Sanctions and Misallocation. How Sanctioned Firms Won and Russia Lost.*

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Abstract

Using a unique natural experiment of staggered firm-level sanctions against Russia in 2014-2020 and the data on over 600,000 Russian firms, I estimate the effect of sanctions on targeted firms and on the aggregate economy. Surprisingly, sanctioned firms on average *gained* 38% more capital inputs after sanctions relative to the industry trends. Using additional data on subsidies and government contracts, I find that this result is explained by the government protection of targeted firms, that more than compensated for the negative sanctions shock. However, the sanctioned firms were already too large and had too much capital prior to sanctions, I show with a heterogeneous firm framework. The joint effect of sanctions and government protection reallocated capital even more towards the targets. I combine the causal estimates with the heterogeneous firm framework and estimate that government protection of connected firms from the negative shock made the Russian TFP drop at least by 0.33% reaching 3% in relevant sectors, despite the sanctioned firms benefiting.

Keywords: Misallocation, macro development, state-ownership, political connections, SOEs, sanctions, Russia

JEL: D6,F38,F51,F6,O1,O11,O12,O4

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1 Introduction

Allocative efficiency has been shown to play a key role in TFP and GDP differences across countries (Hsieh & Klenow 2009, Bartelsman et al. 2013, Gopinath et al. 2017). This finding implies that targeted policies affecting specific firms may have important aggregate implications if they reallocate resources in the economy. The effects may be particularly strong if the targeted firms are large and subject to large allocative distortions.

Economic sanctions, in particular "smart" sanctions - a policy that targets specific firms - have become increasingly frequent: the US had over 70 countries under such sanctions in 2019 (Felbermayr et al. 2020). However, there is relatively little evidence of how sanctions affect the targets, whether they have collateral damage, how they affect the aggregate economy, let alone to what extent they are successful. Because of the way targets are chosen, it is ambiguous what would be the effect of such sanctions ex-ante, not least because of how they reallocate resources in the economy. Sanctions may be targeting the inputs of firms that are more productive and central for the economy, in which case these sanctions would hurt both the firms and the aggregate economy. Conversely, sanctions may be hurting the inputs of firms that are politically connected and over-resourced, in which case in hurting these firms sanctions could improve allocative efficiency in the aggregate through cleansing the economy of unproductive firms. At the same time, the response of the state by protecting the sanctioned firms may fully reverse the direct effect of sanctions, and such protection can even overshoot and exacerbate misallocation.

In 2014-2020 the US and the EU sanctions targeted a set of specific Russian firms. This created a negative shock to the access of inputs for targeted firms, and in particular, for the state-owned sector.

I find that sanctions targeted firms that were already distorted and associated with implicit subsidies, or had more inputs than it is efficient. I further find that sanctions together with the response of the Russian state have worsened the allocative efficiency: the sanctioned firms gained additional inputs and increased in size

after sanctions were imposed. This effect was more pronounced for the sanctioned SOEs. I estimate that all else equal, this sanctions episode worsened allocation of resources and productivity on the aggregate in Russia.

This experiment with sanctions unrolled in a staggered fashion, allows me to use a difference-in-difference (DID) setup to capture the firm-level within-industry effect of the negative shock as the (differential) response of state-owned firms (SOEs) relative to private sanctioned firms as well as sanctioned firms relative to the non-treated (and/or not-yet treated) firms in the same industry. The response of politically connected private firms and a differential response of SOEs to this negative shock reveals whether there is a link from political connections to the allocation of resources. The DID setup also allows me to alleviate the common concerns in measuring misallocation in cross-sectional data - measurement error, adjustment costs and abstract from other correlated unobserved factors affecting the measurement of misallocation.

I start by constructing a panel of 600,000 medium and large Russian firms in the Services, Manufacturing and Agricultural sectors from 2012-2020 and collect information on firm-by-year sanctions imposed by the US on Russia. I then measure the ex-ante marginal revenue products of capital (MRPK) for these sanctioned firms and all other firms in the economy. I correct for measurement error and transient adjustment costs using firm and year fixed effects and this way avoid attributing all of the cross-sectional dispersion in the observed marginal returns to inputs to misallocation, in contrast to most of the early literature.

I use the panel data and within-firm variation over time to empirically test whether the sanctions on inputs and outputs indeed changed the inputs and outputs of targeted firms, and whether this change lead to a change in their MRPK. I further test whether the inputs to targeted SOEs changed differentially to private sanctioned firms. The staggered nature of sanctions allows me to net out the differential effects on each industry of changes in oil price and devaluation of the Russian rouble that took place in the same period. Further, the DID set-up does not require the sanctioned and non-sanctioned firms, or SOEs and private firms

to have the same fixed characteristics, as they drop out with the firm fixed effects. To estimate the average effect, this method does require that the sanctioned firms would have trended the same way as non-sanctioned firms in a world without sanctions, for which I provide convincing evidence based on pre-trends. To estimate the SOE differential, I rely on a weaker assumption: the differential trends of the SOE and private firms need to be the same between sanctioned and non-sanctioned groups. I also find similar estimates when estimating the effects only within sanctioned firms. The effects I find are robust to controlling for time shocks at the disaggregated industry and size quartiles, and time-by-SOE fixed effects.

Surprisingly, I find that the sanctioned firms gained, not lost, in inputs, such as assets, capital, materials, and labor, and in outputs, such as revenue, value added and profits, after having their inputs and outputs sanctioned. The gains in inputs is more pronounced for the SOEs. On average, the MRPK of sanctioned firms has declined as a result of sanctions, which is driven by the decline in MRPK of the SOEs. I use additional outcomes - firm-level contracts, subsidies and credit cash flow - and find that government contracts and total credit increased for both private firms and SOEs after sanctions, and subsidies increased for SOEs. These three outcomes support the channel of government protection of treated firms.

I then use Hsieh and Klenow's (2009) framework to account for the effects of sanctions and shielding on aggregate TFP. These effects depend on whether the targeted firms were ex-ante low MRPK firms and whether the net effect of sanctions and shielding has increased the total capital resources for these firms, relatively to non-treated firms. An increase in resources going to firms with ex-ante low MRPK would lead to more misallocation.

Combining these empirical estimates as well as the heterogeneous firm model I calculate the aggregate effects of the sanctions episode on the aggregate TFP and find that it reduced productivity by 0.33%. The effects within each industry are mostly negative and range between -3.3% and -0.01% (with several minor exceptions for which TFP mildly improved).

Finally, to put these numbers into perspective, I also measure the contribution

to misallocation in Russia of pre-existing distortions between sanctioned firms and non-sanctioned firms. I then account how these distances to the efficient frontier have widened due to the combined effect of sanctions and shielding and find that the TFP gap from the pre-exisitng wedge grew by 1 percent[1].

In view of these findings, this paper has relevance for two distinct contributions. First, it shows that smart sanctions have not worked as intended. If their goal was to hurt the chosen targets and not the average citizen, they have failed, but this happened because the government responded with protection (at the expense of everyone else). This is relevant for the design of sanctions in 2022 in Russia that should factor in that the government will mitigate the damage of sanctions. Second, the wider relevance of the study is that connected firms and SOEs may be protected from other negative shocks (at the expense of non-connected firms) in developing countries with weak institutions. Given the developing countries with weak institutions are more likely to be sanctioned and are more likely to face other negative shocks such as trade shocks - distorting protection by the state is one channel that hinders their growth.

The paper is organised as follows. Section 2 reviews the related literature and how this paper fits in. Section 3 provides a heterogeneous firm framework for accounting for the effects of wedges; in particular, it derives expressions for accounting for wedges between groups within industries. Section 4 describes the firm-level and sanctions data as well as the context of the sanctions episode. Section 5 discusses the measurement error correction for wedge accounting. Section 6 provides general summary statistics of the state of misallocation in Russia. Section 7 presents the results of the counterfactuals of wedge equalization within and across groups. Section 8 discusses my reduced-form empirical strategy. Section 9 reports the reduced-form effects of sanctions on sanctioned private and state-

[1]I find that Russia could double its aggregate TFP if all misallocation was removed, as measured by the heterogeneous firms model. I find that Russia could walk 31% of that distance if it removed the wedge between the group of to-be-sanctioned firms and all other firms, and coincidentally its TFP would increase by the same amount. The natural experiment of sanctions shows that Russia appears to be walking in the wrong direction: sanctioned firms are ex-ante low MRPK firms, and the have been shielded so that they got 14% lower MPRK and 38% higher capital inputs than to non-sanctioned firms) after the sanctions treatment. The TFP gap driven by this wedge has gotten larger by 1% due to the joint effect of sanctions and government shielding.

owned firms, as well as the aggregate effects of the sanction episode. Section 10 concludes.

2 Related literature

In this paper, I quantify the effects of sanctions on aggregate productivity through the lens of an allocative efficiency model with the so-called "indirect approach" and causally estimate the differential response of firms to shocks. In doing so, I add to three strands of literature. First, I contribute to the literature that highlights the role of allocative efficiency for aggregate outcomes (Hsieh & Klenow 2009, Restuccia & Rogerson 2008, Baqaee & Farhi 2020, Busso et al. 2013). Second, I look at the effects of economic sanctions both at the firm-level and in the aggregate (Ahn & Ludema 2020, Tuzova & Qayum 2016, Crozet & Hinz 2016, Haidar 2017, Draca et al. 2019, Stone 2016, Gold et al. 2019).

The first-generation literature on misallocation has developed an accounting framework that allows calculating by how much the inefficient allocation of inputs affects the aggregate TFP (Restuccia & Rogerson 2008, Hsieh & Klenow 2009). This branch of work also called the "indirect approach" allows one to diagnose the allocative inefficiencies in an economy, while not making any assumptions about the sources of such inefficiencies. Hsieh & Klenow (2009) used dispersion in revenue productivity (TFPR) as a measure of misallocation within sectors in India, China and the US. Jones (2011), Baqaee & Farhi (2020) have incorporated the role of Input-Output linkages in measuring misallocation and generalized earlier models.

My paper has the advantage of the indirect approach by not making specific modelling assumptions about a particular source of misallocation but also makes the next step by quantifying how much of the misallocation is explained by a particular source *in the data*: in my case, the ownership status of a firm. I account for the role of state-ownership at a given point in time and, using causal inference, reveal a particular channel through which state-ownership comes to bring misal-

location: differential shielding from negative exogenous shocks. This is one of the first papers to connect causal inference and misallocation accounting, along with Rotemberg (2019), who uses a similar approach to quantify the effects of small-firm subsidies in India, and Bau & Matray (2020) who look at the effects of India's capital market liberalization. Therefore, this paper contributes to the nascent literature on the sources of misallocation[2].

My paper is the first paper to evaluate the effect of sanctions on the aggregate economy using micro data. I add to the work that measures the micro- and macroeconomic effects of sanctions on different countries (Ahn & Ludema (2020), Tuzova & Qayum (2016), Crozet & Hinz (2016), Haidar (2017), Draca et al. (2019), Stone (2016), Gold et al. (2019), Huynh et al. (2022), Mamonov & Pestova (2021) and a set of new papers due to the most recent sanctions episode Bachmann et al. (2022), Itskhoki & Mukhin (2022), Balyuk & Fedyk (2022)). I distinguish myself from these papers in that I not only causally estimate the effect of sanctions on treated firms, but also use the causal estimates to guide my calibration of a firm model to the sanctioned economy and calculate the aggregate effect of the 2014-2020 sanctions episode on Russion TFP.

Two papers - Ahn & Ludema (2020) and Huynh et al. (2022) also look at the effect of the first wave of sanctions on Russian firms. My results and method differ from both papers: I find positive effects of sanctions on most firm-level variables, as opposed to a negative effect in the first paper and an insignificant effect in the second paper. I distinguish myself from the first paper by focusing on specifically Russian-based firms look at the effects over several years and several waves of sanctions. The first paper finds a negative effect of sanctions, because it conflates the effect of sanctions on Russian firms with the effect on foreign firms owned by Russian individuals abroad, whose assets were frozen. As opposed to the second paper, I estimate the causal effect of sanctions on the actual firms that were sanctioned, rather than the effect of the number of sanctions on the stock market in

[2]Several other papers use the direct approach, and explicitly model the sources of misallocation (Pellegrino & Zheng 2021, Midrigan & Xu 2014, Buera et al. 2011, Asker et al. 2014, Gopinath et al. 2017, Peters 2020, David & Venkateswaran 2019, David et al. 2016). Restuccia & Rogerson (2017) and Hopenhayn (2014) both provide extensive reviews of the literature.

Russia (a joint effect on treated and non-treated publicly listed firms).

Finally, a later contribution by Keerati (2022) replicates the results of this paper and proposes a complementary channel: the differential bank lending to sanctioned firms due to market incentives. The channel is consistent with my finding that sanctioned firms being bolstered by the government and therefore were able to attract more lending. However, the Russian banking sector is dominated by the state and therefore likely supported sanctioned firms directly, and not due to market incentives.

3 Model

I use a standard framework from the misallocation literature where firms have heterogeneous productivities and wedges on inputs K and L are modelled as taxes or subsidies τ_i^K and τ_i^L. These wedges create an arbitrary allocation of resources by increasing the effective price on inputs that a firm faces. Looking from another angle, the distortions in the operation of firms are represented as wedges that would rationalize the observed use of inputs by profit-maximizing firms.

The firm i maximizes its profits while facing taxes or subsidies τ^K and τ^L.[3]

$$\pi_i = P_i Q_i - (1 + \tau_i^L) w L_i - (1 + \tau_i^K) r K_i \tag{1}$$

I assume each firm produces a different variety i and the output of the industry Q in which the firm operates is demanded via a CES demand. All misallocation is within industry, and for simplicity, the industry index is omitted. I also assume a Cobb-Douglas production function $Q_i = A_i K_i^{\alpha} L_i^{1-\alpha}$, which is standard in the literature (see appendix for the derivations of every step). P is the industry CES price index:

[3]The model can be analogously extended to misallocation of not only capital and labour, but also intermediate inputs. This model also allows for the case that there is misallocation in output, rather than inputs, for example, from transport costs. This can be added as a wedge on output $(1 - \tau_i^Y) P_i Q_i$, but the effect of τ_i^Y cannot be separately identified from the joint effect of τ_i^L and τ_i^K. Therefore, I keep only τ_i^L and τ_i^K, bearing in mind that these two wedges jointly can mean a distortion on output.

$$\underset{L_i, K_i}{max} \pi_i = PQ^{\eta}(A_i K_i^{\alpha} L_i^{1-\alpha})^{1-\eta} - (1+\tau_i^L) w L_i - (1+\tau_i^K) r K_i$$

I assume w and r are the common and exogenous costs of labour and capital, so every variation in these prices manifests itself in τ^K and τ^L[4]. The firm optimal labour and capital allocation will satisfy these equations:

$$\{L_i\} : (1-\alpha)(1-\eta)\frac{P_i Q_i}{L_i} = (1+\tau_i^L) w \equiv MRPL_i \tag{2}$$

$$\{K_i\} : \alpha(1-\eta)\frac{P_i Q_i}{K_i} = (1+\tau_i^L) r \equiv MRPK_i \tag{3}$$

The firm's marginal revenue to each input is equal to the marginal cost of this input. The term $(1-\eta)$ is the constant markup that comes from the monopolistic competition assumption. The τ^K and τ^L are backed out as wedges that would explain the observed firm decision if the firm was profit maximising. Positive τ^K and τ^L represent implicit taxes on inputs, and negative τ^K and τ^L represent implicit subsidies.[5]

I define $MRPK_i$ and $MRPL_i$ as measures of the direction of misallocation. The higher are $MRPK_i$ and $MRPL_i$ the higher are the implicit taxes on capital and labour inputs of firm i.[6]

Furthermore, the model allows me to define a model-based firm TFP. With the assumption of CES demand and monopolistic competition, the size or market share of a firm is related to its real productivity (A_i or $TFPQ_i$):

$$A_i = \kappa \frac{(P_i Q_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha} L_i^{1-\alpha}} \equiv TFP_i \equiv TFPQ_i \tag{5}$$

[4]While it is implausible that wages are common across regions, the results related to misallocation across private and state ownership are robust to looking within regions. The wage variation across regions does contribute to overall misallocation, which may be desirable for calculating the full distance to the efficient frontier.

[5]In the calculation of the overall TFP and country TFP only the *relative* τ^K and τ^L will matter, rather than the absolute levels because each industry will be aggregated into the country output with a Cobb-Douglas production function.

[6]The measures $MRPK_i$ and $MRPL_i$ can be summarized with another measure $TFPR_i$ or "Total Factor Productivity Revenue":

$$TFPR_i \equiv \frac{P_i Q_i}{K_i^{\alpha} L_i^{1-\alpha}} \propto MRPK_i^{\alpha} * MRPL_i^{1-\alpha} \tag{4}$$

$$\kappa = \left(PQ^{\eta}\right)^{-\frac{1}{1-\eta}} \tag{6}$$

How do the wedges affect the aggregate TFP? I follow Hsieh & Klenow (2009), CES aggregation within industries. I first calculate the aggregate output and TFP of an industry, TFP_s. From such aggregation exercise provided in the Appendix, industry TFP can be expressed as the following equation:

$$TFP_s = \left(\sum_i \left(A_i \left(\frac{\overline{MRPL}}{MRPL_i} \right)^{1-\alpha} \left(\frac{\overline{MRPK}}{MRPK_i} \right)^{\alpha} \right)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{1-\eta}} \tag{7}$$

In which whenever $MRPK_i$ and $MRPL_i$ deviate from their industry harmonic averages $\overline{MRPL}$ and $\overline{MRPK}$ the industry TFP becomes lower than the efficient level. in an industry. Therefore, the TFP_s when you have the efficient allocation (without wedges) is a CES aggregate of firm-level productivities[7]:

$$TFP_s^* = \left(\sum_i \left(A_i \right)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{1-\eta}} \tag{8}$$

To get the country aggregate TFP, I follow Hsieh and Klenow and take a Cobb-Douglas average of each of the industry TFP_s, using the industry value added shares as exponents.

Four things are important to note here. First, only the relative tax in a 4-digit industry will matter for misallocation, an average tax that is equal across firms will lead to efficient allocation across firms within a 4-digit industry. Second, and related, all misallocation in this model comes from the misallocation within a 4-digit industry, and misallocation across sectors will not affect aggregate TFP in this model[8]. An increase in the tax that is the same for every firm in an industry (and, therefore, an increase in the industry price index), will reduce the total physical

[7] In the appendix I show that the equivalent exercise that maximizes total output and taking the distribution of productivities and total inputs in an economy as given, means allocating more resources to more productive firms, but only up to a point, that point being equalized marginal revenue products of each input.

[8] Baqaee & Farhi (2020) show that misallocation across sectors may play a smaller role than within sectors because sectors tend to be less substitutable with each other and therefore, reallocation from a sector that faces an increase in an average wedge to other sectors will be smaller.

output, but not the aggregate TFP. This comes from each sector being aggregated a-la Cobb-Douglas and the aggregate TFP term being separable from total sector inputs K_s and L_s[9]. Third, even though I assume monopolistic competition and therefore constant markups, if other forms of competition are present in the data, the different mark-ups will be reflected in wedges, which is desirable in accounting for the overall distance to the efficient frontier. Finally, this model is static, but the level of misallocation and the wedges can be calculated for any given year as a separate exercise.

My starting point is calculating the distance of the aggregate TFP to the efficient (frontier) as a share.

$$\frac{TFP}{TFP^*} - 1 \tag{9}$$

Using this framework I conduct two counterfactual exercises, which together give me how much of the distance to the productivity frontier is explained by the variation in wedges due to the treatment status (see appendix for details).

4 Data and context

4.1 Firm-level data

My firm-level data comes from the Spark-Interfax database that contains official balance-sheet, tax, employment and ownership information at the firm-by-year level. Spark provides a firm-level panel dataset of Russian private and state-owned firms covering manufacturing, agriculture and services sectors. The panel dimension of this dataset is useful for quantifying how firms change over time and will be

[9]The aggregate output can be grouped into the TFP term, and the aggregate input terms: $Y = \prod_{s=1}^{S}(TFP_s K_s^{\alpha_s} L_s^{1-\alpha_s})^{\theta_s}$, in which the $\theta_s < 1$ are the elasticities of substitution across sectors that sum up to 1. If one sector faces a homogeneous tax increase, K_s and L_s will shift to other sectors, but the $\prod_{s=1}^{S} TFP_s^{\theta_s}$ will remain intact. Meanwhile, the shift of K_s and L_s to other sectors will not be enough to maintain the same level of output, and the output will drop. This is because sectors are complements: $\theta_s < 1$ of any s. This model when applied to the data will not be able to back out the average 4-digit sector wedge separate from the sector elasticity in the aggregate production function. Therefore, while I care about the total output, being affected by the average τ_i^K and τ_i^L as well, I will only be able to confidently measure the drop in average output from the misallocation within sectors.

also crucial to my adjustment procedure to measurement error. An additional beneficial feature of this dataset for this study is that it is firm-level and not plant-level. My goal is to study misallocation across decision-makers, which makes it crucial to identify the boundary of the firm. I also expect a lesser role of measurement error and unobserved shocks and a higher role of misallocation in a firm-level dataset, as opposed to a plant-level dataset.

I extract information on firm revenues, capital stock (as measured by book value) wage bill and payments to materials. The total number of firms that reported at least one of these variables in 2019 or 2020, as shown in Table 1, was 946,956[10]. For my analysis I only use for-profit firms, including for-profit SOEs. Only firms above 100 employees or with revenues over 800m rubles (roughly 10m USD) are legally obliged to report materials and wage bill, therefore the firms that report wage bill and materials are medium and large for-profit firms. The value added of these firms covered 61% of Russian value added in 2018 and 30% of official employment (note that the total revenue of these firms *exceeds* Russian GDP by more than twice due to intermediate inputs being double-counted in the buyers' and sellers' revenues).

The table below summarizes the sample by firm groups: private for-profit firms, state-owned for-profit firms.

State-owned firms are defined by Spark, as listed in the official Russian statistics bureau list of SOEs, and include not only firms that are directly owned by the state (e.g "PAO Rosneft"), but also private firms that are owned by the state-owned firms (e.g. "OOO RN-Vankor"). The total number of for-profit SOEs is 4,414 and their value added is 7% of GDP in 2018 (their revenues are 16% of GDP).

[10]The coverage of firms that reported *all* variables steadily grew, from just under 60,000 in 2012 to aroung 150,000 firms in 2020. The number of firms that report both book value of capital and revenues are 600,000.

4.2 Sanctions on Russia 2014-2020

Sanctions were rolled out by the US and EU against Russian entities and individuals as a response to the situation in Ukraine, through years 2014-2020[11]. The sanctions are generally of two types: SDN (Specially Designated National) and SSI (Sectoral Sanctions Identifications). The SDN-type sanctions forbid any transaction (e.g. export, import, lending, issuing stock, leasing) with a sanctioned firm or individual, as well as any firm owned by an SDN individual or an SDN firm by more than 50 per cent (this rule is called "OFAC rule of 50"). Further, the sanctions freeze any assets in the United States of the SDN firm or individual. SSI sanctions instead, affect inputs: they restrict long-term (longer than 14 days) debt issuance, equity financing and transactions with any such debt of equity of the sanctioned firm[12].

The SSI sanctions were issued mostly against Russian banks and companies, military or double-use technology firms and companies in the oil and gas sector. However, after applying the OFAC 50% rule, the coverage extends to a large number of industries.

I create a dataset of sanctions at the firm level that includes not only the firms directly listed by the US Department of Treasury but also the historical subsidiaries of these firms as well as the subsidiaries of the firms of the SDN individuals with confirmed ownership at the time of imposition of sanctions. I use the list of firms and names and announcement dates from the US Department of Treasury announcements on the official website. Then, I add all one-level-down historical subsidiaries of these companies and business individuals with Spark Database that keeps track of historical ownership[13].

I create a dataset of 2,857 sanctioned firms, for 1,487 of which I have firm-level

[11] Japan, Canada, Australia, New Zealand and Ukraine have followed the US and EU and largely repeated list of sanctions entities of the US.

[12] Most companies under the SSI sanctions were also treated with the US stopping certain technology exports to these companies. I consider this as still the negative capital inputs shock

[13] For individuals, the match is made using the first, middle, and last name. Sometimes, the political figures are matched with a business simply because the owners have the same name, but are different individuals. Since the list contains political figures as well, who cannot legally own business, I drop them by manually checking using open sources whether the individual matched with any firm is a business person or a political figure.

data at least for one year. The appendix describes the creation of the sanctioned dataset in detail. The sanctions date and indicator are based on two key sources: the official US Department of Treasury's announcements of sanctioned people and entities, and the Spark data on ownership chains. I use ownership chains to fulfil the OFAC rule of 50, which directs that any other entity owned by sanctioned entities by a total of 50% or more is also sanctioned. I match other Russian firms to directly sanctioned individuals using the full First, Middle and Last name match of the firms' reported owner, reported as owner anytime since one year before the sanctioning event[14]. Analogously, I add the majority-owned subsidiaries of directly sanctioned firms to the sample. The ownership information in Spark comes from three sources: Rosstat, the firm's annual report and the official firm registry EGRUL. I use the union of these three sources after I retrieve this information from Spark Database.

I record the distinction between the two types of sanctions in the US[15]: SSI and SDN. I look at both types of sanctions and each treatment separately. SSI only negatively affects inputs, rather than inputs and outputs, and the SDN is a complete embargo on all transactions, which affects both inputs and outputs. The SDN treatment is not made on a strict subset of the SSI, but there is an overlap of firms from both groups. I assign the year of treatment as the year of the imposition of the sanctions if the announcement happened before May that year. Otherwise, I assign the following year as the year of treatment, since the application of sanctions takes place 60 days after the announcement[16]

Sanctioned firms with all subsidiaries, cover 1% in total Russian employment and thei value added is 13% of total Russian GDP.

[14] I assign the sanction date to the owned companies even if they are reported as owned after the sanctioning event because there are often lags in reporting of owners

[15] the EU follows the US in the type of treatment with almost identical lists

[16] "Russian Sanctions Update", Morgan Lewis, April 7th, 2020

Sample	Count	Share of Value Added	Share of Revenue	Share of employment	Share of Value Added in Russian GDP	Share of Revenue in Russian GDP	Share of Russian employment
All firms	946,956	100	100	100	61	218	30
Firms with all variables	154,825	92	75	68	56	164	21
Private firms	942,542	89	93	94	54	202	29
State-owned firms	4,414	11	7	6	7	16	2
Sanctioned firms	1,046	21	13	4	13	28	1

Notes: This table reports the sample coverage for the firms in the SPARK dataset in 2020 or 2019 if data for year 2020 is missing. An observation is at the firm level. Russian GDP in columns "Share of Value Added in Russian GDP" and "Share of Revenue in Russian GDP" and Russian employment in column "Share of Russian employment" are taken from Rosstat for the year 2018.

Table 1: Sample used for analysis

4.3 Coverage of the economy

Table 2 shows the coverage of the full dataset I use across the three broad sectors: Manufacturing, Services and Agriculture. The first line of each panel in this table gives the shares of the sector in the total dataset. All other lines give shares within the sector, shares in Russian GDP and Russian employment become shares in Russian sectoral GDP and employment.

Manufacturing and Services predictably take up most of the dataset in terms of value added. The Services sector has more firms that are smaller. The Services and Manufacturing sectors both have a comparable share in value added of SOEs, but Manufacturing is disproportionately more hit by sanctions in terms of value added and firm count.

Sample	Count	Share of Value Added	Share of Revenue	Share of employment	Share of Value Added in Russian GDP	Share of Revenue in Russian GDP	Share of Russian employment
Manufcaturing							
All firms (share in total sample)	143,777	48	32	37	18	70	11
All firms	143,777	100	100	129	64	251	63
Firms with all variables present	33,426	98	80	100	63	202	49
Private for-profit firms	142,915	93	88	122	60	220	60
State-owned for-profit firms	862	7	12	8	4	31	4
Sanctioned firms	332	17	20	7	11	49	4
Services							
All firms (share in total sample)	768,116	48	66	57	18	143	17
All firms	768,116	100	100	164	30	246	24
Firms with all variables present	108,251	96	73	100	29	179	14
Private for-profit firms	764,986	88	95	155	27	234	22
State-owned for-profit firms	3,130	12	5	9	4	12	1
Sanctioned firms	695	13	10	4	4	25	1
Agriculture							
All firms (share in total sample)	35,062	4	2	6	1	5	2
All firms	35,062	100	100	116	38	134	28
Firms with all variables present	13,148	99	87	100	38	117	24
Private for-profit firms	34,640	99	99	112	38	132	27
State-owned for-profit firms	422	1	1	3	1	2	1
Sanctioned firms	19	0	0	0	0	0	0

Notes: This table reports the sample coverage for the firms in the SPARK dataset in 2020 or 2019 if data for year 2020 is missing. An observation is at the firm level. Russian sectoral GDP in columns ”Share of Value Added in Russian GDP” and ”Share of Revenue in Russian GDP” and Russian sectoral employment in column ”Share of Russian employment” are taken from Rosstat for the year 2018. The first row of every panel represents the share of the sector in the full sample. All other rows represent the shares within each sector.

Table 2: Sample used for analysis

5 Measuring firm productivity and distortions

Using the framework in the model Section 3, I compute $MRPK_i$, $MRPL_i$, $TFPQ_i$ and $TFPR_i$. I use book value of capital for K_i, total wage bill for L_i and firm cash revenue in that year minus cash paid to materials for P_iY_i, the value added[17]. To compute $TFPQ_i$ and $TFPR_i$ I also need the production function parameter α. I take α as one minus the labor share in total value added for private firms in a 4-digit sector[18]. Finally, to calculate a model-based $TFPQ_i$ I need the elasticity of demand η. I follow Hsieh & Song (2015) and use $\eta = 0.143$, which corresponds to the elasticity of substitution of 7. Using the values of α and η, I use equations 2, 3, 4 and 5 to calculate TFP_i, $MRPK_i$, $MRPL_i$ and $TFPR_i$ for each firm in each year.

The measures calculated this way are prone to measurement error in inputs and outputs (Bils et al. (2020), Rotemberg & White (2017), Gollin & Udry (2021)). Even non-systematic measurement error will result in higher measured misallocation and higher gaps between real and efficient TFPs. I apply a state-of-the-art method to adjust for measurement error. I start with the baseline approach and winzorise top and bottom 1% of firm observations in their $TFPR_i$ and the model-based productivity measure $TFPQ_i$. As an alternative, I also follow Adamopoulos et al. (2017) and regress the $TFPQ_i$ and $TFPR_i$ on firm and year fixed effects. This removes the transient shocks short-term measurement error in inputs and outputs and gives me the time-invariant firm productivity and wedges.[19] I then separate the firm effect from the sector component by taking the firm fixed effect and regressing these fixed effects on 4-digit-sector dummies to extract the residuals that

[17] The use of book value of capital is standard in the literature. Book value by Russian accounting includes, among other items, buildings and structures, machinery and equipment, computers, vehicles, household equipment, productive and pedigree livestock, perennial plantations. These items are subject to yearly amortization, which is usually linear.

[18] I drop a small number of sectors that are under 10 firms and or those that have α over 1 or under 0 in the data

[19] The regressions I run to correct for measurement error are shown below:

$$ln(TFPQ_i) = \beta_0^{TFPQ} + \gamma_t^{TFPQ} + \phi_i^{TFPQ} + \epsilon_{it}^{TFPQ} \tag{10}$$

$$ln(TFPR_i) = \beta_0^{TFPR} + \gamma_t^{TFPR} + \phi_i^{TFPR} + \epsilon_{it}^{TFPR} \tag{11}$$

Where β_0^{TFPQ} and β_0^{TFPR} are common intercepts, γ_t^{TFPQ} and γ_t^{TFPR} are the year fixed effects that capture time-varying shocks, such as a common component in trends in mark-ups or oil prices, and ϕ_i^{TFPQ} and ϕ_i^{TFPR} are the firm fixed effects and incorporates all firm-sector components. Finally, ϵ_{it}^{TFPQ} and ϵ_{it}^{TFPR} are the errors, including the transient measurement error and adjustment costs and noise.

are the pure permanent firm $ln(TFPQ_i)$ and $ln(TFPR_i)$ components. The $TFPQ_i$ and $TFPR_i$ are the exponentials of the residual, after regressing the firm fixed effects on industry dummies.

For the counterfactual exercises, I follow this procedure using the full panel 2012-2018, including the period of sanctions. I get the measures of firm $TFPQ_i$ and $TFPR_i$ that do not change over time and do not differ across sectors[20]. The firm fixed effect estimate controls for transient measurement error which is absorbed by the residual. I calculate the counterfactual results with this procedure, but also include the winzorised results based on raw data in the following sections. As expected, the dispersion of the adjusted measures of firm TFP and TFPR is lower than that of the unadjusted measures.

The discussion of how accurate is the $TFPR_i$ measure as a measure of misallocation is in due course.

6 Static misallocation in Russia

Table 3 is a summary table of all variables used in the current exercise. Each observation is firm-year. The sample has 602,926 observations, which is 194,095 firms and 897 industries. The typical firm is a domestic firm. There are 1,132 firms under any sanctions, of which 498 firms are under the input sanctions specifically, which is 0.96% of the dataset. State-owned firms add up to 4,378 and represent 3.6%. The variables include value added, capital, wage bill, materials bill, employment, age and a type of firm. I additionally include the statistics from the Hsieh & Klenow (2009) model (HK), each divided by the sector harmonic average: firm TFPQ, TFPR, MRPK, MRPL. I also include versions of these variables that are adjusted for the measurement error using firm and year fixed effects. All the balance sheet variables are in 1000s of Rubles.

Do resources in Russia appear misallocated through the lens of the framework

[20]When I quantify the aggregate effect of sanctions I will use an equivalent approach to get the pre-treatment wedges, but for years 2012-2014, the pre-period.

	(1)				
	count	mean	sd	min	max
Labor count, latest year	5,865,074	28	204	0	16,757
Firm age, yrs	6,177,338	9.1	7	0	108
Revenue, rub	5,621,811	298,867,506	24,361,516,040	-202,930,000	39,149,843,354,000
Value added, rub	1,488,387	190,612,354	8,262,448,419	-601,160,548,352	5,261,399,949,312
Book value of capital, rub	5,651,784	108,793,040	11,789,788,445	-155,114,000	8,002,629,050,000
Payment to labor, rub	1,526,079	64,135,436	1,327,653,226	-8,446,435,000	531,865,337,000
Materials, rub	1,653,280	601,631,449	13,543,482,197	-122,617,309,000	4,820,693,835,000
assets	4,768,430	265,420,929	22,254,057,758	-155,068,000	20,986,162,315,264
Private for-profit firm dummy	6,238,848	.99	.073	0	1
SOE	6,238,848	.0053	.073	0	1
Foreign-owned firm dummy	6,238,848	.00035	.019	0	1
Suppliers to state and SOEs dummy	6,177,579	.14	.35	0	1
Any Sanction	6,238,848	.0015	.038	0	1
Firm under blocking sanction	6,238,848	.00082	.029	0	1
(max) sdn	6,238,848	.00031	.017	0	1
Firm MRPK	5,138,357	882	239,055	-374,481	447,111,333
Firm MRPL	1,437,266	195	7,513	-175,174	4,877,622
Observations	6238848				

Notes: This table reports summary statistics for the firms in the SPARK dataset from 2012 to 2020. An observation is at the firm-year level. Firms' book value of capital, value added, payments to labor, materials and revenues are measured in rubles.

Table 3: Summary statistics of key variables

from the "Model" Section 3? If capital and labour markets were not distorted, more capital and labour would flow to the relatively more productive firms. This means that input use and firm TFP should be positively related, while the marginal revenue products of labour and capital should be unrelated to firm TFP because inputs flow to more productive firms up until these marginal products are equalised. Specifically, the revenue productivity, TFPR, which is the summary measure of MRPK and MRPL, should be unrelated to physical productivity, TFPQ.

In Russia, I observe different patterns. The Figure 2 shows that more productive firms face higher wedges in *both* labour and capital and confirms again our findings. Firms that experience high productivity do not have a scope to grow because both capital and labour flows to less productive firms. These less productive firms could be the firms under state protection. Equally, higher distortions in more productive firms could also come from the market power of those productive firms, and export tariffs that prevent these firms' expansion into foreign markets. Overall, these patterns point at large institutional and economic frictions that prevent the

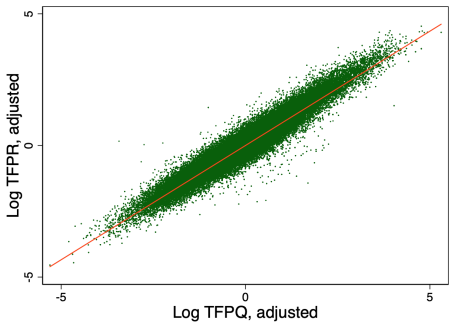


Figure 1: TFPR on TFPQ

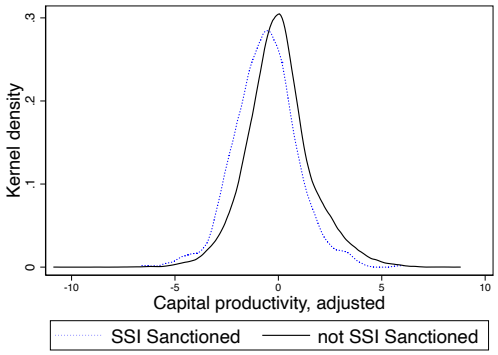
Notes: Each observation (green dot) is a firm. Raw TFPQ is calculated using the expression $TFPQ_i = \kappa \frac{(P_i Q_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha} L_i^{1-\alpha}}$. $TFPR_i$, or revenue productivity, is a summary measure of distortions faced by each firm, with higher $TFPR_i$ implying higher distortions. The TFPR and TFPQ measures are adjusted for measurement error with firm and year fixed effects and de-meaned by 4-digit industry using the firm panel 2012-2018. The solid orange line is the line of best fit.

Figure 2: Factor allocations by firm productivity

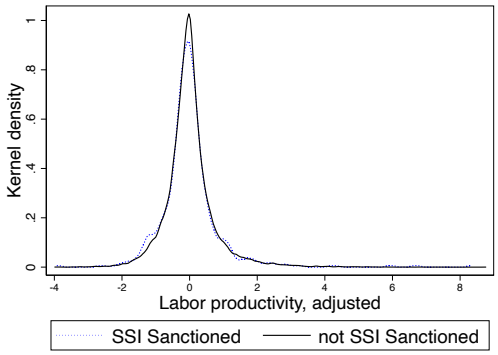
flow of labour and capital resources to the most productive firms. In Appendix C, I break down the correlation of TFPR and TFPQ on that of MRPK and MRPL with physical productivity. I also show a correlation between capital or labor inputs and physical productivity. It is negative for capital. In the same appendix I also compare the misallocation in Russia to findings of Hsieh and Klenow in India and China and find that Russia is slightly further away from the efficient frontier than India and China.

This paper studies how much of this relationship is explained by the state taking away capital and labour from more productive private firms and giving it to less productive SOEs and politically connected firms.

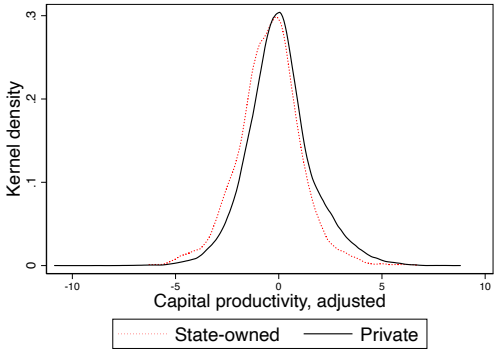
I have shown the allocative efficiency characteristics of the whole economy. What role in overall misallocation play specific wedges, such as wedges between a group of to-be sanctioned firms and all other firms, or state-owned firms versus the private firms? Could such distortions explain, at least in part, the barriers faced by more productive firms? Figure 3 below compares the density distributions of the firm-level log capital and labour productivity between state-owned firms and private firms as well as between to-be sanctioned firms and not sanctioned firms. These measures of MRPK and MRPL are adjusted for measurement error using



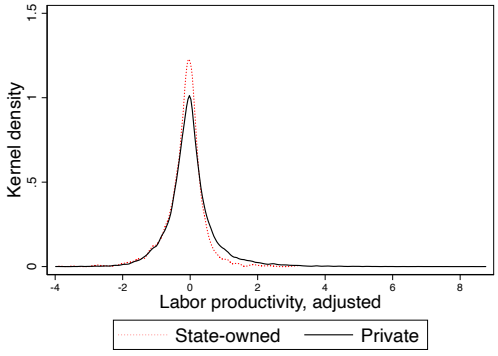
(a) MRPK of sanctioned versus other firms pre-2015



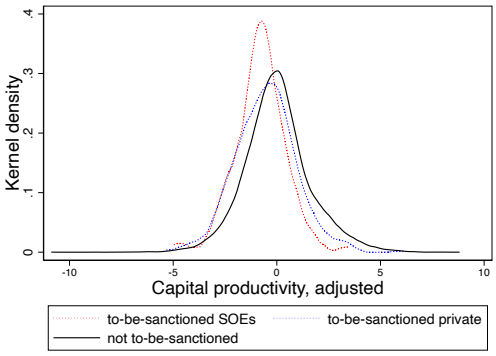
(b) MRPL of sanctioned versus other firms pre-2015



(c) MRPK of SOEs versus private firms pre-2015



(d) MRPL of SOEs versus private firms pre-2015



(e) MRPK of to-be sanctioned firms, split by SOE and private pre-2015

Notes: The plots show the kernel density of natural logs of MRPK and MRPL in the period before sanctions. First row: the blue dotted lines are the kernel densities for the sanctioned sample. The black lines in the top two graphs are the kernel densities for the sample of not sanctioned firms. Second row: the red dotted lines are the kernel densities for the SOEs sample. The black lines are the kernel densities for the sample of private firms. Third row: the red dotted line indicates the kernel density for the to-be-sanctioned SOEs, the blue dotted line indicates the to-be sanctioned private firms, and the black line indicates the never-sanctioned firms. Labour productivity (or $MRPL_i$) refers to value added per unit of wage bill and capital productivity (or $MRPK_i$) refers to value added per unit of capital, both of which are proportional to the marginal products of each factor in my framework. The MRPK and MRPL measures are time-invariant because they are adjusted for measurement error with firm and year fixed effects and de-meaned by 4-digit industry using the firm panel for 2012-2014.

Figure 3: Allocations before 2015

firm and year fixed effects as explained in Section 5.

These plots (a) and (b) in Figure 3 demonstrate that to-be sanctioned firms have on average lower MRPK than the non-sanctioned group (but not MRPL). This points at that to-be sanctioned firms were already over-resourced in terms of capital prior to sanctions and productivity gains could me made by reallocating capital from the to-be treated group to the rest of the economy. The plots (c) and (d) show that the state-owned enterprises also have lower average MRPK relative to private firms, and on top of that, a lower labor productivity, MRPL, at the higher end of the distribution. This last finding that SOEs have both too much capital and too much labor is intuitive, since labour hoarding could be still taking place in some state-owned enterprises, if they are the only main employers in a city - which is Soviet heritage[21].

The sanctioned group contained disproportionately more SOEs, but also some private firms. Do to-be-sanctioned firms have low MRPK because they have too many SOEs? Plot (e) shows that not only SOEs are the reason. The private to-be sanctioned firms also have a lower average MRPK relative to the economy-wide distribution, as well as the the to-be-sanctioned SOEs.

In sum, I confirm that the to-be sanctioned firms were also already "too large" before the sanctions at least in terms of capital. Since the sanctioned firms were chosen by the US intelligence services as connected to the current government, this finding points out that there is potential misallocation not only across ownership status but also between connected firms and all other firms. How sizeable was this wedge prior to sanctions?

6.1 How does the pre-existing misallocation between sanctioned and non-sanctioned firms affect the aggregate TFP?

To measure the contribution to overall misallocation from different groups (SOEs versus private, to-be-sanctioned versus not sanctioned), I conduct two counterfactual exercises. First, I get the overall distance to the frontier, by equalizing all

[21]The labour hoarding may be desirable from the equity perspective, but just not from the efficiency perspective.

wedges (or TFPR) across firms within each four-digit industry, keeping total capital and labour fixed within industries, and comparing the aggregate TFP as measured in the data to this new efficient TFP (I call it TFP*). This comparison will give a full distance to the efficient frontier from the current status quo in Russia. Second, I equalize wedges only within sanctioned-status-by-industry groups and compare the resulting TFP, call it TFPc, to the TFPe from the first exercise. The remaining distance to the frontier is attributed to the wedges *between* to-be-sanctioned and not sanctioned firms. I also repeat these exercises for the SOEs and private firms.

1) TFPe: Equalize all wedges within industries
2) TFPc: Equalize wedges within sanction status-industry groups (or ownership-industry groups)

Measures	Count	TFP/TFP*	TFPc/TFP*	Gap explained by between-group wedge
To-be-sanctioned versus not	57,279	49.9%	84.7%	30.5%
SOE versus private	57,279	49.9%	94.7%	10.4%

Table 4: Counterfactual exercises: to-be-sanctioned versus non-sanctioned

Table 4 shows the results of the counterfactual exercises. The overall distance to the frontier of Russian TFP will slightly more than double if all wedges were equalized. The sanctioned vs non-sanctions wedge explains (100-84.7)/(100-49.9)=30.5% of the distance to the frontier. In the second row, the wedges across ownership groups will add roughly (100-94.7)/49.9=11% to the current TFP if they are removed. The wedge between to-be-sanctioned firms and not-sanctioned firms explains a large share of the distance to the frontier and justifies further analysis. The SOE versus private wedge explains a smaller but still sizable distance to the frontier of (100-94.7)/(100-51.1)=10.4%.

Sanction type	Ownership Private	State-owned	Total
SDN	555	113	668
SSI	402	51	453
SSI and SDN	315	51	366
Total	1,272	215	1,487

Notes: This table is a cross-tabulation of the sanctioned firms (reporting balance sheet data) by ownership. SDN is the group of firms that are sanctioned by blocking sanctions, SSI indicated the group of firms sanctioned by input sanctions. The sample includes firms that are sanctioned by association with the directly sanctioned firm via majority ownership.

Table 5: Sanctions by ownership

Sanction type	Sector Manufcaturing	Services	Agriculture	Total
SDN	218	434	16	668
SSI	101	342	10	453
SSI and SDN	122	236	8	366
Total	441	1,012	34	1,487

Notes: This table is a cross-tabulation of the sanctioned firms (reporting balance sheet data) by sector. SDN is the group of firms that are sanctioned by blocking sanctions, SSI indicated the group of firms sanctioned by input sanctions. The sample includes firms that are sanctioned by association with the directly sanctioned firm via majority ownership.

Table 6: Sanctions by sector

7 The effect of sanctions on firms

Table 7 shows the summary of the key variables by sanction type and compares the averages of these key variables. The sanctioned firms, either SSI, SDN or both are larger in terms of average value added, total revenue, the book value of capital and wage bill. The average raw MRPK is lower in the sanctioned firms relative to non-sanctioned firms, as expected. In Figure 3 we also saw the whole distribution of this variable showing a substantial heterogeneity within the group. Appendix Tables 2.A3 and 2.A5 also summarize the groups of sanctioned firms by waves, and the types of industries sanctioned each wave. Each wave of sanctioned firms is comparable to each other, and a wide set of industries is represented by the first three waves.

Assuming politically connected SOEs and private firms already have "too much capital", the first hypothesis is that sanctions, hitting the inputs would reduce misallocation. However, there is anecdotal evidence that the politically connected firms, both private and state-owned, managed to secure more funding from the

	(1)				
	Not Sanctioned	SDN	SSI	SSI and SDN	Total
Labor count, latest year	26.51	1005.2	772.1	997.9	27.68
	(193.0)	(1710.4)	(1702.9)	(1827.7)	(205.4)
Firm age, yrs	8.059	12.76	12.40	13.40	8.064
	(6.442)	(7.445)	(7.441)	(8.462)	(6.446)
Private firm dummy	0.995	0.839	0.869	0.848	0.995
	(0.0693)	(0.368)	(0.338)	(0.360)	(0.0705)
SOE dummy	0.00482	0.161	0.131	0.152	0.00499
	(0.0693)	(0.368)	(0.338)	(0.360)	(0.0705)
Direct sanction dummy	0	0.124	0.468	0.216	0.000295
	(0)	(0.330)	(0.500)	(0.412)	(0.0172)
Ln value added	15.83	19.37	20.00	19.82	15.85
	(2.572)	(2.414)	(2.791)	(2.914)	(2.586)
Ln revenue	16.27	20.07	20.35	20.17	16.28
	(2.235)	(2.782)	(3.438)	(3.383)	(2.240)
Ln book value of capital	13.43	18.54	19.10	19.12	13.44
	(2.819)	(3.314)	(4.089)	(3.640)	(2.825)
Ln payment to labor	14.77	18.00	18.32	18.10	14.79
	(2.459)	(2.871)	(2.928)	(2.869)	(2.473)
Ln materials	16.40	19.06	19.01	18.97	16.42
	(3.066)	(3.300)	(3.745)	(3.622)	(3.074)
Foreign-owned firm dummy	0.000490	0	0	0	0.000489
	(0.0221)	(0)	(0)	(0)	(0.0221)
Suppliers to state and SOEs dummy	0.117	0.591	0.598	0.668	0.118
	(0.321)	(0.492)	(0.491)	(0.472)	(0.322)
Ln firm MRPK	2.718	1.601	1.348	1.154	2.716
	(2.837)	(2.780)	(3.440)	(3.043)	(2.838)
Ln firm MRPL	2.500	1.975	1.841	1.757	2.496
	(1.964)	(1.787)	(1.865)	(2.074)	(1.964)
Observations	915478				

Notes: This table reports summary statistics for the firms in the SPARK dataset in the pre-preiod: 2012 to 2014 by type of sanction. An observation is at the firm level, and the latest year 2012, 2013 or 2014 of the firm reporting data is kept. SDN is the group of firms that are sanctioned by blocking sanctions, SSI indicated the group of firms sanctioned by input sanctions. The sample includes firms that are sanctioned by association with the directly sanctioned firm via majority ownership. The share of the indirectly sanctioned firms is shown by the statistics for the "Sanctioned as a subsidiary dummy" variable.

Table 7: Summary by sanction type

Russian government as a response to sanctions. Sberbank, Russia's largest state bank had the central bank purchase a significant amount of the bank's new debt since sanctioning. Viktor Vekselberg, Renova Group's owner has had the credit line extended by Promsvyazbank in 2018[22]. Leonid Mikhelson has been reported to request the government to help fund the creation of deepwater drilling equipment to replace the U.S. imports[23]. Promsvyazbank was nationalized and then re-purposed to compensate the losses from sanctions of Russia's defence sectors[24]. By 2015 the Russian state started a bank recapitalization program worth about 1.4 trillion rub, or 1.2% of GDP to support all banks directly or indirectly affected by the sanctions.[25] Further, the government strategically granted contracts to sanctioned firms, it provided sanctioned Bank Rossiya the sole contract to service the $36 billion domestic wholesale electricity market, granted the contract to build a bridge linking the Russian mainland with Crimea to a sanctioned construction company (Stroygazmontazh), and selected a sanctioned bank (VTB) to be the sole manager of the government's international bond sales.[26]. Therefore, due to this governmental response, the misallocation may have actually worsened on the net after sanctions were imposed.

The SSI sanctions were imposed on groups of Russian firms in waves every year starting effectively from 2015. The staggered experiment of SSI sanctions allows me to test the joint effect of the negative input shock and the government response. I run the following regression:

$$Y_{it} = \gamma_{jt} + \phi_i + \theta_{st} + \beta_1 * InputSanctions_{it} + X_{it}\delta + u_{ijt} \tag{12}$$

[22]https://www.reuters.com/article/us-russia-renova-idUSKCN1IF2AG

[23]https://www.bloomberg.com/opinion/articles/2018-05-08/russia-sanctions-have-had-some-unexpected-consequences+cd=1hl=enct=clnkgl=ruclient=safari

[24]Max Seddon, "Moscow Creates Bank To Help It Avoid US Sanctions," Financial Times, January 19, 2018, https://www.ft.com/content/90c73fe4-fd15-11e7-9b32-d7d59aace167

[25]IMF, Russian Federation: Staff Report for the 2015 Article IV Consultation, August 2015, pp. 7. https://www.imf.org/external/pubs/ft/scr/2015/cr15211.pdf

[26]Moscow Times, "Sanctioned Bank Rossiya Becomes First Major Russian Bank to Expand in Crimea," April 15, 2017; Jack Stubbs and Yeganeh Torbati, "U.S. Imposes Sanctions on 'Putin's Bridge' to Crimea," Reuters, September 1, 2016; Thomas Hale and Max Seddon, "Russia to Tap Global Debt Markets for a Further $1.25 Billion," Financial Times, September 22, 2016. See the Congressional Research Service (2020), pp 53 for a more extensive list of measures by the Russian Government. https://fas.org/sgp/crs/row/R45415.pdf

I use the annual measures of $ln(MRPK_{it})$, $ln(ValueAdded_{it})$, $ln(Revenue_{it})$ or $ln(K_{it})$ for Y_{it} and regress these variables on firm-level time-variant sanctions dummy. The sanctions variable of interest is the SSI sanctions, which was targeted to inputs alone. In every specification, I also control for the SDN sanctions, which are included in X_{it} to account for the fact that some firms were also treated by SDN (”blocking”) sanctions in both the treated and control groups. To control for firm-level heterogeneity I include firm FE ϕ_i. Further, I add a 4-digit industry-year FE γ_{jt} to remove common industry changes over time, including the oil price shocks that were large in the period 2014-2016 and could have differentially affected some industries, which also have more sanctioned firms. Moreover, I include a size-by-year fixed effects θ_{st} to difference out the trends that larger firms experience as opposed to smaller firms. The size s is defined by the pre-treatment quartile of average firm capital. I cluster the errors by firm and 4-digit industry-by-year to account for possible serial correlation at firm level or across firms within an industry at a given point in time.

If β_1 is negative and significant and Y_{it} is ln(MRPK) in specification 12, this is the evidence that sanctioned firms, which already had ”too much capital” received relatively more capital as a result of sanctions. This result can appear not just because the capital inputs grew, but also because the input-sanctioned firms had more inputs *relative* to the value added. But what if the value added dropped for these firms, due to some de-risking by their foreign customers? If I further find that ln(MRPK) increased because the inputs grew more rather than because the value added dropped (for instance, by β_1 being non-negative when Y_{it} is $ln(ValueAdded_{it})$ and by β_1 being positive and significant when Y_{it} is $ln(K_{it})$), this will be the evidence of shielding of sanctioned firms that over-shot the direct (negative) effect of input sanctions on inputs.

This experiment also helps me see whether the SOEs have responded differently to this negative input shock as opposed to private firms. The finding that β_1 is negative alone is evidence that misallocation increased on average for the sanctioned firms, but no distinction is made about the response of SOEs versus private firms.

To separate the effect of political connections driving misallocation versus the state ownership driving misallocation I run the following regression:

$$Y_{it} = \gamma_{jt} + \phi_i + \theta_{st} + \beta_1 * InputSanctions_{it} + \beta_2 * InputSanctions_{it} * SOE_i + X_{it}\delta + u_{ijt} \tag{13}$$

In Specification 13, I repeat the specification 12 but add an interaction term $Sanctions_{it} * SOE_i$ to check if there is a differential effect with respect to the state owned firms. If in Specification 13 we see the evidence of only the SOEs being saved, β_1 will be zero and β_2 will be negative when Y_{it} is ln(MRPK). This will show that misallocation got worse through the act of protection of the SOEs alone.

Identification. Below, I discuss the extent to which my estimation is prone to two possible sources of bias: (1) non-random assignment of sanctions across firms, and (2) measurement error in sanctions and SOE status.

One worry is that sanctioned firms have different characteristics relative to non-sanctioned firms. As shown in Table 7, the sanctioned firms have higher revenues, capital, employ more people and are on average four years older than the non-sanctioned firms and there may also be unobserved differences between these firms. However, so long as these observed or unobserved differences are time-invariant, these differences are fully accounted for by firm fixed effects. The firm fixed effects also account for any differences between SOEs and private firms. Therefore, this empirical strategy does not require that the sanctions were randomly assigned.

Another concern is that the SSI sanctions were over-represented in some industries, such as the Oil and Gas sector, which also differentially experienced a negative oil price shock in the same period. So long as these shocks affected firms within a narrow 4-digit industry similarly, my industry-by-year fixed effect fully controls for these time-variant industry shocks.

Therefore, this set-up does not require that the industries that had more sanctioned firms evolve in parallel over time, and it does not require that the sanctioned and non-sanctioned firms share the same time-invariant characteristics. The esti-

mation of β_1 in Specifications 12 and 13 does rely on the classic assumption that the sanctioned firms evolve in parallel to the non-sanctioned firms at the time of sanctioning. I provide visual evidence that the pre-trends evolved in parallel in the next section.

The estimation of β_2 in Specification 13 requires that SOEs are trending in parallel to private firms. Such differential trends can be controlled for. In the Appendix Table 2.A1, I control for the SOE-by-year fixed effects to absorb the bias from SOEs trending differently to private firms. In effect, Specification 13 after additionally controlling for SOE-by-year fixed effects becomes a triple difference regression. I show that β_1 and β_2 do not change from including the SOE-by-year fixed effects. As a result, I can still identify β_2 if treated and untreated industries have different industry-level time trends, as they are controlled for by the $InputSanctions_{it}$ dummy. I can also still identify β_2 if SOEs and private firms are trending differently, as these are absorbed by SOE-by-year fixed effects. I rest on a milder assumption to identify β_2: the differential between the sanctioned SOEs and sanctioned private firms need to evolve in parallel to that differential in the non-sanctioned group in the absence of sanctions.

Measurement error in $MRPK_i$, the outcome variable, is not a great concern in the estimations I present. First, the non-systematic measurement error on the outcome variable $MRPK_i$ does not bias the coefficients that I find. If the measurement error is systematic, but fixed at firm-level, or is time-variant, but common for all firms in a 4-digit industry, it will be absorbed by the industry-by-year fixed effects and firm fixed effects. Only the non-classical measurement error that varies by sanction and SOE status may be an issue. However, if anything such a hypothetical error is likely to work against me finding the shielding effects: the SOEs and other sanctioned firms may be motivated to under-report the capital that is received as a result of shielding.

7.1 Event studies

As mentioned above, to identify β_1 in Specifications 12 and 13 I rest on the assumption that the sanctioned firms would have been on the same trends as the non-sanctioned firms at the time of sanctioning. To partially alleviate this concern, I include event studies that 1) test for sanction effect within sanctioned firms (Specification 14) and identifying the treatment effect off timing 2) test for the differential trends between sanctioned and non-sanctioned firms before 2015, the first year of sanctions taking an effect (15)[27].

$$Y_{it} = \gamma_{jt} + \phi_i + \theta_{st} + \alpha_s * \sum_{s=-4, s\neq 0}^{s=3} InputSanctions_i * 1_{t=s} + X_{it}\delta + u_{ijt} \tag{14}$$

Specification 14 is identical to the regression 12, except that the average treatment on the treated effect is split into seven year-to-sanction effects. Each α_s identifies each year-to-sanction effects relative to the average outcome in the first year of sanctions. Only the variation within the sanctioned firms is used to identify α_s, however, the non-sanctioned firms can still be used to identify the γ_{jt} and θ_{st}.

$$Y_{it} = \gamma_{jt} + \phi_i + \theta_{st} + \alpha_s * \sum_{s=2012, s\neq 2015}^{s=2018} InputSanctions_i * 1_{t=s} + X_{it}\delta + u_{ijt} \tag{15}$$

Specification 15 is aimed to test whether the sanctioned and non-sanctioned firms were trending in the same way prior to sanctions. Here, unlike in the previous specification, the full sample is used to identify the coefficients α_s, which show the difference in outcomes of the sanctioned firms in each year versus in 2015, compared to such difference in outcomes of the non-sanctioned firms.

[27] Even though officially sanctions began in 2014, because of the two month cool-down period, only a small number of firms are effectively treated in 2014

8 Results

8.1 Regression results

Table 8 shows my baseline results of any sanctions on firm's inputs. Both SSI (input) sanctions and SDN (input and output) sanctions affected input sourcing of sanctioned firms in the West. The sanctions however have led to an expansion of input value across the key balance sheet variables that represent labor, material and capital inputs. The sanctioned firms have not shrunk their input value as a response to sanctions

First, in columns (1) and (2) we see an average increase in 37% in assets and 37% in capital of sanctioned firms relative to non-sanctioned firms after sanctions are imposed. Capital increased for sanctioned firms on average. In columns (5)-(8) we see a similar pattern in payments to materials and to labor. Then, in column (4), we see the heterogeneity of this effect for the SOEs. The SOEs see their capital rising differentially to sanctioned private firms.

If the increase in the value of inputs is driven by the increase in the volume of inputs through substitution from domestic and non-western sources, this points at all sanctioned firms have been protected from sanctions and have seen full shielding of their assets and capital and all had "too much" shielding.

One could argue that de-risking against Russian sanctioned firms could have lead to a simple reduction in sales, especially the sales abroad. Table 9 give us the answer: the sales and value added increased, too, along with profits. There is no differential for the SOEs in this increase. Revenue results are provided along the value added because revenue is a direct measure reported in the balance sheets, rather than the constructed value added, and therefore may have better measurement. Interestingly, the gross profits, as recorded in the balance sheets have grown as well for sanctioned firms after being sanctioned. Revenue or sales have increased (!) in value for sanctioned firms after sanctioning, which included a ban on sales for some firms in the west.

Table 12 shows my baseline results for specifications 12 and 13 on misallocation.

The first thing to note is in columns (1) and (2) we see that the MRPK went down on average for sanctioned firms and this effect is mainly driven by MRPK going down differentially for the sanctioned SOEs relative to sanctioned private firms. There is no statistically significant change in MRPK for sanctioned private firms relative to non-sanctioned firms. This tells us two things 1) The negative input shock did not correct the implicit subsidies that politically connected private firms had and we saw in Figure 3 2) The negative input shock has lead to a response that made SOEs appear as if they had experienced a positive input shock and stronger implicit subsidies.

Does this negative MRPK result come from the capital input increase (denominator) or the output reduction (numerator)? From Tables 9 and 8 we know that both the capital inputs and revenues have increased, just the capital inputs increased more than the revenues.

The complete shielding of capital inputs would have kept misallocation at the same level as pre-sanctions, but the excessive shielding has, in fact, worsened it.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ln Assets	ln Assets	Ln Book Value of Capital	Ln Book Value of Capital	Ln Materials	Ln Materials	Ln payment to labor	Ln payment to labor
Any Sanction	0.349***	0.336***	0.381***	0.338***	0.225***	0.235***	0.116**	0.113**
	(0.050)	(0.055)	(0.059)	(0.064)	(0.053)	(0.059)	(0.047)	(0.052)
Any Sanction × SOE		0.080		0.257**		-0.065		0.016
		(0.110)		(0.121)		(0.103)		(0.091)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firms	641084	641084	678996	678996	180437	180437	175686	175686
Sanctioned firms	932	932	928	928	922	922	921	921
Industries	863	863	865	865	767	767	768	768
Observations	3313614	3313614	3852682	3852682	865680	865680	846422	846422
R-squared	.996	.996	.996	.996	.997	.997	.998	.998

Clustering: Firm and industry-by-year

Notes: All dependent variables are in logs. Firms are classified as SOEs according to Rosstat. Industry×Year FE are 4-digit industry by year fixed effects. Size×Year are quartile fixed effects for firms' average pre-treatment capital interacted with year fixed effects. Sanction firms give the count of any sanction firm - SSI or SDN. Standard errors are two-way clustered at the firm and 4-digit industry by year level. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Table 8: Average effects of sanctions: key outcome variables

Using the anecdotal evidence that the funds were taken from the Russian budget, one can conclude that the connected SOEs and private firms were saved at the

	(1) Ln Value Added	(2) Ln Value Added	(3) Ln Revenue	(4) Ln Revenue	(5) Ln Profit	(6) Ln Profit
Any Sanction	0.087**	0.093**	0.213***	0.213***	0.121**	0.101*
	(0.040)	(0.045)	(0.054)	(0.058)	(0.051)	(0.055)
Any Sanction × SOE		-0.034		-0.001		0.124
		(0.098)		(0.126)		(0.122)
Firm FE	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓	✓	✓
Firms	150244	150244	635159	635159	570952	570952
Sanctioned firms	828	828	916	916	865	865
Industries	750	750	847	847	839	839
Observations	675187	675187	3577896	3577896	2789751	2789751
R-squared	.998	.998	.997	.997	.996	.996

Clustering: Firm and industry-by-year

Notes: All dependent variables are in logs. Firms are classified as SOEs according to Rosstat. Industry×Year FE are 4-digit industry by year fixed effects. Size×Year are quartile fixed effects for firms' average pre-treatment capital interacted with year fixed effects. Sanction firms give the count of any sanction firm - SSI or SDN. Standard errors are two-way clustered at the firm and 4-digit industry by year level. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Table 9: Average effects of sanctions: key outcome variables

	(1) Ln MRPK	(2) Ln MRPK	(3) ln_MRPLi	(4) ln_MRPLi	(5) ln_MRPMi	(6) ln_MRPMi
Any Sanction	-0.137**	-0.098	0.062	0.066	-0.023	-0.033
	(0.056)	(0.064)	(0.045)	(0.049)	(0.041)	(0.043)
Any Sanction × SOE		-0.232**		-0.021		0.057
		(0.106)		(0.118)		(0.114)
Firm FE	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓	✓	✓
Firms	628071	628071	170783	170783	173785	173785
Sanctioned firms	910	910	903	903	902	902
Industries	847	847	764	764	763	763
Observations	3502816	3502816	815812	815812	826283	826283
R-squared	.91	.91	.936	.936	.684	.684

Clustering: Firm and industry-by-year

Notes: All dependent variables are in logs. Firms are classified as SOEs according to Rosstat. MRPK is calculated as Revenue/K, MRPL as Revenue/wage bill, MRPM as Revenue/Materials. Industry×Year FE are 4-digit industry by year fixed effects. Size×Year are quartile fixed effects for firms' average pre-treatment capital interacted with year fixed effects. Sanction firms give the count of any sanction firm - SSI or SDN. Standard errors are two-way clustered at the firm and 4-digit industry by year level. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Table 10: Average effects of sanctions: key outcome variables

expense of all other firms and Russian taxpayers. This also has implications for the goals that sanctioning countries hoped to achieve: the sanctions were meant to be targeted and narrow. However, the shielding that took place in response has made the effects being borne by everyone *but* the original targets!

The results in Tables 8 and 9 differ from early firm-level sanctions results of

Ahn & Ludema (2020), who find a negative result on revenue and assets. This is for two reasons. First, they measure the combined effect of sanctions on all assets, including companies owned by Russian oligarchs abroad. Some of the foreign companies had to indeed seize operation and eventually close, which may likely be driving the early negative result. Second, they only observe results till 2016, so mainly for only one effective year of sanctions, before the full effect of sanctions (and protection) unravels.

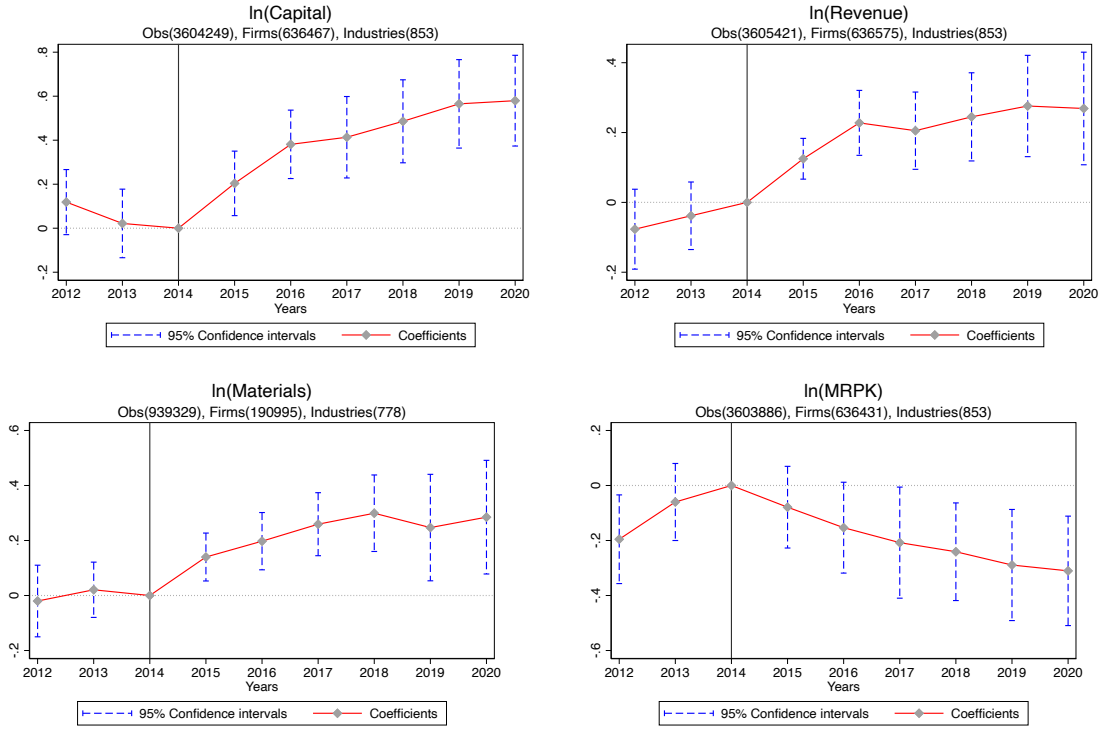
Finally, the results above could be consistent with the idea that sanctioned firms have fully passed through the sanction shock to the consumer: input value is price multiplied by volume, and the increase in inputs could mean that volume increased or the price of inputs increased. While disentangling these is not possible without data on quantities and customs data, if it was simply the higher price of inputs that is passed through to the consumer at a higher price, it is not clear why the profits also rose. The fact that profits increased along with revenues demonstrate that at least some shielding was taking place.

8.2 Event studies results

The identification in Tables 8-12 is subject to one obvious problem. What if the sanctioned firms would have seen their MRPK reduced in any case regardless of sanctions and shielding. It is possible that the sanction dummies just pick up such trends?

In Figure 4, I show three event studies with ln(Capital), ln(Revenue) and ln(MRPK) as outcome variablesin which the control group is the never-sanctioned firms. I cannot reject that the group of sanctioned firms was on the same trends as the group of non-sanctioned firms before 2014, the first year of sanctioning in Figure 4. If anything the treated firms' MRPK were on the upward trend before the sanctions, so the regression results I find in Table 12 are a lower bound. In this case, the control group is the average time trend in the 4-digit industry and the treatment is the average outcome of the sanctioned firm in each year-to-sanction. The sample used

to identify the coefficients in the event study is the full sample of firms, sanctioned or not.



Notes: This figure reports event study graphs for the average effects of the sanctions on sanctioned firms relative to non-sanctioned firms. Each dot is the coefficient on the interaction between being observed in the year 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019 and 2020 and being sanctioned with SSI or SDN sanctions. The same control variables are used as in baseline regression: SDN sanction, firm fixed effects, 4-digit industry-year fixed effects and the size-year fixed effects. Effectively, each dot is the deviation of the sanctioned firm log MRPK from the 4-digit-industry-by-year fixed effects. The dependent variables are in logs. The confidence intervals are at the 95% level.

Figure 4: Pre-post 2014 event study with never-sanctioned firms in the control group

In Figure 5, I show an event study within the group of sanctioned firms and confirm that the positive effects persist even when the required assumption is weaker: the firms that are sanctioned sooner are not on a different trend compared to the firms that are sanctioned later. In this case, the control group is the average outcome of the sanctioned firm in the year 0, the year it was sanctioned, and the treatment is each year-to-sanction. I emphasize that the coefficients in Figure 5 come from a specification, where I control for the industry-year fixed effects, pre-treatment size-by-year fixed effects and firm fixed effects. The full sample is used in this event study in order to identify the fixed effects only. Figure 5 shows that

there is a trend break at the time of sanctioning for capital, material and MRPK. There seems to be some pre-existing increases in trends for the revenue result, which could be an anticipation effect or the true differential pre-trends. In any case, considering instead that all revenue increases are driven by trends and the true causal effect of sanctions+shielding on revenues is 0 will not fundamentally alter the increase in capital and misallocation result.

Event studies within treatment may be biased if there is treatment effect heterogeneity and dynamic effects, since this specification uses the already treated observations as controls for the not-yet -treated observations. I therefore estimate these effects using the De Chaisemartin & d'Haultfoeuille (2020) estimator in Figure 2.A1 and show that the estimated effects are qualitatively the same and quantitatively close to the effects estimated in the Figure 4.

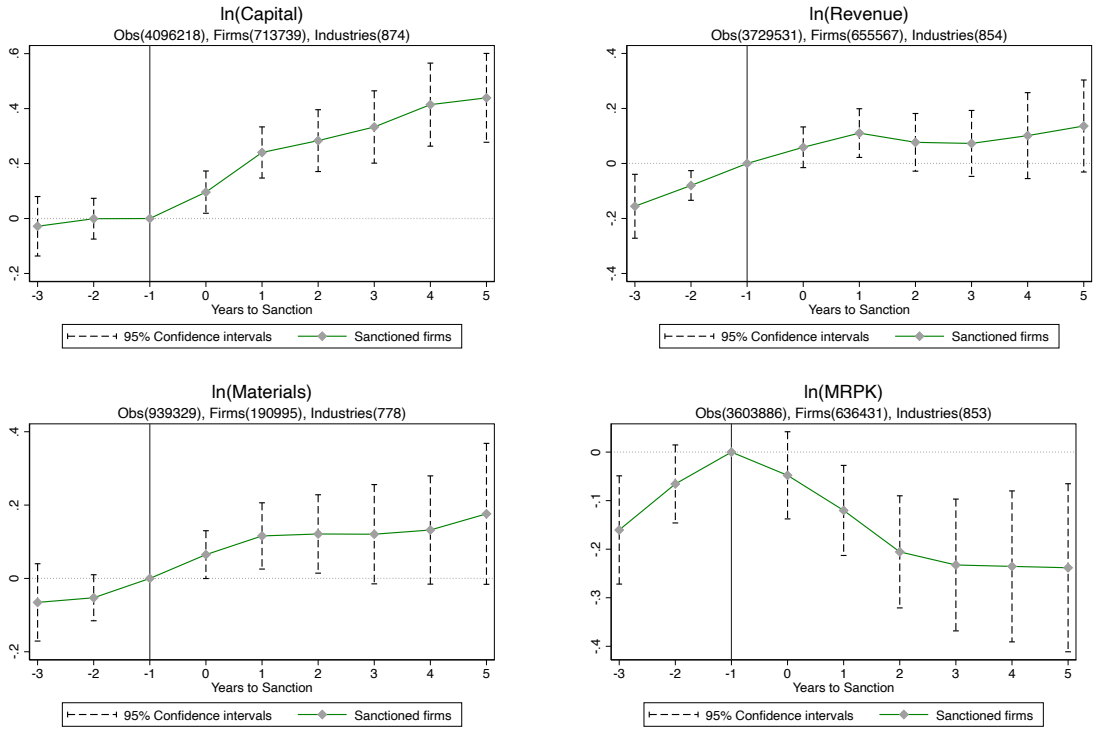
8.3 Channels: Contracts, Subsidies, and Loans

What are the main drivers of the increases in revenue and book value of capital? What would explain such dramatic increases after sanctions? I look at three possible drivers: government subsidies, government contracts, and loans.

	(1) ln Contracts	(2) ln Contracts	(3) Ln Subsidy Volume	(4) Ln Subsidy Volume
sanc_all	2.348***	2.363***	0.108	-0.014
	(0.451)	(0.507)	(0.095)	(0.092)
sanc_all × SOE		-0.082		0.791**
		(0.966)		(0.340)
Firm FE	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓
Firms	107703	107703	88822	88822
Sanctioned firms	1116	1116	1045	1045
Industries	705	705	698	698
Observations	496809	496809	351387	351387
R-squared	.746	.746	.724	.724
Dependent Variable: ; Clustering: Firm and industry-by-year				

Notes: All dependent variables are in logs. Size×Year are quartile fixed effects for firms' average pre-treatment capital interacted with year fixed effects. Sanction firms give the count of any sanction firm - SSI or SDN. Standard errors are two-way clustered at the firm and 4-digit industry by year level. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Table 11: Average effects of sanctions: Subsidies and Contracts



Notes: This figure reports event study graphs for the average effects of the sanctions on sanctioned firms. The effect is identified within sanctioned firms: sanctioned firms are compared to not-yet sanctioned firms. The first year of firm sanction is normalized to take place in year 0. Each dot is the coefficient on the indicator of being observed t years after the sanctions announcement. The same control variables are used as in baseline regression: SDN sanction, firm fixed effects, 4-digit industry-year fixed effects and the size-year fixed effects. Non sanctioned firms are used to identify the 4-digit industry-year fixed effects and the size-year fixed effects. The dependent variables are in logs. The confidence intervals are at the 95% level.

Figure 5: Event study with not-yet sanctioned firms in the control group.

	(1) ln LT Loans	(2) ln ST Loans	(3) ln Investment	(4) ln Credit cash-in	(5) ln Credit cash-out
Any Sanction	0.142	0.097**	0.102	0.278***	0.365***
	(0.086)	(0.046)	(0.068)	(0.092)	(0.092)
Firm FE	✓	✓	✓	✓	✓
4-digit industry-yr FE	✓	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓	✓
Firms	243404	624138	51826	86786	80712
Sanctioned firms	858	932	741	610	604
Industries	793	855	652	685	666
Observations	1129383	3232395	250688	358052	338991
R-squared	.846	.89	.764	.805	.806
Clustering: Firm and industry-by-year					

Notes: All dependent variables are in logs. Size×Year are quartile fixed effects for firms' average pre-treatment capital interacted with year fixed effects. Sanction firms give the count of any sanction firm - SSI or SDN. Standard errors are two-way clustered at the firm and 4-digit industry by year level. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Table 12: Average effects of sanctions: Proxies for borrowing

Table 11, columns (1) and (2) show that contracts increased significantly after sanctions, but there was no effect on the SOE differential. Subsidies, on the contrary did not increase overall for sanctioned firms, but they increased significantly for the SOEs after being sanctioned.

From the anecdotal evidence described in the Data section, credit, including via the special banks, was one of the policies that the Russian government has extended to the sanctioned firms to replace the treatment of being sanctioned. In Table 12, I look at a series of balance sheet variables that can proxy for the changes in loaned money flowing into the company. Columns (1) and (2) show the effect of sanctions on the stock of long-term and short-term loans respectively. I see a significant 10% increase in short-term loans. Column (3) looks at the "investment" variable which I have for a limited number of firms, and it also increases, albeit insignificantly. Finally, columns (4) and (5) are taken form the cash-flow statement and they demonstrate the increases in the flows of cash for both getting more credit and paying for more credit. The increase in short-term credit is noteworthy, as most large Russian banks are state-owned and extending credit to sanctioned firms could have been one of the mechanisms of their protection.

8.4 Heterogeneity

My data allows me to explore interesting dimensions of heterogeneity of sanctioned firms in their reaction to being sanctioned. Table 2.A4 looks at heterogeneity of the firms' response by being sanctioned directly or via the "OFAC rule of 50%" and there is no differential (positive) response for the indirectly sanctioned firms. All firms appear to be shielded in the same way. In columns (3) and (4) I look at the heterogeneity of sanctioned firms by the type of sanction, and again, there is no difference in shielding whether a firm is sanctioned by the input sanction (SSI) or by a fully blocking sanction (SDN). Columns (5) and (6) demonstrate that the minority-owned firms see a dampened effect of being shielded, relative to those directly sanctioned or those that are majority-owned by directly sanctioned firms.

Columns (7) and (8) show that the sanctioned firms in the energy sector did not see a differential effect (after controlling for the 4-digit industry-by-year FE), so despite the strong oil price fluctuations in the same period, the energy firms have not experienced worse outcomes. The last two columns are very interesting as they look at the heterogeneity by sanctioned exporters. Revenues increase more for the exporters relative to non-exporters, even though one of the sanctioned treatment was to block all economic transactions with the sanctioned firms. This points out that sanctioned firms found other ways to export their produce, potentially re-orienting to other countries.

8.5 Robustness

In this section I explore whether my results are robust to alternative sample and differential attrition.

First, the results on revenue and capital I find could be driven by sanctioned firms that have low revenue and capital more likely to exit or stop reporting after sanctioning, that the untreated firms. I create a balanced sample with dummy variable indicating the existence of the firm. I find that sanctioned firms are more likely to exist and less likely exit in Table 2.A2.

Furthermore, I look at the event studies using only the firms that exist in every of the 9 years and again confirm the baseline increases in capital and revenue and fall in MRPK in Figures 2.A2 and 2.A3.

8.6 Aggregate effects

I use the estimates from the results in the previous section and a simple formula from Hsieh & Klenow (2009) based on the model in Section 3 to calculate the effects on aggregate sector TFP from the change in $TFPR_i$. The use of the formula requires an additional assumption: that the distribution of firm TFP_i and $TFPR_i$ are jointly log-normal[28]. This assumption is used for convenience, to get a simple expression

[28] Bau & Matray (2020) show another way to calculate the aggregate effects as a first-order approximation with the benefit of fewer assumptions. However, their formula is a function of $\frac{\tau_i^K}{1+\tau_i^K}$ and will necessarily give an improvement in TFP_s from

from the change in TFPR for some firms to the aggregate TFP. I assume that the $TFPQ_i$ did not change for sanctioned SOE and private firms due to policy, so the HK formula reduces to:

$$\Delta logTFP_s = -\frac{1}{2\eta} * VAR(logTFPR_i + \alpha \Delta logMRPK_i) \tag{16}$$

The value of $\Delta logMRPK_i$ is taken from Table 12 as the coefficient on the interaction term in column (2). The value of $logTFPR_i$, the log revenue productivity of each firm, and also a summary measure of distortions to these firms, is obtained as a pre-2015 level using the methodology in Section 5. Whereby the $logTFPR_i$ is the residual from regressing $logTFPR_{it}$ on year and firm fixed effects (and then removing the common 4-digit industry component) for the pre-sanction period years 2012, 2013 and 2014. I conservatively assume that the labour productivity $MRPL_i$ stays the same as the pre-sanction level.

The overall effect on country TFP from sanctions is 0.33% and is calculated with a Cobb-Douglas aggregator of TFP_s from each sector s with powers as value added shares. However, the results for each industry (appendix Figure **??**) differ vastly due to the different exposure and underlying level of the treated companies' $TFPR_i$, of 50 industries that experienced changes, 41 experienced negative productivity changes ranging between -3%–0.01%, and 9 minor positive changes all under 1% (with one exception: "Manufacture of television receivers, including video monitors and video projectors" had a 4% productivity increase).

How large are the aggregate effects relative to the baseline misallocation? To put the worsening of misallocation from sanctions into perspective, I compare it to the efficiency gains of reallocating resources across ownership groups and across the to-be-sanctioned and not-to-be-sanctioned groups. Sanctions (0.33% reduction of TFP) explain about 1% of the "sanctioned group"-driven distance to the frontier.

a capital increase for the firms that are "too big" when $\tau_i^K < -1$, which is common in my setting

9 Conclusion

Using structural and reduced-form evidence, I show that sanctions combined with government shielding have helped the targeted firms, but harmed the Russian economy.

More generally, I show that SOEs and politically connected firms are a large source of allocative inefficiency, both in terms of how inputs are allocated to such firms at a given point in time, and in terms of how these firms respond to negative input shocks. Thus, I address a key challenge in the literature and provide direct evidence of how policies can change allocative efficiency and productivity.

I use a unique natural experiment - the US sanctions on Russia to causally estimate the combined effect of sanctions and shielding that affected sanctioned firms relative to non-sanctioned and whether the effects of sanctions on SOEs differed from that on the private firms. I use the state-of-the-art tools to combine the estimates from this natural experiment with a heterogeneous firm model and quantify the effects of sanctions on misallocation and, in turn, on the aggregate TFP.

I find that the to-be-sanctioned firms are less productive relative to private firms, but use relatively more capital and labour. This creates allocative inefficiency within industries and would improve current TFP by 31% if the wedges between sanctioned and non-sanctioned firms were removed. My empirical estimation demonstrates one channel through which the sanctioned firms-the SOEs and other politically connected firms get so large: such firms differentially respond to negative input shocks by getting subsidies that over-shoot the negative shocks. The sanctions, combined with shielding have led the sanctioned firms to gain 34% more capital relative a non-sanctioned firm. I quantify that this joint sanctions and shielding effect reduced the aggregate TFP by 0.33%, which varied between 0.1% and 3% reductions in different sectors.

This paper has important policy implications. First, the sanctions policy, specifically about Russia, has come to the forefront of international economics in the recent year. Due to the evidence of excessive shielding that I find, the ”smart”

sanctions failed to be targeted and narrow. Instead, they have provided a trigger for shielding some firms at the expense of the taxpayers and other non-politically connected firms. Sanctions have spilt over to the rest of the economy and had collateral damage because of inefficient reallocation of resources. The estimate of 0.33% lower TFP (and therefore, 0.33% lower GDP assuming total resources stayed at the pre-sanction level) is likely an underestimate in terms of GDP, as total resources have likely shrunk over this period, as well.

Second, my paper shines a light on state ownership and political connections as one of the strong drivers of misallocation in the economy. When an economy with such firms is hit by a negative trade or financial shock, it may suffer more, as the politically connected firms will attract a larger share of a shrinking pie.

Future research will study how reallocation of resources works under a much stricter regimes of sanctions, when resources become much more limited. Which types of targeted firms and sectors receive more support, and at whose expense.

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10 Appendix

11 Appendix A. Heterogeneous firm model

One-industry model.

This is the standard model that almost every "indirect approach" paper on misallocation is using. It shows that a **dispersion** of wedges (taxes or subsidies) lead

to the dispersion of MRPK and MRPL (marginal revenue products of labour and capital) and thus allocative inefficiency, and as a result, lower aggregate TFP. (Aggregate output in this model may also depend on the average **level** of the wedges (if they are driven by, for example, corruption), but the level is harder to identify without stronger assumptions. For now, I focus on the allocative inefficiency aspect, and thus the dispersion of wedges.)

Firms.

$$Q_i = A_i K_i^{\alpha} L_i^{1-\alpha} \tag{17}$$

For simplicity of exposition I assume α is the same across firms. In empirical analysis, I will relax this assumption by industry. Each firm's output is aggregated to a CES aggregate:

$$Q = \left(\sum_{i=1}^{N} Q_i^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{18}$$

The aggregating firm demands outputs of individual firms and maximizes profits:

$$\max_{Q_i} P \left(\sum_{i=1}^{N} Q_i^{1-\eta} \right)^{\frac{1}{1-\eta}} - \sum_{i=1}^{N} P_i Q_i$$

$$FOC_{Q_i}: \ \frac{1}{1-\eta} P \left(\sum_{i=1}^{N} Q_i^{1-\eta} \right)^{\frac{1}{1-\eta}-1} (1-\eta) Q_i^{-\eta} - P_i = 0$$

$$P \left(\sum_{i=1}^{N} Q_i^{1-\eta} \right)^{\frac{\eta}{1-\eta}} = P_i Q_i^{\eta}$$

$$P Q^{\eta} Q_i^{*1-\eta} = P_i Q_i^{*} \tag{19}$$

The above equation (implicitly) shows how much Q_i is demanded for each firm given P_i, and it is expressed as revenue each firm gets in equilibrium. Each firm i maximizes profits $\pi_i = P_i Q_i - (1+\tau_i^L) w L_i - (1+\tau_i^K) r K_i$.

Or, substituting the implicit expression of quantities demanded for the revenue:

$$\underset{L_i, K_i}{max} \pi_i = PQ^{\eta} Q_i^{*1-\eta} - (1+\tau_i^L) w L_i - (1+\tau_i^K) r K_i$$

s.t.

$$Q_i = A_i K_i^{\alpha} L_i^{1-\alpha}$$

I assume w and r are the **common** and **exogenous** costs of labor and capital. Whereas τ_i^L and τ_i^K are firm-specific distortions to the cost of labor and capital.

$$\{L_i\} : (1-\alpha)(1-\eta)\frac{PQ^{\eta}(A_i K_i^{\alpha} L_i^{1-\alpha})^{1-\eta}}{L_i} = (1+\tau_i^L) w \tag{20}$$

The optimal labor allocation will satisfy this equation:

$$\{L_i\} : (1-\alpha)(1-\eta)\frac{P_i Q_i}{L_i} = (1+\tau_i^L) w \equiv MRPL_i \tag{21}$$

$$\boldsymbol{\{L_i\} :\ L_i = (1-\alpha)(1-\eta)\frac{P_i Q_i}{MRPL_i}} \tag{22}$$

Similarly, this equation will be satisfied by the optimal capital allocation:

$$\{K_i\} :\ \alpha(1-\eta)\frac{P_i Q_i}{K_i} = (1+\tau_i^K) r \equiv MRPK_i \tag{23}$$

$$\boldsymbol{\{K_i\} :\ K_i = \alpha(1-\eta)\frac{P_i Q_i}{MRPK_i}} \tag{24}$$

It is useful to add the definition of TFPR_i, which is often used in the literature and is a summary measure of distortions.

$$TFPR_i \equiv \frac{P_i Q_i}{K_i^{\alpha} L_i^{1-\alpha}} = \left(\frac{MRPK_i}{\alpha}\right)^{\alpha} \left(\frac{MRPL_i}{1-\alpha}\right)^{1-\alpha} \frac{1}{(1-\eta)} \tag{25}$$

Re-arranging optimal output in terms of parameters that constitute the costs of firm i, we get:

$$P_iQ_i = PQ^{\eta}(A_iK_i^{\alpha}L_i^{1-\alpha})^{1-\eta} = PQ^{\eta}\left(A_i\left[\frac{(1-\alpha)(1-\eta)}{(1+\tau_i^L)w}P_iQ_i\right]^{1-\alpha}\left[\frac{\alpha(1-\eta)}{(1+\tau_i^K)r}P_iQ_i\right]^{\alpha}\right)^{1-\eta} \tag{26}$$

$$P_iQ_i = PQ^{\eta}(P_iQ_i)^{1-\eta}(1-\eta)^{1-\eta}\left(A_i\left[\frac{(1-\alpha)}{(1+\tau_i^L)w}\right]^{1-\alpha}\left[\frac{\alpha}{(1+\tau_i^K)r}\right]^{\alpha}\right)^{1-\eta} \tag{27}$$

$$P_iQ_i = P^{\frac{1}{\eta}}Q\left((1-\eta)A_i\left[\frac{(1-\alpha)}{(1+\tau_i^L)w}\right]^{1-\alpha}\left[\frac{\alpha}{(1+\tau_i^K)r}\right]^{\alpha}\right)^{\frac{1-\eta}{\eta}} \tag{28}$$

$$P_iQ_i \propto \left(\frac{A_i}{(1+\tau_i^L)^{1-\alpha}(1+\tau_i^K)^{\alpha}}\right)^{\frac{1-\eta}{\eta}} \tag{29}$$

Combine 21 , 23 and 29 to get that more labor and capital in the absence of τ_i^K and τ_i^L will go to the more productive firm - firm with higher A_i

$$L_i \propto \frac{1}{1+\tau_i^L}\left(\frac{A_i}{(1+\tau_i^L)^{1-\alpha}(1+\tau_i^K)^{\alpha}}\right)^{\frac{1-\eta}{\eta}} \tag{30}$$

$$K_i \propto \frac{1}{1+\tau_i^K}\left(\frac{A_i}{(1+\tau_i^L)^{1-\alpha}(1+\tau_i^K)^{\alpha}}\right)^{\frac{1-\eta}{\eta}} \tag{31}$$

Equivalently,

$$1+\tau_i^L \propto \frac{P_iQ_i}{wL_i} \tag{32}$$

$$1+\tau_i^K \propto \frac{P_iQ_i}{K_i} \tag{33}$$

Expressing 29 in terms of how we can measure each of the distortions:

$$P_iQ_i \propto \left(\frac{A_i}{(\frac{P_iQ_i}{L_i})^{1-\alpha}(\frac{P_iQ_i}{K_i})^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \qquad (4) \tag{34}$$

Revenues of firms will be negatively correlated to the geometric average of the distortions (themselves proportional to labour and capital productivities, implying higher labour and capital productivity - labour and capital input is too small) and positively correlated with their productivity A_i. Again, remember that this assumes: α, w, r, η are identical across firms. Any deviation in these will manifest itself in deviations in τ_K, and/or τ_L.

It is also useful to derive a model-based firm productivity:

$$PQ^{\eta}(A_iK_i^{\alpha}L_i^{1-\alpha})^{1-\eta} = P_iQ_i \tag{35}$$

$$A_i = (PQ^{\eta})^{\frac{-1}{1-\eta}} \frac{(P_iQ_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha}L_i^{1-\alpha}} \tag{36}$$

$$A_i = \kappa \frac{(P_iQ_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha}L_i^{1-\alpha}} \tag{37}$$

$$\kappa = (PQ^{\eta})^{-\frac{1}{1-\eta}} \tag{38}$$

Aggregation

$$P_iQ_i = P^{\frac{1}{\eta}}Q \left((1-\eta)A_i \left[\frac{(1-\alpha)}{(1+\tau_i^L)w} \right]^{1-\alpha} \left[\frac{\alpha}{(1+\tau_i^K)r} \right]^{\alpha} \right)^{\frac{1-\eta}{\eta}} \tag{39}$$

$$PQ = \sum P_iQ_i \tag{40}$$

Use the exact expressions for optimal L_i and K_i

$$L_i = \frac{(1-\alpha)(1-\eta)P^{\frac{1}{\eta}}Q\left((1-\eta)A_i\left[\frac{(1-\alpha)}{(1+\tau_i^L)w}\right]^{1-\alpha}\left[\frac{\alpha}{(1+\tau_i^K)r}\right]^{\alpha}\right)^{\frac{1-\eta}{\eta}}}{(1+\tau_i^L)w} \tag{41}$$

$$K_i = \frac{\alpha(1-\eta)P^{\frac{1}{\eta}}Q\left((1-\eta)A_i\left[\frac{(1-\alpha)}{(1+\tau_i^L)w}\right]^{1-\alpha}\left[\frac{\alpha}{(1+\tau_i^K)r}\right]^{\alpha}\right)^{\frac{1-\eta}{\eta}}}{(1+\tau_i^K)r} \tag{42}$$

$$L = \sum L_i = (1-\alpha)(1-\eta)\sum \frac{1}{(1+\tau_i^L)w}P_iQ_i = \tag{43}$$

$$L = (1-\alpha)(1-\eta)PQ\sum \frac{1}{(1+\tau_i^L)w}\frac{P_iQ_i}{PQ} \tag{44}$$

$$L = (1-\alpha)(1-\eta)PQ\frac{1}{\overline{MRPL}} \tag{45}$$

Equivalently, the expression from the market clearing condition for aggregate capital is:

$$K = \alpha(1-\eta)PQ\frac{1}{\overline{MRPK}} \tag{46}$$

Let's define the aggregate TFP the following way:

$$TFP \equiv \frac{Q}{K^{\alpha}L^{1-\alpha}} \tag{47}$$

$$TFP = \frac{Q}{\left(\alpha(1-\eta)PQ\frac{1}{\overline{MRPK}}\right)^{\alpha}\left((1-\alpha)(1-\eta)PQ\frac{1}{\overline{MRPL}}\right)^{1-\alpha}} \tag{48}$$

$$TFP = \frac{\overline{TFPR}}{P} = \frac{1}{P(1-\eta)}\left(\frac{\overline{MRPK}}{\alpha}\right)^{\alpha}\left(\frac{\overline{MRPL}}{1-\alpha}\right)^{1-\alpha} \tag{49}$$

To get P, aggregate the expression 49

$$PQ = \sum_i P^{\frac{1}{\eta}} Q \left((1-\eta) A_i \left[\frac{(1-\alpha)}{(1+\tau_i^L)w} \right]^{1-\alpha} \left[\frac{\alpha}{(1+\tau_i^K)r} \right]^{\alpha} \right)^{\frac{1-\eta}{\eta}} = \tag{50}$$

$$PQ = P^{\frac{1}{\eta}} Q \left((1-\alpha)^{1-\alpha} \alpha^{\alpha} \right)^{\frac{1-\eta}{\eta}} \sum_i \left(\frac{(1-\eta) A_i}{\left((1+\tau_i^L)w\right)^{1-\alpha} \left((1+\tau_i^K)r\right)^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \tag{51}$$

$$P^{\frac{\eta-1}{\eta}} = \left((1-\alpha)^{1-\alpha} \alpha^{\alpha} \right)^{\frac{1-\eta}{\eta}} \sum_i \left(\frac{A_i (1-\eta)}{(MRPL_i)^{1-\alpha} (1+\tau_i^K)^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \tag{52}$$

$$P = \frac{1}{(1-\eta)} \left((1-\alpha)^{1-\alpha} \alpha^{\alpha} \right)^{-1} \left(\sum_i \left(\frac{A_i}{(MRPL_i)^{1-\alpha} (MRPK_i)^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{\eta-1}} \tag{53}$$

Plug 53 into 49.

$$TFP = \frac{1/(1-\eta) \left(\frac{\overline{MRPK}}{\alpha} \right)^{\alpha} \left(\frac{\overline{MRPL}}{1-\alpha} \right)^{1-\alpha}}{1/(1-\eta) \left((1-\alpha)^{1-\alpha} \alpha^{\alpha} \right)^{-1} \left(\sum_i \left(\frac{A_i}{(MRPL_i)^{1-\alpha} (MRPK_i)^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{\eta-1}}} \tag{54}$$

Aggregate TFP if you have decentralized allocation with wedges.

$$TFP = \left(\sum_i \left(A_i \left(\frac{\overline{MRPL}}{MRPL_i} \right)^{1-\alpha} \left(\frac{\overline{MRPK}}{MRPK_i} \right)^{\alpha} \right)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{1-\eta}} \tag{55}$$

Aggregate TFP if you have efficient allocation without wedges.

$$TFP^e = \left(\sum_i (A_i)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{1-\eta}} \tag{56}$$

Distance of aggregate TFP to the efficient (frontier)

$$\frac{TFP^e}{TFP} - 1 \tag{57}$$

Equalizing TFPR within groups

I also consider a separate counterfactual in which I look at two groups in each sector: state-owned and private, and I redistribute existing labour and existing capital of each group across firms within each group to equalize their MRPL's and MRPK's (i.e. all firms within each group have the same average wedge).

Thus, I get two expressions of group MRPL and MRPK:

1)

$$\frac{\left(L_{priv}\right)^{\eta}\left(\frac{L_{priv}}{K_{priv}}\right)^{\alpha(1-\eta)}}{(1-\alpha)(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}} = \frac{1}{MRPL_{priv}} \tag{58}$$

2)

$$\frac{\left(K_{priv}\right)^{\eta}\left[\frac{Kpriv}{L_{priv}}\right]^{(1-\alpha)(1-\eta)}}{\alpha(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}} = \frac{1}{MRPK_{priv}} \tag{59}$$

3) I combine (1) and (2) to get an expression for group TFPR for private and state-owned group (the expression for state-owned TFPR is similar):

$$1/TFPR_{priv} = \left[\frac{\left(K_{priv}\right)^{\eta}\left[\frac{Kpriv}{L_{priv}}\right]^{(1-\alpha)(1-\eta)}}{\alpha(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}}\right]^{\alpha}\left[\frac{\left(L_{priv}\right)^{\eta}\left(\frac{L_{priv}}{K_{priv}}\right)^{\alpha(1-\eta)}}{(1-\alpha)(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}}\right]^{1-\alpha} = \tag{60}$$

$$= \frac{\left(K_{priv}\right)^{\alpha\eta}\left(L_{priv}\right)^{(1-\alpha)\eta}}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}} \tag{61}$$

$$TFPR_{priv} = \frac{\left(\sum \left(\frac{A_i}{\kappa}\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}}{\left(K_{priv}\right)^{\alpha\eta}\left(L_{priv}\right)^{(1-\alpha)\eta}} \tag{62}$$

$$\kappa = \left(PQ^{\eta}\right)^{-\frac{1}{1-\eta}} \tag{63}$$

where kappa cancels out in the aggregate TFP expression.

4) Note that this means that the Industry-level output, and thus industry-level TFPR (and industry-level MRPL's and MRPK's) will increase because adjustments towards a more optimal allocation are made.

Aggregate TFP after efficiently allocating capital and labour across firms within ownership-industry groups.

$$TFP = \left(\sum_{o\in\{priv,so\}} \left(\frac{\overline{MRPL}}{MRPL_o}\right)^{1-\alpha} \left(\frac{\overline{MRPK}}{MRPK_o}\right)^{\alpha} \sum_{i\in o} \left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\frac{\eta}{1-\eta}} \tag{64}$$

or, equivalently:

$$TFP = \left(\sum_{o\in\{priv,so\}} \left(\frac{\overline{TFPR}}{TFPR_o}\right) \sum_{i\in o} \left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\frac{\eta}{1-\eta}} \tag{65}$$

12 Appendix B. Additional tables and figures

	(1) Ln MRPK	(2) Ln MRPK	(3) Ln Book Value of Capital	(4) Ln Book Value of Capital	(5) Ln Value Added	(6) Ln Value Added	(7) Ln Revenue	(8) Ln Revenue
SSI dummy	-0.041	-0.016	0.159**	0.136*	0.038	0.023	0.160***	0.171***
	(0.073)	(0.084)	(0.070)	(0.077)	(0.050)	(0.057)	(0.052)	(0.064)
SDN dummy	-0.037	-0.035	0.097*	0.095*	0.069	0.067	0.101*	0.103**
	(0.055)	(0.056)	(0.057)	(0.057)	(0.047)	(0.047)	(0.048)	(0.049)
SSI dummy × SOE		-0.153		0.147		0.094		-0.067
		(0.142)		(0.136)		(0.104)		(0.140)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓	✓	✓
SOE-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Firms	77647	77647	87736	87736	77648	77648	87731	87731
Sanctioned firms	991	991	1084	1084	991	991	1084	1084
Industries	751	751	763	763	751	751	763	763
Observations	347702	347702	417568	417568	347708	347708	417554	417554
R-squared	.888	.888	.995	.995	.996	.996	.997	.997

Notes: All dependent variables are in logs. Firms are classified as SOEs according to Rosstat. MRPK is estimated with the Value added/K method. Industry-year FE are 4-digit industry-by-year fixed effects. SOE-by-year FE are the SOE dummy interacted with year dummies. Sanction firms give the count of any sanction firm - SSI or SDN. Standard errors are two-way clustered at the firm and 4-digit industry by year level. *, **, and *** denote 10%, 5%, and 1% statistical significance respectively.

Table 2.A1: Average effects of sanctions triple difference

	(1) stop_exist_share	(2) stop_report_share	(3) exist dummy	(4) report dummy
Any Sanction	-0.007***	-0.035***	0.002	0.047***
	(0.002)	(0.004)	(0.001)	(0.007)
Firm FE			✓	✓
Industry-year FE			✓	✓
Size-year FE			✓	✓
Firms			721884	721884
Sanctioned firms			936	936
Industries			874	874
Observations	9310	9310	4196031	4196031
R-squared	.00337	.0152	.514	.692

Clustering: Columns (1) and (2) 4-digit industry; columns (3)-(6) firm and industry-by-year

Notes:

Table 2.A2: Exit as a result of sanctions

	(1) Ln Revenue	(2) Ln Book Value of Capital	(3) Ln Revenue	(4) Ln Book Value of Capital	(5) Ln Revenue	(6) Ln Book Value of Capital
post2014 × large	-0.121***	-0.312***				
	(0.013)	(0.019)				
post2014 × exporter			0.208***	0.263***		
			(0.016)	(0.015)		
Any Sanction					0.134***	0.119**
					(0.050)	(0.052)
very small × Any Sanction					1.117**	1.935***
					(0.503)	(0.533)
small × Any Sanction					-0.505	0.638*
					(0.435)	(0.372)
medium × Any Sanction					0.339	0.248
					(0.240)	(0.254)
large × Any Sanction					0.000	0.000
					(.)	(.)
Constant	17.722***	15.939***	18.116***	15.965***	18.215***	16.090***
	(0.003)	(0.006)	(0.008)	(0.007)	(0.000)	(0.000)
Firm FE	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓
Size-year FE						
Firms	336456	236353	173877	165818	173877	165818
Sanctioned firms	1225	1178	902	908	902	908
Industries	799	773	759	751	759	751
Observations	1329189	992585	826910	786327	826910	786327
R-squared	.886	.915	.891	.917	.89	.917

Clustering: Firm and industry-by-year

Notes:

Table 2.A3: Effects of the sanction period for large versus small firms.

	(1) Ln Revenue	(2) Ln Book Value of Capital	(3) Ln Revenue	(4) Ln Book Value of Capital	(5) Ln Revenue	(6) Ln Book Value of Capital	(7) Ln Revenue	(8) Ln Book Value of Capital	(9) Ln Revenue	(10) Ln Book Value of Capital
Any Sanction	0.219***	0.372***	0.187**	0.336***	0.260***	0.414***	0.228***	0.410***	0.156**	0.365***
	(0.062)	(0.069)	(0.082)	(0.074)	(0.065)	(0.067)	(0.061)	(0.065)	(0.065)	(0.071)
Any Sanction × Direct sanction	-0.021	0.028								
	(0.113)	(0.120)								
Any Sanction × SDN Sanction			0.045	0.077						
			(0.096)	(0.090)						
Any Sanction × minority					-0.151*	-0.196**				
					(0.089)	(0.087)				
Any Sanction × energy							-0.104	-0.184		
							(0.109)	(0.148)		
Any Sanction × exporter									0.228**	0.063
									(0.092)	(0.101)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firms	635159	678996	635159	678996	635159	678996	635159	678996	635159	678996
Sanctioned firms	916	928	916	928	916	928	916	928	916	928
Industries	847	865	847	865	847	865	847	865	847	865
Observations	3577896	3852682	3577896	3852682	3577896	3852682	3577896	3852682	3577896	3852682
R-squared	.858	.889	.858	.889	.858	.889	.858	.889	.858	.889

Clustering: Firm and industry-by-year

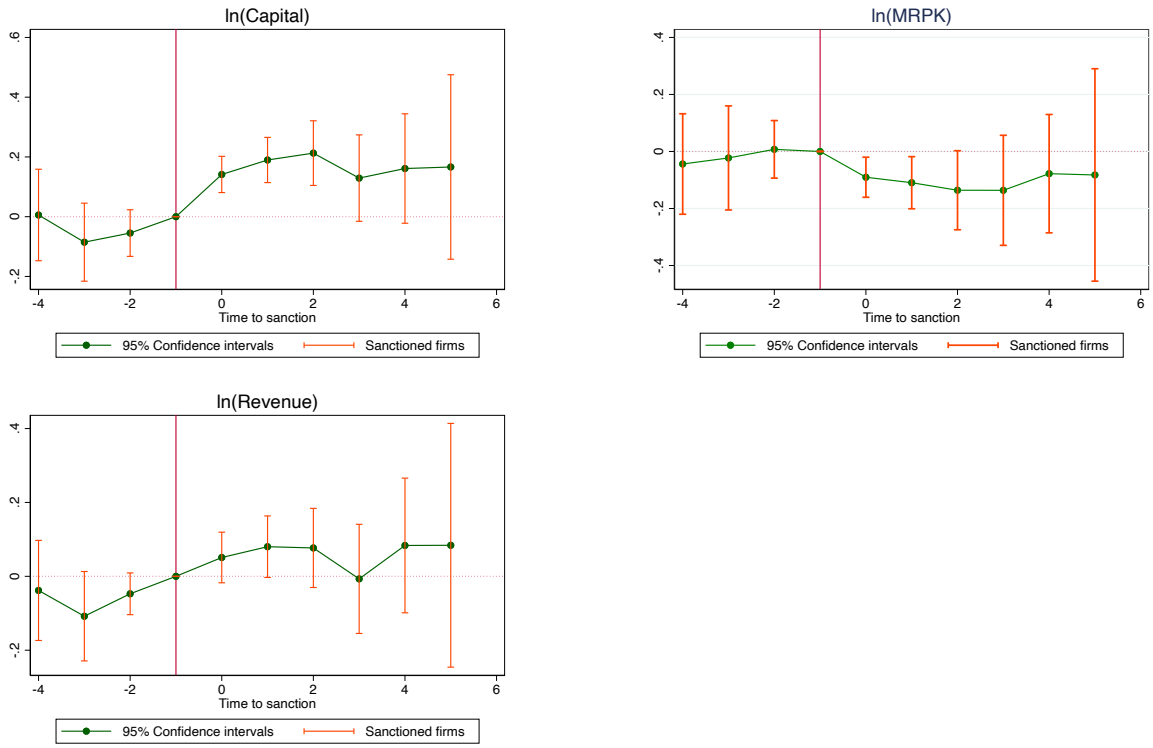
Notes:

Table 2.A4: Heterogeneity

	year_sanc							
okved2_name	2014	2015	2016	2017	2018	2019	2020	Total
Activities auxiliary to financial services and insurance	2	4	7	2	6	0	0	21
Activities for the maintenance of buildings and territories	0	0	1	0	1	0	0	2
Activities for the provision of other personal services	0	1	0	0	0	0	0	1
Activities for the provision of places for temporary residence	3	1	2	3	3	1	0	13
Activities in the field of architecture and engineering	13	15	12	8	18	2	0	68
Activities in the field of law and accounting	3	1	2	1	2	0	0	9
Activities in the field of sports, recreation and entertainment	1	0	2	0	2	0	1	6
Activities in the field of telecommunications	0	3	0	0	5	0	0	8
Activities in the field of television and radio broadcasting	0	0	0	0	5	0	0	5
Activities of libraries, archives, museums and other cultural objects	0	0	0	0	1	0	0	1
Activities of state administration bodies to ensure military security, compulsory social security	1	0	1	0	1	0	0	3
Administrative activities	0	1	4	2	1	0	0	8
Advertising activities and market research	29	8	3	1	1	0	0	42
Air and space transport activities	0	1	3	0	0	0	0	4
Beverage production	5	0	1	0	1	0	1	8
Building	3	1	2	5	10	3	1	25
Coal mining	0	0	0	0	1	0	0	1
Construction of engineering structures	10	2	0	7	6	0	0	25
Creative activities, arts and entertainment activities	0	0	0	0	1	0	0	1
Crop and livestock production, hunting and related services in these areas	8	3	2	2	2	0	0	17
Development of computer software, consulting services in this area and other related services	10	7	0	1	3	0	0	21
Electricity, gas and steam supply; air conditioning	6	11	3	10	21	1	0	52
Employment and recruiting activities	0	0	0	1	0	0	0	1
Extraction of oil and natural gas	17	17	4	11	6	0	0	55
Extraction of other minerals	2	0	0	0	0	0	0	2
Film, video and television program production, sound recording and sheet music publishing	0	0	0	1	1	0	0	2
Financial services activities other than insurance and pension services	17	48	44	18	22	0	0	149
Food and beverage provision activities	0	0	0	1	2	0	0	3
Food production	5	1	0	0	4	0	1	11
Forestry and logging	0	0	0	1	9	0	0	10
Head office activities; management consulting	27	12	20	13	12	0	0	84
Healthcare activities	2	1	2	2	3	3	0	13
Information technology activities	5	6	1	3	2	0	0	17
Insurance, reinsurance, activities of non-state pension funds	0	1	0	0	0	0	0	1
Land and pipeline transport activities	1	12	1	12	14	0	2	42
Manufacture of chemicals and chemical products	6	3	1	5	2	0	0	17
Manufacture of computers, electronic and optical products	48	9	6	0	1	2	0	66
Manufacture of electrical equipment	7	0	3	0	2	0	0	12
Manufacture of finished metal products, except for machinery and equipment	12	3	3	4	0	0	0	22
Manufacture of leather and leather products	2	0	0	0	0	0	0	2
Manufacture of machinery and equipment not included in other categories	8	2	1	4	2	2	0	19
Manufacture of motor vehicles, trailers and semi-trailers	3	1	0	0	3	0	0	7
Manufacture of other finished goods	1	0	0	0	0	0	0	1
Manufacture of other non-metallic mineral products	3	3	0	0	1	1	0	8
Manufacture of other vehicles and equipment	36	9	7	0	1	2	0	55
Manufacture of paper and paper products	0	1	0	0	1	0	0	2
Manufacture of rubber and plastic products	0	1	0	0	1	0	0	2
Manufacture of textiles	0	0	2	0	0	0	0	2
Manufacture of wearing apparel	1	0	0	0	0	0	0	1
Metallurgical production	3	0	0	1	7	0	0	11
Mining of metal ores	0	0	0	0	3	0	0	3
Other professional scientific and technical activities	0	0	0	0	2	0	0	2
Printing activities and copying of information carriers	2	1	0	0	0	0	0	3
Production of coke and petroleum products	4	9	7	2	4	0	0	26
Production of medicines and materials used for medical purposes	3	0	0	0	0	0	0	3
Provision of services in the field of mining	2	7	1	2	5	0	0	17
Publishing activities	0	0	1	1	1	0	0	3
Real estate operations	39	20	21	23	24	0	0	127
Rent and lease	0	1	1	0	1	0	0	3
Repair and installation of machinery and equipment	14	2	0	4	2	2	0	24
Research and development	102	12	19	2	6	3	1	145
Retail trade, excluding trade in motor vehicles and motorcycles	1	3	3	0	7	0	0	14
Security and investigation activities	1	0	0	0	1	0	0	2
Specialized construction works	1	1	0	4	3	0	0	9
Warehousing and auxiliary transport activities	7	6	5	18	8	0	5	49
Water intake, purification and distribution	1	0	1	0	0	0	0	2
Water transport activities	0	1	0	2	2	0	0	5
Wholesale and retail trade in motor vehicles and motorcycles and their repair	1	0	0	0	0	0	2	3
Wholesale trade, except for the wholesale trade of motor vehicles and motorcycles	20	19	7	9	16	1	0	72
Wood processing and manufacture	0	0	1	0	5	0	0	6
Total	498	271	207	186	277	23	14	1,476

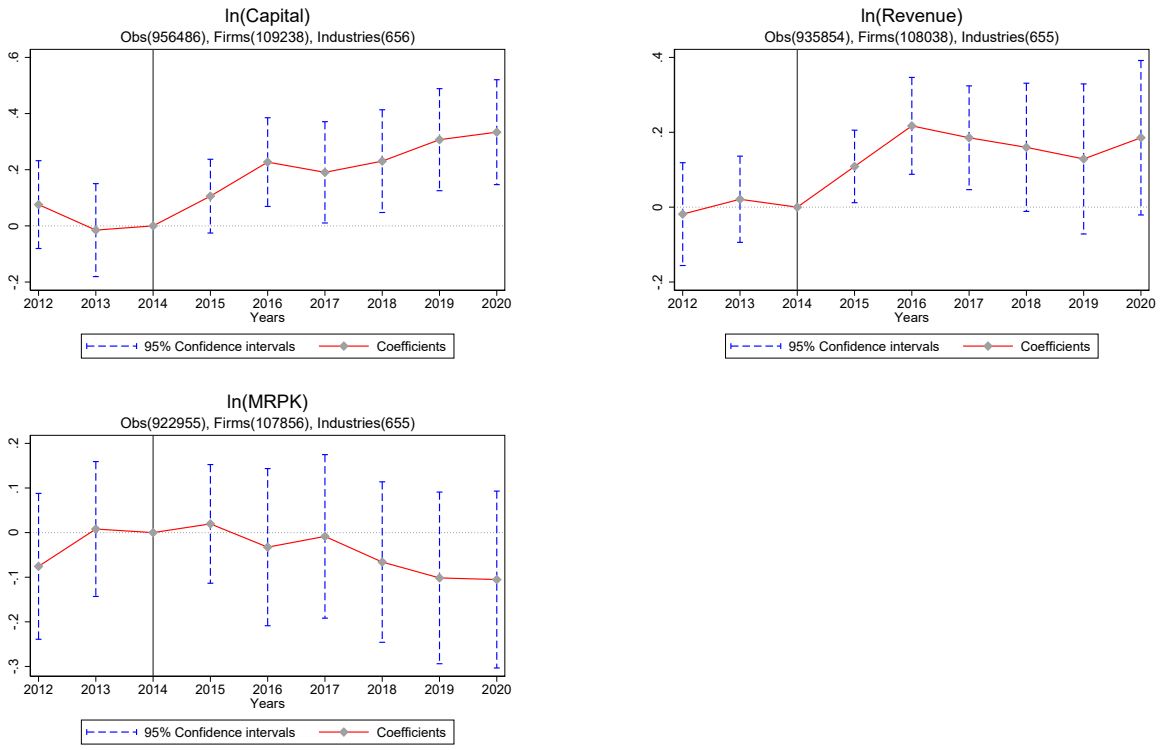
Notes: This tabulates the sanctioned firms by year of treatment and the 2-digit industry in which the sanctioned firms operate.

Table 2.A5: Industry by year



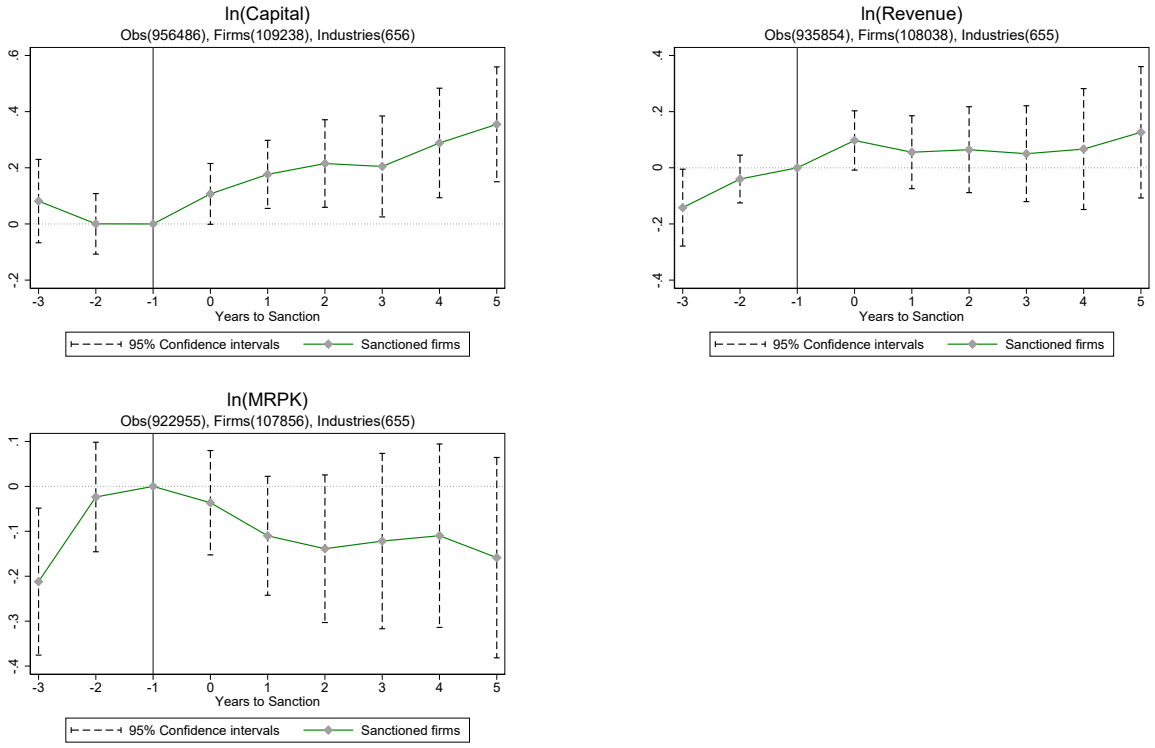
Notes: This figure reports event study graphs using the estimator de Chaisemartin, C and D'Haultfoeuille (2020b) for the average effects of the sanctions on sanctioned firms. The effect is identified within sanctioned firms: sanctioned firms are compared to not-yet sanctioned firms. The first year of firm sanction is normalized to take place in year 0. Each dot is the coefficient on the indicator of being observed t years after the sanctions announcement. Control variables used are firm fixed effects and 4-digit industry-year fixed effects. Non sanctioned firms are used to identify the 4-digit industry-year fixed effects and the size-year fixed effects. The dependent variables are in logs. The confidence intervals are at the 95% level.

Figure 2.A1: Event study with not-yet sanctioned firms in the control group (de Chaisemartin, C and D'Haultfoeuille (2020b) estimator).



Notes: This figure reports event study graphs with the average effects of the sanctions on sanctioned firms for a constant sample of firms (firms with observations in every period). The effect is identified relative to non-sanctioned firms. The first year of firm sanction is normalized to take place in year 0. Control variables used are firm fixed effects and 4-digit industry-year fixed effects. Non sanctioned firms are used to identify the 4-digit industry-year fixed effects and the size-year fixed effects. The dependent variables are in logs. The confidence intervals are at the 95% level.

Figure 2.A2: Event study, constant sample of firms.



Notes: This figure reports event study graphs using the estimator de Chaisemartin, C and D'Haultfoeuille (2020b) for the average effects of the sanctions on sanctioned firms. The effect is identified within sanctioned firms: sanctioned firms are compared to not-yet sanctioned firms. The first year of firm sanction is normalized to take place in year 0. Each dot is the coefficient on the indicator of being observed t years after the sanctions announcement. Control variables used are firm fixed effects and 4-digit industry-year fixed effects. Non sanctioned firms are used to identify the 4-digit industry-year fixed effects and the size-year fixed effects. The dependent variables are in logs. The confidence intervals are at the 95% level.

Figure 2.A3: Event study with not-yet sanctioned firms in the control group.

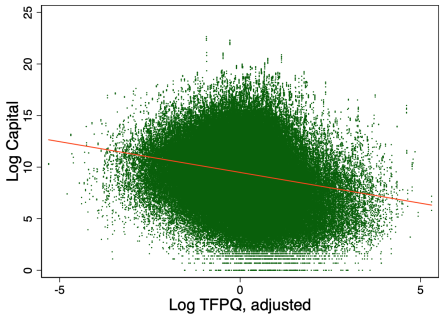
13 Appendix C. Misallocation in Russia

In Figure 2 the top two graphs demonstrate the overall distribution of capital and labour relative to the productivity of firms, the middle two graphs (c) and (d) show the capital and labour productivity on firm TFPQ, and the bottom graph (e) shows revenue productivity, TFPR on TFPQ. The measures of TFPQ, TFPR, capital and labour productivity are adjusted for measurement error. In an efficient economy, the slopes of the relationships between productivity and inputs are positive. In Russia, on the contrary, we see that at least capital to be lower on average in more productive firms. On the second row, where the efficient relationship between MRPL and MRPK and firm TFPQ should be flat if the marginal revenue of each input should be equalized across firms. Again, it is evident that more productive firms face larger positive wedges, this time in both capital and labour. Both relationships - between $TFPQ_i$ and $MRPK_i$, and between $TFPQ_i$ and $MRPL_i$ are positive, while in an efficient economy there should be no correlation between TFPQ and labour or capital productivity. Both capital and labour distortions to a firm can be summarised with a $TFPR_i$, the revenue productivity measure, defined in equation 4. The revenue productivity is correlated with physical productivity, as is MRPK and MRPL, whereas in an efficient economy it should be uncorrelated.

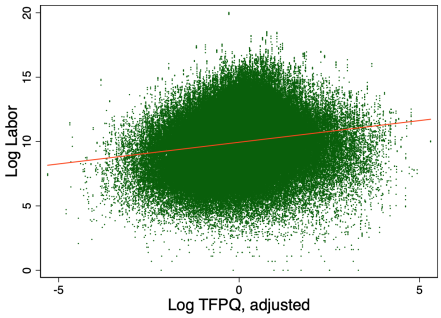
In addition, in Table 2.A6 I show comparable statistics to those reported in HK so that the key measures from the model can be cross-checked. Before adjusting for measurement error, I find that in Russia the dispersions of both TFPR and TFPQ are substantially larger than what HK find in China and India. HK report the p75-p25 variation in ln(TFPQ) of 1.28 and p90-p10 of 2.44 for China in 2005, while for India the corresponding values are 1.60 and 3.11. In Russia, without measurement error adjustment, the 2018 ln(TFPQ) variation is: p75-p25 is 2.14 and p90-p10 is 3.49.

Equally, ln(TFPR) variation in Russia is also larger: I find 1.18 and 2.71 in Russia in 2018 compared to 0.82 and 1.59 (China), 0.81 and 1.60 (India). However, Hsieh and Klenow only use the manufacturing sector, whereas my data include services and agriculture, and the diverse services sector can show much more variation in wedges and productivity[29]. Looking at Panel B, with only the manufacturing sector, the percentile variation in ln(TFPR) (1.00 and 2.25) and ln(TFPQ) (1.83 and 3.40) reduces but is still larger than in HK. Additionally, adjusting these measures for firm and year fixed effects further reduces the variation and gives the percentile variation of ln(TFPR) (0.82 and 1.78) and ln(TFPQ) (0.90 and 1.95) making the values on par or even smaller than numbers found in Hsieh and Klenow for India and China.

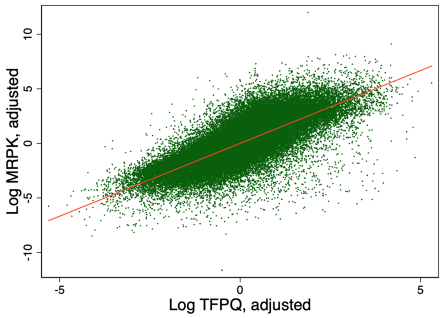
[29]The higher variation may also arise because of the way 4-digit industries are defined. As the country is transforming to the services economy, the level of detail may be much lower in the services sector, relative to manufacturing, so each 4-digit industry in the services sector may contain somewhat more diverse firms than a 4-digit industry in manufacturing



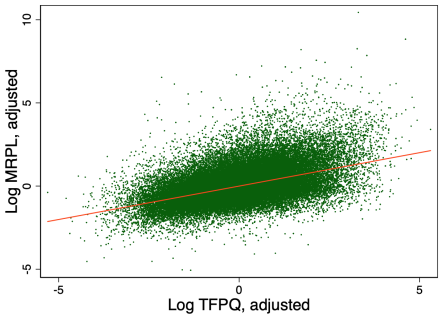
(a) Capital on TFPQ



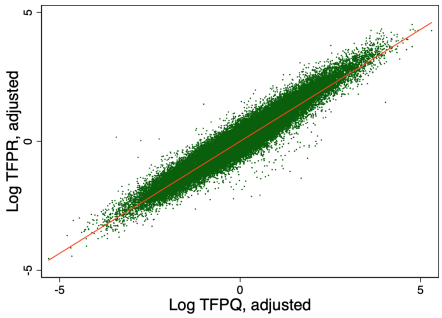
(b) Labor on TFPQ



(c) Capital productivity on TFPQ



(d) Labor productivity on TFPQ



(e) TFPR on TFPQ

Notes: Each observation (green dot) is a firm. Labour productivity (or $MRPL_i$) refers to value added per unit of wage bill and capital productivity (or $MRPK_i$) refers to value added per unit of capital, both of which are proportional to the marginal products of each factor in my framework. Raw TFPQ is calculated using the expression $TFPQ_i = \kappa \frac{(P_i Q_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha} L_i^{1-\alpha}}$. $TFPR_i$, or revenue productivity, is a summary measure of distortions faced by each firm, with higher $TFPR_i$ implying higher distortions. The MRPK, MRPL, TFPR and TFPQ measures are adjusted for measurement error with firm and year fixed effects and de-meaned by 4-digit industry using the firm panel 2012-2018. The solid orange line is the line of best fit.

Figure 2.A4: Factor allocations by firm productivity

Panel A : Full dataset				
Variable	Statistic	Industry and Firm Fixed Effects	2018 Raw measures	Cross-section Average
ln(TFPR)	SD	0.86	1.13	1.13
	p75-p25	0.91	1.17	1.16
	p90-p10	2.03	2.68	2.66
ln(MRPL)	SD	0.77	1.02	1.02
	p75-p25	0.65	0.89	0.89
	p90-p10	1.60	2.18	2.16
ln(MRPK)	SD	1.66	2.03	2.03
	p75-p25	1.93	2.41	2.39
	p90-p10	4.09	5.07	5.04
ln(TFPQ)	SD	0.94	1.50	1.49
	p75-p25	1.03	2.09	2.07
	p90-p10	2.24	3.86	3.84
Panel B : Only the manufacturing sector				
Variable	Statistic	Industry and Firm Fixed Effects	2018 Raw measures	Cross-section Average
ln(TFPR)	SD	0.76	0.98	0.98
	p75-p25	0.82	1.00	0.99
	p90-p10	1.78	2.25	2.25
ln(MRPL)	SD	0.61	0.83	0.83
	p75-p25	0.53	0.71	0.71
	p90-p10	1.18	1.68	1.66
ln(MRPK)	SD	1.49	1.77	1.76
	p75-p25	1.72	1.98	1.97
	p90-p10	3.61	4.26	4.24
ln(TFPQ)	SD	0.83	1.34	1.32
	p75-p25	0.90	1.83	1.77
	p90-p10	1.95	3.40	3.35

Notes: For firm i, $TFPQ_i = \kappa \frac{(P_i Q_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha} L_i^{1-\alpha}}$. Statistics are for deviations of log(TFPQ) from industry means. SD = standard deviation, p75 p25 is the difference between the 75th and 25th percentiles, and p90 p10 the 90th vs. 10th percentiles. Values in the column "Industry and Firm Fixed Effects" are adjusted for measurement error using firm and year fixed effects and de-meaned by 4-digit industry averages. Values in the column "2018 Raw measures" are the logs of raw measures of $TFPQ_i$, $MRPK_i$, $MRPL_i$, $TFPR_i$ for each firm, divided by the harmonic average of the same measure in the 4-digit industry. Values in the column "Cross-section Average" are the average of the statistics calculated as in the previous column, but the statistics are calculated for each cross-section of the panel 2012-2018 and then averaged across years. Panel A is calculated for the full sample of for-profit firms, and Panel B is calculated for the Manufacturing sector only.

Table 2.A6: Dispersion of ln(TFPR), ln(TFPQ), ln(MRPL), ln(MRPK)

14 Appendix D. Data appendix

I construct a dataset of sanctioned firms.

1) firm SDN sanctions+subsidiaries (variable "sdn")

2) firm SSI sanctions +subsidiaries (variable "ssi")

3) person SDN sanctions + owned firms (variable "ind")

4) EU sanctions, which mimic the US sanctions, be it SDN or SSI.

In the regressions, I then take the unions of the variables (1), (3) and the "blocked" firms by the EU (4) to make a combined SDN variable. There are only 9 firms that are sanctioned by the EU but not the US (some of them are subsidiaries). I have coded them as SDN is the EU treatment was to stop all transactions, and SSI if these were input sanctions.

I create separate treatment year variables for the SSI and SDN categories. However, even within categories, some firms have several treatment years, because they are sanctioned both by association with other sanctioned firms and directly. Priority of the first treatment year assignment for companies that fall into several sanction categories is the following:

(1) the year of mother company's treatment (if the company is majority-owned)
(2) the year of the company is explicitly listed on the Department of Treasury, if (1) does not exist.
(3) If the company is minority-owned by multiple sanctioned firms (where the total shares from different companies add up to more than 50%) with different sanctioned years AND (1) and (2) years do not exist, the assigned year is earliest among potential SDN years, "individual SDN" sanction years for the SDN variable, and the earliest among the SSI owner company years, for the SSI variable.

I used the sanction announcement date to assign the year according to the April 30th split: if you get sanctioned after April 30th, your treatment year is the year after.

These sanctions do not include sanctions that took place before 2014 and sanctions that are not to do with the Ukraine conflict. I also exclude firms that are in Crimea (around 40 firms), since they are embargoed based on their location in Crimea only, and not based on the connections to the current government.