.3) KAZ (31.7) LKA (6.4) TTO (48.2) UGA (1.4)	BWA (3) DOM (2) LAO (36.3) LKA (37.6) OMN (16) QAT (5.2) 0.06 0.66	COG (8.8) GHA (15) KAZ (6.2) LKA (52.2) QAT (9.5) SUR (8.4) -0.09 0.58	BHS (0,6) CRI (13.9) KAZ (43.5) KOR (19.2) TTO (22.8)	CRI (7.3) HKG (8.5) KAZ (44.6) PAK (11.1) QAT (0,4) TTO (28.2) -215.46 [-1.06] 425.09	DOM (36.2) KAZ (21.6) KOR (39.7) MEX (2) MKD (0,5)	DOM (35.2) KAZ (20) KOR (41.7) MEX (3.1)	CRI (69.3) DOM (9.5) KAZ (10.5) ZAF (10.7) 35.36 [0.42] 700.39	DOM (34.2) KOR (13.2) ZAF(52.6) -5.95 [ -0.07] 737.45
Post-inter	Post-intervention period									
Difference RMSPE <b>p-value</b>	$ \begin{array}{r} 0.53 \\ 0.54 \\ \hline 1/18 \end{array} $	$0.54 \\ 0.54 \\ \hline 2 / 47$	$ \begin{array}{r} -2.06 \\ 2.23 \\ \hline 1/26 \end{array} $	$   \begin{array}{r}     -2.63 \\     \hline     3.31 \\     \hline     1 / 47   \end{array} $	-1337.11 [-5.13] 1393.49 3 / 28	-1039.59[-4.38] 1092.57 16 / 47	-0.01 0.01 1 / 13	-0.01 0.01 1 / 16	3932.95[39.22] 4100.85 1/26	3924.58[39.10]   4085.73   3 / 43

Note: The weights of countries in the synthetic unit (in percent) are given in parentheses and due to rounding may not sum exactly to 100. For each period, the difference is calculated as the difference between the averages of the variables for the actual and synthetic countries over that period of time. For GDP per capita and agriculture value added per worker, the percentage differences between the averages are provided in brackets.



Figure 1 shows that the pre-intervention period counterfactual provides a close fit for FDI (net inflows, % of GDP) and that there would have been greater net inflows of FDI as a percentage of GDP in the absence of sanctions and counter-sanctions. The average difference between actual and counterfactual data in the post-intervention periods is equal to around -2 percentage points of GDP. In other words, FDI net inflows as a percentage of GDP would have been about 2 percentage points higher annually after 2014 had there been no sanctions or counter-sanctions. This finding comports with the finding of Mirkina (2018) that sanctions had a negative impact on FDI in many sanctions episodes in the 1990s.

As Figure 1 depicts, real GDP per capita also would have been considerably higher had there been no sanctions and counter-sanctions imposed in 2014. The negative effect diminishes over time. Note, however, that the largest loss estimated for 2015 (\$1,685) is still much smaller than the real GDP per capita loss of \$3,236.80 (16.4% of real GDP per capita) estimated for Iran in 2014 by Gharehgozli (2017) using the SCM.

Table 1 indicates that real GDP per capita for the entire 2014–2017 period would have averaged \$1,337 more per year in the absence of sanctions and counter-sanctions and that the loss is around 5% of average annual GDP of synthetic Russia for that period. This estimate is closer to the medium-run estimate reported by the IMF (2015). Note the tiny average percentage difference in the pre-intervention period of -0.7% (i.e. \$ 148 lower on average), confirming a good fit for the pre-sanctions period.

The next-to-last panel of Figure 1 depicts the baseline results obtained for inequality measured by the Gini coefficient.<sup>6</sup> Synthetic Russia experiences higher inequality than actual Russia. The figures in Table 1 suggest that the sanctions and counter-sanctions programs reduced inequality on average by 1 percentage point annually. In contrast, Afesorgbor and Mahadevan (2016) find that sanctions increased inequality in their cross-country analysis of 68 target countries of the period 1960–2008. Because sanctions targeted Russia's elite and counter-sanctions improved the agriculture sector, a possible explanation may be that the negative impacts of sanctions manifested at the high end of the income distribution and the positive effects at the low end. A quick glance at the data displayed in Table A2 in the Appendix confirms the decrease after 2013 in the shares of total income/consumption of the richest Russians (top 1%,10%, 20%), while other groups experience a relative increase. Due to the data limitations and unavailability of data, however, it is not possible to quantify these effects rigorously by constructing



<sup>&</sup>lt;sup>6</sup>The baseline donor pool is constructed with a requirement that the value for Russia be the median in the donor pool. The pre-intervention values are already within 80%, but constructing the restricted set this way allows checking of the sensitivity of results to random donor pools.

Russia (solid line) vs Synthetic Russia (dashed line) Russia (black line) vs control countries (gray line) Agriculture share (value added, % of GDP)) Effects - Agriculture share FDI (net inflows, % of GDP) Effects - FDI ဂ 9-GDP per capita (PPP, 2011 USD) 000 25000 Effects – GDP per capita 0 5000 10000 -5000 .02 Effects – Gini coefficient -.04 –.02 0 .C Gini coefficient 1 .35 .36 90.-.33 Time Time Agriculture value added per worker (constant 2010 US\$) Effects – Agriculture, value added per worker -5000 0 5000 

Figure 1: Results of baseline estimations



counterfactuals.<sup>7</sup> On the other hand, the estimation results in the last panel of Figure 1 bolster the suggested explanation. We see a considerable increase in agriculture value added per worker, which is indicative for improvement in productivity and standard of living of those engaged in agricultural sector. As Table 1 reports, the estimated average annual increase is around \$3,900 per worker for the period 2014–2017.

As a final note regarding these estimates, Table 1 baseline estimation results discussed are similar to those obtained with larger donor pools (which involve unaffected countries with available data for considered predictors). Thus, these baseline estimates are robust to larger donor pools. This conclusion remains broadly unchallenged when the significance of these estimates is considered in the next subsection.

#### 4.2 Inference about the estimated effects

To determine the significance of the baseline results, a placebo intervention is assigned to each country in the donor pool and the counterfactuals are estimated (see e.g. Abadie et al., 2010). An estimated effect for Russia is not considered significant if it is not large enough relative to the placebo estimates. Figure 1 (see right columns for each outcome variable) reports the results, where in black color is the gap estimated for Russia and the placebo gaps are in gray. If the estimated placebo effect is large due to a poor fit in the pre-intervention period, the distribution of ratios of post- to pre-sanctions RMSPEs are further analyzed (which is common for this type of placebo test). These ratios are reported in the Figure 2.

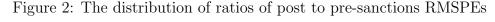
The ratios when the outcome variables are agriculture share, FDI, inequality and agriculture value added per worker are the largest in the corresponding donor pools, with probabilities of random assignment of intervention to generate as large post/pre RMPSEs as for Russia being equal to 1/18, 1/26, 1/13, and 1/26, respectively (see Table 1). Thus, the estimated effects are significant. The ratio for Russia, when the outcome variable is GDP per capita, is the third largest, meaning that if the intervention is assigned at random, the probability of achieving a post/pre RMPSE ratio as large as Russias is 3/28=0.11, which can be regarded as marginally significant.

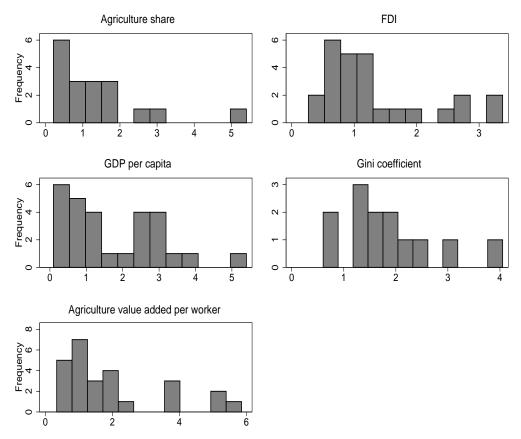
The p-values for the cases with donor pools including all the potential control countries for corresponding model specifications are reported in Table 2. They confirm that the baseline results are robust to larger donor pools, not only in terms



<sup>&</sup>lt;sup>7</sup>If the data for Russia in a given dataset were available for the periods of interest (2015, the latest), the donor pools were reduced to a handful of countries, i.e. just two countries with UNU-WIDER (2018), five countries with the World Bank's WDI, and four countries with the WID. This made it impossible to match the outcome variables appropriately. Note that the same applies to the poverty rate, measured by the percentage of the population living below \$5.50 a day, purchasing power parity adjusted (in this case the pool is reduced to three control countries, source: WDI).

of the estimated effects but also in terms of the levels of their significance. In most cases, we see an improvement in significance levels. The sole exception is GDP per capita, which also comes with the poorer pre-intervention fit.





Following Cavallo et al. (2013), I report the lead-specific p-values in Figure 3. The estimated effects for agriculture share are significant for all periods at all conventional levels. For 2014, 2015, 2016, and 2017, the estimated gaps are 0.47; 0.6; 0.64; 0.43 percentage points of GDP, respectively. For FDI, the estimated gaps are significant for all periods except 2016. The estimated gaps are -2.18, -2.27, -0.69, and -3.08 percentage points of GDP for 2014, 2015, 2016, and 2017, respectively.

In the case of real GDP per capita, the decline in 2015 is significant, which is estimated to be a \$1,685 loss (6.4%) compared to the synthetic counterpart. The probability of observing a decline of \$1,522 in 2016, which accounts for 5.9% of its synthetic counterpart, is 11%, which is marginally significant. The differences estimated for the other periods are not statistically significant (for 2014 and 2017, the estimated losses are \$672 and \$1,470, respectively).



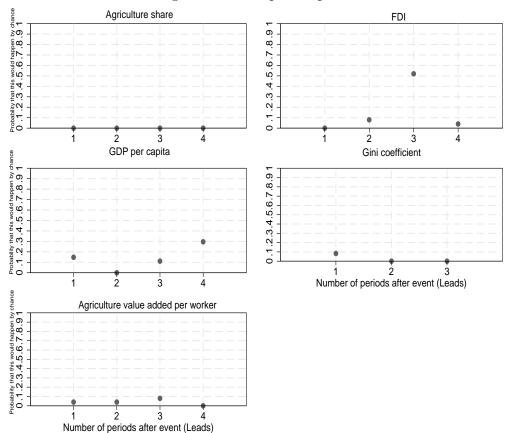


Figure 3: Lead-specific p-values

The estimated Gini coefficient effects are significant for all leads. The estimated gaps are -0.65, -1.08, and -1.56 percentage points for 2014, 2015, and 2016, respectively.

The effects estimated for agriculture value added per worker are significant at all periods. The estimated effects are quite large; for 2014, 2015, 2016, and 2017 they are \$2,465, \$3,983, \$3,586, and \$5,698, respectively. The largest effect is estimated for 2017.

## 4.3 Results with random donor samples

Following Campos et al. (2019) to assess the sensitivity of the baseline results to specific composition of the baseline donor pool, I make 5,000 random draws from a larger donor pool consisting of 46 countries, 8 where each random donor pool consists



<sup>&</sup>lt;sup>8</sup>For Gini coefficient, the larger pool consists of 15 countries and thus number of possible combinations is 455. For agriculture value added per worker, the larger donor pool includes 42 countries.

of as many control countries as the baseline donor pool (see Table 1). The results reported in Table 2 generally confirm the baseline estimated effects.

Table 2: The estimated effects using 5,000 random donor pools: some statistics

	Agriculture share	FDI	GDP per capita	Gini co- efficient	Agriculture value added per worker
Effect in the baseline estimation	0.53	-2.06	-1337.11 [-5.13]	-0.01	3932.95 [39.22]
Percentage of estimation with negative effects (out of 5,000 random samples)	12.14	99.90	77.88	100	0
Percentage of estimation with positive effects (out of 5,000 random samples)	87.86	0.10	22.12	0	100
Median effect across random 5,000 samples	0.41	-2.34	-743.18 [-2.91]	-0.02	3693.76 [35.97]
Average effect across 5,000 random samples	0.35	-2.32	-665.74 [-2.53]	-0.02	3398.16 [33.05]
Effect using comparable presanction fit	0.55	-1.84	-1107.78 [-4.28]	-0.01	2472.21[22.05]

Note: For GDP per capita and agriculture value added per worker, the percentage differences are also reported in brackets.

Most of the estimates from random donor samples obtained for all outcome variables have the same signs as the baseline estimate. In particular, all the estimates obtained with random donor pools for inequality and agriculture value added per worker have the same signs as the baseline estimates. Further, the average (median) across random samples is quite close to the baseline estimate (with the exception of real GDP and Gini coefficient). For GDP per capita the median (average) estimates of the intervention effects are lower in absolute value than the baseline estimate, indicating that the baseline overestimates the effects of sanctions. For Gini coefficient, there is an underestimation of the effect with the baseline estimate, i.e. random donor samples provide effects twice as large. However, when cases with comparable pre-intervention fit are considered, the average estimates across those random samples are more in line with the baseline estimates (see Table 2 for details). Figure 4 displays the results, with baseline effects depicted by black lines.



<sup>&</sup>lt;sup>9</sup>Cases that have pre-intervention fits as good as the baseline models.

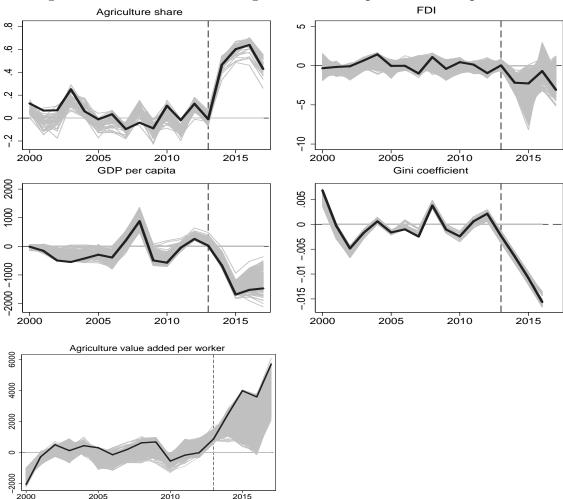


Figure 4: Estimated effects using random donor pools with comparable fits

Figure 4 shows that agriculture value added per worker and GDP per capital baseline results overestimate the effects compared to the results from random donor pools with comparable fits. In the case of FDI, models with random donor samples estimate a larger drop for 2015 and higher increase for 2016 than the baseline model.

## 5 Concluding remarks

This paper studied the economic impact on the Russian economy of the Western sanctions and Russian counter-sanctions launched in 2014. The synthetic control method (SCM) was applied to construct counterfactuals and estimate how the economy would have evolved since 2014 had there been no sanctions and countersanctions. Focusing on five outcome variables, the analysis revealed that sanctions



induced decreases in real GDP per capita, FDI net inflows and income inequality, while the ban on food imports introduced by Russia triggered an expansion of the domestic agricultural sector.

In the case of real GDP per capita, on average a loss of \$1,337 per year is estimated, i.e. 5% of synthetic Russia's annual average GDP. This finding is close to an early estimate reported by the IMF (2015) for the medium run, but smaller than the estimate for Iran's sanction regime (Gharehgozli, 2017). Some of the mitigation in sanction impacts may have come from an increase in the value-added contribution of agriculture to GDP, which was 0.54 percentage points higher than in the counterfactual. Sanctions and counter-sanctions on average reduced FDI inflows (as a percentage of GDP) by 2 percentage points a year. The negative effect on the Russian economy from sanctions with respect to FDI inflows comports with the findings of Mirkina (2018), who reports similar adverse effects in numerous sanctions episodes during the 1990s.

Income inequality is found to be lower on average by 1 percentage point in comparison to the counterfactual. This finding contradicts the cross-country analysis of Afesorgbor and Mahadevan (2016), who find sanctions aggravate inequality. A possible explanation for the Russian case is that smart sanctions targeted top income earners, while Russia's counter-sanctions helped expand the agriculture sector, positively affecting lower income groups in that sector. Specifically, it is estimated that the agriculture value added per worker for the period 2014–2017 has increased on average by about \$3,900 per year. This indicates improvements in the productivity and standard of living of agricultural laborers and supports the suggested mechanism behind the effects on inequality.

Various placebo studies confirm significance of the obtained estimates. Results are robust to random donor samples.

## 6 References

- [1] Abadie, A., Diamond, A., Hainmueller, J., 2015. Comparative politics and the synthetic control method. *American Journal of Political Science* 59(2), 495-510.
- [2] Abadie, A., Diamond, A., Hainmueller, J., 2010. Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. *Journal of American Statistical Association* 105, 493-505.
- [3] Abadie, A., Gardeazabal, J., 2003. The economic costs of conflict: A case study of the Basque Country. *American Economic Review* 93, 113-132.



- [4] Acemoglu, D., Johnson, S., Kermani, A., Kwak, J., Mitton, T., 2016. The value of connections in turbulent times: Evidence from the United States. *Journal of Financial Economics*, Elsevier, 121(2), 368-391.
- [5] Afesorgbor, S. K., Mahadevan, R., 2016. The Impact of Economic Sanctions on Income Inequality of Target States. World Development, Elsevier, 83(C), 1-11.
- [6] Ahn, D. P., Ludema, R. D., 2019. The sword and the shield: the economics of targeted sanctions. *CESifo Working Paper Series* 7620, CESifo Group Munich.
- [7] Anderson, J., Larch, M., Yotov, Y., 2017. Trade and Investment in the Global Economy. National Bureau of Economic Research. NBER Working Paper Series No. w23757.
- [8] Asiedu, E. 2006. Foreign direct investment in Africa: The role of natural resources, market size, government policy, institutions and political instability. *World Economy* 29(1), 63-77.
- [9] Belin, M., Hanousek, J., 2019. Which Sanctions Matter? Analysis of the EU/Russian Sanctions of 2014, CEPR Discussion Paper 13549.
- [10] Billmeier, A., Nannicini, T., 2013. Assessing Economic Liberalization Episodes: A Synthetic Control Approach. *Review of Economics and Statistics*, MIT Press, 95(3), 983-1001, July.
- [11] Blonigen, B., Piger, J., 2014. Determinants of foreign direct investment. *Canadian Journal of Economics* 47(3), 775-812.
- [12] Campos, N. F., Coricelli, F., Moretti, L., 2019. Institutional integration and economic growth in Europe. *Journal of Monetary Economics*, Elsevier, 103(C), 88-104.
- [13] Cavallo, E., Galiani, S., Noy, I. and Pantano, J., 2013. Catastrophic Natural Disasters and Economic Growth. *Review of Economics and Statistics* 95, 1549-1561.
- [14] Crozet, M., Hinz, J., 2016. Friendly fire the trade impact of the Russia sanctions and counter-sanctions. Kiel Working Papers 2059, Kiel Institute for the World Economy (IfW).
- [15] Dreger, C., Fidrmuc, J., Kholodilin, K., Ulbricht, D., 2016. Between the hammer and the anvil: The impact of economic sanctions and oil prices on Russia's ruble. *Journal of Comparative Economics*, 44(2), 295-308.



- [16] Gharehgozli, Orkideh, 2017. An estimation of the economic cost of recent sanctions on Iran using the synthetic control method. *Economics Letters*, Elsevier, 157(C), 141-144.
- [17] Hufbauer, G.C., Schott, J.J., Elliott, K.A., Oegg, B., 2007. *Economic Sanctions Reconsidered*, 3rd ed. Peterson Institute for International Economics, Washington DC.
- [18] International Monetary Fund (2015), Russian Federation: 2015 Article IV consultation- press release; and staff report. IMF Country Report, 15/211. http://www.imf.org/external/pubs/ft/scr/2015/cr15211.pdf
- [19] International Monetary Fund (2019), Russian Federation: 2019 Article IV consultation- press release; and staff report. IMF Country Report, 19/260. https://www.imf.org/en/Publications/CR/Issues/2019/08/01/Russian-Federation-2019-Article-IV-Consultation-Press-Release-Staff-Report-48549
- [20] Kholodilin, K. A., Netunajev, A., 2019. Crimea and punishment: the impact of sanctions on Russian economy and economies of the euro area. *Baltic Journal of Economics*, 19(1), 39-51.
- [21] Kholodilin, K., Ulbricht, D., Wagner, G., 2014. Are the Economic Sanctions against Russia Effective? *DIW Roundup: Politik im Fokus* No. 28, Deutsches Institut fr Wirtschaftsforschung (DIW), Berlin.
- [22] Korhonen, I., Simola, H., Solanko, L., 2018. Sanctions, counter-sanctions and Russia Effects on economy, trade and finance. BOFIT Policy Brief No. 4, 2018.
- [23] Mirkina, I., 2018. FDI and sanctions: An empirical analysis of short- and long-run effects. European Journal of Political Economy, Elsevier, 54(C), 198-225.
- [24] Neuenkirch, M., Neumeier, F., 2015. The impact of UN and US economic sanctions on GDP growth. European Journal of Political Economy. 40(PA), 110-125.
- [25] Neuenkirch, M., Neumeier, F., 2016. The impact of US sanctions on poverty. Journal of Development Economics, Elsevier, 121(C), 110-119.
- [26] Peeva, A., 2019. Did sanctions help Putin? Diskussionsbeitrge No. 2019/7, Freie Universitt Berlin, Fachbereich Wirtschaftswissenschaft, Berlin, http://nbn-resolving.de/urn:nbn:de:kobv:188-refubium-24769-4
- [27] Puzzello, L., Gomis-Porqueras, P., 2018. Winners and losers from the € uro. European Economic Review, Elsevier, 108(C), 129-152.



- [28] Reuters, 2014. Russia puts losses from sanctions, cheaper oil at up to \$140 billion per year. November 24, 2014. Accessed on August 12, 2019 at: https://www.reuters.com/article/us-russia-siluanov/russia-puts-losses-from-sanctionscheaper-oil-at-up-to-140-billion-per-year-idUSKCN0J80GC20141124.
- [29] Reuters, 2017. Russia risks decades of low growth under U.S. sanctions: Putin adviser. July 27, 2017. Accessed on August 12, 2019 at: https://www.reuters.com/article/us-russia-economy-sanctions/russia-risks-decades-of-low-growth-under-u-s-sanctions-putin-adviser-idUSKBN1AC1K8.
- [30] Roine, J., Vlachos, J., Waldenstrom, D., 2009. The long-run determinants of inequality: What can we learn from top income data? *Journal of Public Economics* 93(78), 974-988.
- [31] Russell, M., 2018. Sanctions over Ukraine: Impact on Russia. European Parliamentary Research Service. PE 579.084
- [32] Schneider, F., Frey, B. S., 1985. Economic and political determinants of foreign direct investment, World Development, Elsevier, 13(2), 161-175,
- [33] Solt, F., 2019. The Standardized World Income Inequality Database, Version 8. https://doi.org/10.7910/DVN/LM4OWF, Harvard Dataverse, V2.
- [34] Stone, M., 2016. The Response of Russian Security Prices to Economic Sanctions: Policy Effectiveness and Transmission. U.S. Department of State Office of the Chief Economist Working Paper. https://2009-2017.state.gov/e/oce/rls/papers/262748.htm#\_ftn1
- [35] Tuzova, Ye., Qayum, F., 2016. Global oil glut and sanctions: The impact on Putins Russia. *Energy Policy*, 90, 140-151.
- [36] UNU-WIDER (2018). World income inequality database. Downloaded on 6 June 2019 from http://www.wider.unu.edu/research/Database/en\_GB/wiid/
- [37] WDI: World Development Indicators. Downloaded on June 11, 2019 from https://databank.worldbank.org/source/world-development-indicators
- [38] WID: World Wealth and Income Inequality Database (WID.world). Downloaded on August 5, 2019 from https://wid.world/data



## 7 Appendix

Table A1: Predictor Means Before 2014

	Russia	Synthetic Russia I	Donor Pool
Panel A. Outcome variable: Agriculture share			
Agriculture share (2000)	5.75	5.62	5.13
Agriculture share (2007)	3.78	3.88	3.90
Agriculture share (2013)	3.16	3.17	3.43
GDP per capita (PPP)	20482.11	19089.95	16412.14
GDP per capita growth, annual	5.20		1.95
Gross capital formation	21.93		25.50
Inflation rate Oil rents (% of GDP)	$11.92 \\ 10.94$		$   \begin{array}{r}     5.57 \\     8.30   \end{array} $
Trade openness	54.36		93.69
Panel B. Outcome variable: FDI net inflows, %		02.00	
FDI net inflows, % of GDP (2001)	0.93	3 1.09	1.75
FDI net inflows, % of GDP (2006)	3.80		2.91
FDI net inflows, % of GDP (2011)	2.68		$\frac{2.51}{2.52}$
FDI net inflows, % of GDP (2013)	3.01		2.33
GDP per capita (PPP)	20482.11		14739.30
GDP per capita growth, annual	5.20		2.84
Inflation rate	11.92	7.89	5.84
Oil rents (% of GDP)	10.94		5.15
Trade openness	54.36	77.53	77.83
Panel C. Outcome variable: GDP per capita (I			
Agriculture share	4.32		7.32
GDP per capita (PPP) 2000	14050.85		10997.13
GDP per capita (PPP) 2013	25551.09		15455.62
GDP per capital formation	5.20 $21.93$		$   \begin{array}{r}     1.75 \\     26.45   \end{array} $
Gross capital formation Industry share	$\frac{21.93}{30.55}$		$\frac{20.45}{31.04}$
Inflation rate	11.92		5.87
Oil rents (% of GDP)	10.94	10.12	4.78
Schooling	88.09		79.99
Trade openness	54.36	88.64	98.20
Panel D. Outcome variable: Gini coefficient			
Agriculture Share	4.32		9.21
GDP per capita (PPP)	20482.11		13325.32
Gini coefficient (2001)	0.37		0.39
Gini coefficient (2006)	0.37		0.39
Gini coefficient (2008)	0.37		0.39
Gini coefficient (2013)	0.35		$0.38 \\ 3.14$
Oil rents (% of GDP) Population growth	10.94 -0.18		$\frac{3.14}{1.07}$
Rural population as percent of total population	26.45		40.14
Schooling	88.09		80.18
Tax revenue as percent of GDP	14.42	13.65	14.42
Trade openness	54.36	6 76.88	84.60
Panel E. Outcome variable: Agriculture value a	added per	worker	
Agriculture value added per worker (2001)	6459.84	6743.41	5963.61
Agriculture value added per worker (2010)	9357.36		7130.72
Agriculture value added per worker $(2013)_{4}$	12056.46		7626.49
GDP per capita (PPP)	20497.69		17604.33
GDP per capita growth, annual	5.13		1.74
Gross capital formation	21.93		25.83
Inflation rate Oil rents (% of GDP)	$11.92 \\ 10.94$		5.43 5.83
Trade openness	54.36		95.78
	51.50	10.00	

Table A2: Russian inequality data for 2013–2015 obtained from WID, UNUWIDER, and WDI

Source	Indicator	2013	2014	2015
WID	Gini coefficient	0.54	0.52	0.52
(based on fiscal income)	Bottom $50\%$	0.17	0.18	0.18
	Middle $40\%$	0.37	0.39	0.39
	Top $10\%$	0.45	0.43	0.43
	Top $1\%$	0.20	0.19	0.18
UNU-WIDER (2018)	Gini coefficient	40.88	39.88	37.74
(based on consumption)	Q1	6.37	6.59	6.91
	Q2	10.28	10.58	11.11
	Q3	14.40	14.69	15.18
	Q4	20.96	21.02	21.51
	Q5	48.01	47.12	45.29
WDI (World Bank)	Gini index (World Bank estimate)	40.90	39.90	37.70
	Income share held by lowest $10\%$	2.60	2.60	2.80
	Income share held by highest 10%	32.40	31.90	29.70
	Income share held by second $20\%$	10.30	10.60	11.10
	Income share held by third $20\%$	14.40	14.70	15.20
	Income share held by fourth $20\%$	21.00	21.00	21.50
	Income share held by highest $20\%$	48.00	47.10	45.30

© 2019. This work is published under NOCC (the "License"). Notwithstanding the ProQuest Terms and Conditions, you may use this content in accordance with the terms of the License.

