Misallocation and State Ownership: Evidence from the Russian Sanctions*

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November 13, 2021

Abstract

I quantify the effect of political connections on misallocation of resources in the Russian economy. With firm panel data and a quantitative framework, I find large wedges between state-owned and private firms that prevent labour and capital inputs from flowing to more productive private firms. The aggregate TFP would increase by at least 11% if all wedges between state-owned enterprises and private firms are removed. Using a unique natural experiment of staggered firm-level sanctions in Russia, I estimate the effect of sanctions on distortions between connected and not connected firms. Surprisingly, input-sanctioned firms on average *gained* 16.3% more capital inputs after sanctions. The effect is driven by sanctioned state-owned firms, getting 37% more capital relative to non-sanctioned firms. Using additional data on subsidies, I find that this result is explained by the government protection of targeted firms. On aggregate, misallocation was exacerbated due to a joint effect of sanctions and shielding. I combine the causal estimates with the quantitative framework and estimate that the Russian TFP dropped at least by 0.33% reaching 3% in relevant sectors.

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

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

*I thank Daniel Albuquerque, Charlie Becker, Andy Bernard, Cagatai Birkan, Kirill Borusyak, Loren Brandt, Francisco Buera, Felipe Carozzi, Amanda Dahlstrand, Benjamin Faber, Stephen Gibbons, Sergei Guriev, Vernon Henderson, Rocco Macchiavello, Isabela Manelici, Guy Michaels, Tanner Regan, Olmo Silva, Daniel Sturm, Bilal Tabti, Jose P. Vasquez, the participants of the STEG workshop, participants of the EBRD OCE seminar, participants of International WIP and participants of the Economic Geography WIP for helpful comments. I thank Ilya Munerman and Spark for the great help in acquiring the data. All omissions are my own.

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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 is hopeful because it implies that low-income countries may be able to accelerate catch up by redistributing existing resources optimally, rather than having to invest in expensive technological upgrades to improve productivity for each firm. However, it is still unknown what allocative distortions explain a bigger share of the gap. It is impossible to implement policies for economic efficiency without knowing what are the main drivers of misallocation. Ownership and political connections of owners is a potentially large channel that can favour the allocation of resources to firms not based on efficiency, but based on the interests of those with political power. A unique firm-level dataset and a natural experiment allow me to make progress on this front.

This paper measures the contribution of state ownership and political connections to misallocation in Russia[1]. Russia, with its 20% SOE revenue share in GDP, provides a good test case to account for misallocation from state ownership for countries with over 10-30% shares of SOEs' revenue in GDP, such as China, India and Brazil (Kowalski et al. 2013) and post-Communist countries (EBRD 2020). Such high shares of state-owned activities in these countries have the potential to be large sources of allocative inefficiency. These sources may be further amplified via relationships between state-owned firms and private firms.

Allocative inefficiency can arise, for example, if the state-owned enterprises are favoured in capital input markets and receive preferential loans or excessive subsidies. In addition, the state-owned companies may not be profit-maximizing and be directed to participate in projects of political rather than economic interest. While such interest may be well justified, this comes with an economic efficiency cost that may affect aggregate TFP. Both preferential subsidies and allocation of contracts that are not profit-maximizing will make the state-owned firms larger than their

[1] In this paper I define state-owned firms as those majority-owned by the state and all their fully-owned subsidiaries. The terms state-owned enterprises and SOEs are used interchangeably.

efficient size and receive more capital and/or labour relative to the private firms.

Russia in 2014-2019 is also is an excellent case to study the role of state-ownership and political connections in misallocation because of a unique natural experiment: the US and EU sanctions targeted Russian firms connected to the government elites. This created a negative shock to the access of inputs for the state-owned sector, which was disproportionately more targeted by sanctions, as well as it did for some private targeted firms. This experiment 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 relative to private sanctioned firms as well as sanctioned firms relative to the non-treated firms in the same industry. The response of politically connected private firms and a differential response of SOEs to this negative shock will reveal whether there is a link from political connections to the allocation of resources, depending on the degree of the political connections. The DID setup also allows me to alleviate the common concerns in measuring misallocation - measurement error, adjustment costs and abstract from other correlated unobserved factors affecting the measurement of misallocation from SOEs in a cross-section.

The overall effect of sanctions is not clear ex-ante. If sanctions targeted the inputs of those firms that already have more inputs than it is efficient, the treatment should improve allocative efficiency in Russia. However, the response of the Russian state by protecting the sanctioned firms or sanctioned SOEs may fully reverse the direct effect of sanctions, and such protection can even overshoot and exacerbate misallocation.

I find that state ownership is associated with implicit subsidies for the operation of state-owned firms. I further find that sanctions together with the response of the Russian state have worsened the allocative efficiency in Russia: the private sanctioned firms maintained their relative size and have seen the negative shock of sanctions fully reversed, whereas the sanctioned SOEs have not only seen the negative shock reversed but actually gained additional inputs after sanctions were imposed. I estimate that all else equal, this sanctions episode worsened misallocation of resources and productivity on the aggregate in Russia.

I start by constructing a panel of medium and large Russian firms in the Services, Manufacturing and Agricultural sectors from 2012-2018 and measuring the extent of misallocation in Russia using wedge accounting framework a-la Hsieh & Klenow (2009) to get a benchmark level of misallocation. 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 then account for how much of the distance to the efficient frontier is driven by variation in ownership (state-owned versus private status).

I then collect information on firm-by-year sanctions imposed on politically connected (state-owned) and private firms. I then measure the ex-ante marginal revenue products of capital (MRPK) for these sanctioned firms. I use the panel data and within-firm variation over time to empirically test whether the sanctions on inputs 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. Finally, I use a method based on

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.

First, I find that Russia could double its aggregate TFP if all misallocation was removed, as measured by the heterogeneous firms model. Second, I find that Russia could walk 10% of that distance if it removed the wedge between SOEs and private firms[2]. Third, the natural experiment of sanctions shows that Russia appears to be walking in the wrong direction: SOEs that are ex-ante low MRPK firms and that have been targeted by Western input sanctions have been shielded to such an extent that they have 24% lower MPRK and 37% higher capital inputs after the sanctions treatment.

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).

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

[2]By coincidence, the current Russian TFP would also increase by roughly the same amount (11%), if the wedge between SOEs and private firms was removed.

9 reports the reduced-form effects of sanctions on sanctioned private and state-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 state ownership on aggregate productivity through the lens of an allocative efficiency model with the so-called "indirect approach" and causally estimate the differential response of private versus state-owned 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 zoom into the effects of state ownership for firm-level outcomes (Hsieh & Song 2015, Berkowitz et al. 2017, Brandt et al. 2018, Bussolo et al. 2019, Brown et al. 2006). Finally, 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 misallocation: 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[3].

In this paper, I also make an advance in the static accounting of the sources of misallocation. Perhaps the closest paper to mine is Hsieh & Song (2015), an analysis of the privatization reform of SOEs in China through the lens of the "indirect approach" misallocation framework. I build on their work by using state-of-the-art techniques to adjust for measurement error and transient adjustment costs, rather than attributing all cross-sectional variation to misallocation. I also, as mentioned above, use causal inference to pin down a specific channel through which SOEs bring misallocation. Furthermore, to account for misallocation between ownership groups I use the counterfactual of equalizing the wedges within groups, for which I derive the analytical expression of firm marginal revenue products as functions of total resources in each group. Finally, I benefit from the unique feature of my dataset, and include services and agricultural sectors in the analysis of misallocation, whereas all papers I am aware of on the topic consider manufacturing only.

I also fill a gap in the literature on the effects of state-ownership and privatization (Brandt et al. 2018, Bussolo et al. 2019, Brown et al. 2006, Berkowitz et al. 2017), see Megginson (2016) for an extensive review) by quantifying the effects on *the aggregate* TFP. A different literature studies the role of state-ownership (in China) for growth and TFP from a theoretical perspective by explicitly modelling SOEs preferential access to finance: Song et al. (2011), Zilibotti (2017). I add to this literature by leveraging the US sanctions as a source of exogenous variation and documenting

[3]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.

empirically that the excessive shielding of SOEs from negative shocks is one driver of misallocation.

Finally, while using the sanctions as a source of exogenous variation in inputs, I also add to the work that measures the micro- and macroeconomic effects of sanctions (Ahn & Ludema 2020, Tuzova & Qayum 2016, Crozet & Hinz 2016, Haidar 2017, Draca et al. 2019, Stone 2016, Gold et al. 2019). I distinguish myself from these papers in that I not only causally estimate the effect of sanctions on treated firms but also use the estimates to calculate the aggregate effect of the 2014-2018 sanctions episode in Russia on TFP through misallocation.

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.[4]

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

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

[4]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.

price index:

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

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[5]. The firm optimal labour and capital allocation will satisfy these equations:

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

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

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.[6]

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.

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

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

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 $TFPQ_i$):

[5] 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.

[6] 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.

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

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

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]:

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

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

[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.

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 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.

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

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 ownership status.

Counterfactual 1 Removing all differences in wedges across all firms (state-owned or not).

Counterfactual 2 Removing all differences in wedges for firms within the industry-ownership group. Whereby in this counterfactual I look at two groups in each sector: state-owned and private, I then 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).

[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.

[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.

Comparing the gains from equalizing MRPK and MRPL within groups to equalizing MRPL and MRPK everywhere gives me how much distortion comes from between SOE and private groups.

For counterfactual 2 I derive based on the model above counterfactual group expressions for each of MRPL and MRPK:

$$\frac{\left(L_{priv}\right)^{\eta}\left(\frac{L_{priv}}{K_{priv}}\right)^{\alpha(1-\eta)}}{(1-\alpha)(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}} = \frac{1}{MRPL_{priv}} \tag{10}$$

And

$$\frac{\left(K_{priv}\right)^{\eta}\left[\frac{Kpriv}{L_{priv}}\right]^{(1-\alpha)(1-\eta)}}{\alpha(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}} = \frac{1}{MRPK_{priv}} \tag{11}$$

I then combine (10) and (11) to get an expression for group TFPR for private (the expression for state-owned TFPR is analogous):

$$TFPR_{priv} = \frac{\left(\sum\left(\frac{A_i}{\kappa}\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}}{\left(K_{priv}\right)^{\alpha\eta}\left(L_{priv}\right)^{(1-\alpha)\eta}} \tag{12}$$

$$\kappa = \left(PQ^{\eta}\right)^{-\frac{1}{1-\eta}} \tag{13}$$

where κ cancels out in the aggregate TFP expression.

It is important to use these expressions for the counterfactuals, rather than the existing industry-ownership averages $MRPK_{priv}$ and $MRPL_{priv}$, because the group-level outputs $P_{priv}Q_{priv}$ and $P_{SOE}Q_{SOE}$, and thus group-level harmonic average MRPL's and MRPK's will increase because adjustments towards a more optimal allocation are made. Therefore, the industry TFP if you have an allocation with equal wedges within private and public groups of firms is:

$$TFP = \left(\sum_{o \in \{priv, soe\}} \left(\frac{\overline{MRPL}}{MRPL_o} \right)^{1-\alpha} \left(\frac{\overline{MRPK}}{MRPK_o} \right)^{\alpha} \sum_{i \in o} (A_i)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{1-\eta}} \tag{14}$$

or, equivalently:

$$TFP = \left(\sum_{o \in \{priv, soe\}} \left(\frac{\overline{TFPR}}{TFPR_o} \right) \sum_{i \in o} (A_i)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{1-\eta}} \tag{15}$$

I use these equations in the calculation as explained in the following sections.

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 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 this information in 2018, as shown in Table 1, was 102,895[10]. For my analysis I only use for-profit firms, including SOEs, reducing the sample to 90,888. Only firms above

[10]The coverage of firms that reported all variables steadily grew, from just under 60,000 in 2012 to just over 100,000 firms in 2018

100 employees or with revenues over 800m rubles (roughly 10m USD) are legally obliged to report materials and wage bill, therefore the dataset represents medium and large for-profit firms. The value added of these firms covered 66% of Russian value added in 2018 and 18% of official employment (note that the total revenue of these firms *exceeds* Russian GDP by 1.5 times 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 and suppliers to state-owned firms (which can be either private or state-owned themselves). Suppliers to the state and state-owned firms are defined by having supplied in the top quartile of average contract value throughout 2012-2018.

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 3,740 and their value added is 9% of GDP in 2018 (their revenues are 20% of GDP).

4.2 Sanctions on Russia 2014-2019

Sanctions were rolled out by the US and EU against Russian entities and individuals as a response to the situation in Ukraine, through years 2014-2018[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

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

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 2,810 sanctioned firms, for 1,132 of which I have firm-level 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

[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.

[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

Spark Database.

Crucially, I record the distinction between the two types of sanctions in the US[15]: SSI and SDN. My treatment of interest is SSI since it only negatively affects inputs, rather than inputs and outputs, and therefore, makes it straightforward to assess why the outcome of interest, MRPK, changes. In all my specifications, I control for the SDN, 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 the subsidiaries, cover 2% in total Russian employment and 45% of value added total Russian GDP.

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.

[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
Firms with all variables present (Share of full sample)	102,895	100	100	100	66	162	21
Non-for-profit firms	8,467	5	4	13	3	7	3
For-profit firms	90,888	93	93	87	61	151	18
Private for-profit firms	88,657	81	83	81	54	134	17
State-owned for-profit firms	3,726	14	12	10	9	20	2
Sanctioned firms	1,118	34	25	7	23	40	2
Suppliers to the state and to SOEs	31,299	68	66	59	45	106	12

Notes: This table reports the sample coverage for the firms in the SPARK dataset in 2018 for those firms that reported capital, materials, revenue and wage bill variables in 2018. 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

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				
Firms with all variables present (Share of full sample)	22,681	47	39	42	31	63	9
Non-for-profit firms	2,550	4	4	11	5	9	6
For-profit firms	19,293	94	94	89	106	215	44
Private for-profit firms	18,767	81	78	83	91	178	41
State-owned for-profit firms	869	15	18	8	17	40	4
Sanctioned firms	418	42	32	10	47	72	5
Suppliers to the state and to SOEs	8,688	78	74	66	88	168	33
			Services				
Firms with all variables present (Share of full sample)	71,312	51	59	51	33	95	11
Non-for-profit firms	5,555	7	5	15	4	7	2
For-profit firms	63,388	91	93	85	52	152	12
Private for-profit firms	61,883	81	86	78	46	141	11
State-owned for-profit firms	2,510	13	9	12	7	15	2
Sanctioned firms	678	29	21	6	16	35	1
Suppliers to the state and to SOEs	21,725	60	62	59	34	101	8
			Agriculture				
Firms with all variables present (Share of full sample)	8,902	2	2	7	1	3	2
Non-for-profit firms	362	3	4	4	1	3	1
For-profit firms	8,207	93	93	96	37	80	21
Private for-profit firms	8,007	91	91	93	36	79	21
State-owned for-profit firms	347	3	2	5	1	2	1
Sanctioned firms	22	1	1	1	0	1	0
Suppliers to the state and to SOEs	886	21	21	21	8	18	5

Notes: This table reports the sample coverage for the firms in the SPARK dataset in 2018 for those firms that reported capital, materials, revenue and wage bill variables in 2018. 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. The regressions I run to correct for measurement error are shown below:

$$ln(TFPQ_i) = \beta_0^{TFPQ} + \gamma_t^{TFPQ} + \phi_i^{TFPQ} + \epsilon_{it}^{TFPQ} \tag{16}$$

$$ln(TFPR_i) = \beta_0^{TFPR} + \gamma_t^{TFPR} + \phi_i^{TFPR} + \epsilon_{it}^{TFPR} \tag{17}$$

Here β_0^{TFPQ} and β_0^{TFPR} are common intercepts, γ_t^{TFPQ} and γ_t^{TFPR} are the year

[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

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. Analogously to how Adamopoulos et al. (2017) remove the village-specific component, I separate the firm effect from the sector component by (1) estimating equation 16 and extract the firm fixed effect inclusive of the sector fixed effect (2) regressing these fixed effects on 4-digit-sector dummies to extract the residuals that 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[19]. 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.

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

[19]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
Value added, 1000 rub	589,236	332,453	10,633,095	-2,578,904,576	2,560,027,136
Book value of capital, 1000 rub	602,926	568,348	27,645,770	-24,443	7,882,970,562
Payment to labor, 1000 rub	602,926	111,338	1,774,229	-312,268	499,737,000
Materials, 1000 rub	602,926	1,078,618	19,462,179	-122,617,309	4,820,693,835
Labor count, latest year	537,942	174	587	0	16,757
Firm age, yrs	566,257	16	7.3	0	93
Private firm dummy	580,930	1	0	1	1
SOE dummy	602,926	.036	.19	0	1
Foreign-owned firm dummy	602,926	.00023	.015	0	1
Suppliers to state and SOEs dummy	602,926	.31	.46	0	1
Firm under any sanction	602,926	.012	.11	0	1
Firm under input sanction	602,926	.0092	.096	0	1
Firm TFPQ, weighted by sector	415,504	.2	.31	0	4
Firm TFPQ, adjusted for measurement error	366,398	1.7	3.3	0	201
Firm TFPR, weighted by sector	415,504	3.1	7.9	0	239
Firm TFPR, adjusted for measurement error	366,398	1.6	2.6	0	93
Firm MRPL, weighted by sector	415,504	3.5	153	0	73,320
Firm MRPL, adjusted for measurement error	366,398	2.3	88	0	34,215
Firm MRPK, weighted by sector	415,504	52	1,229	0	364,920
Firm MRPK, adjusted for measurement error	366,398	6.6	383	0	162,614
Observations	602926				

Notes: This table reports summary statistics for the firms in the SPARK dataset from 2012 to 2018. An observation is at the firm-year level. Firms' book value of capital, value added, payments to labor, materials and revenues are measured in 1000 of Rubles.

Table 3: Summary statistics of key variables

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.

In addition, in Table 4 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.

Variable	Statistic	Industry and Firm Fixed Effects	2018 Raw measures	Cross-section Average
		Panel A : Full dataset		
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 4: Dispersion of ln(TFPR), ln(TFPQ), ln(MRPL), ln(MRPK)

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[20]. Looking at Panel B, with only the manufacturing sec-

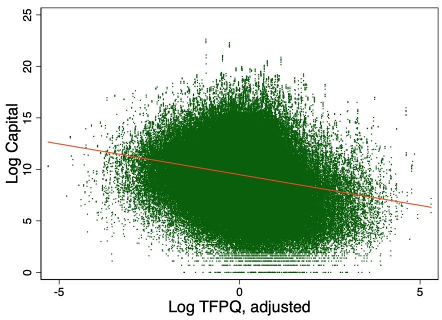
[20]The higher variation may also arise because of the way 4-digit industries are defined. As the country is transforming to

tor, 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.

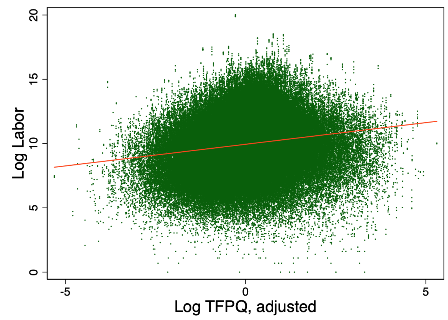
Do resources in Russia appear misallocated through the lens of the framework from the "Model" Section 3? If capital and labour markets were not distorted, more capital and labour would flow to the relatively more productive firms. This means that input use and firm TFP should be positively related, while 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. Likewise, 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. Figure 1 demonstrates the overall distribution of capital and labour relative to the productivity of firms (the top two graphs), and the capital and labour productivity on firm TFPQ (the bottom two graphs), and the measures of TFPQ, capital and labour productivity are adjusted for measurement error. In the top two graphs, the firm productivity is shown on the X-axes and the inputs on the Y-axes. 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, I plot MRPL and MRPK relative to the firm TFPQ, where the efficient relationship should be flat and 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

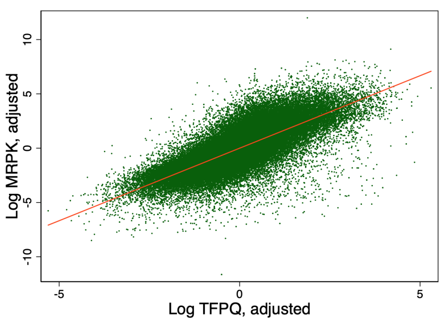
the services economy, the level of detail may be much lower in the services sector, relative to manufacturing, so each 4-digit industry in the services sector may contain somewhat more diverse firms than a 4-digit industry in manufacturing



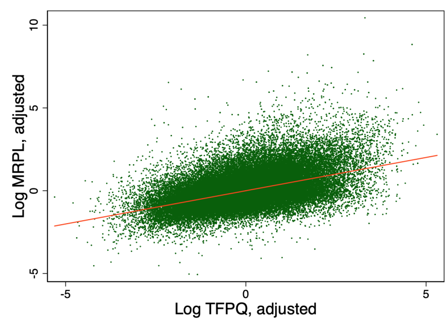
(a) Capital on TFPQ



(b) Labor on TFPQ



(c) Capital productivity on TFPQ



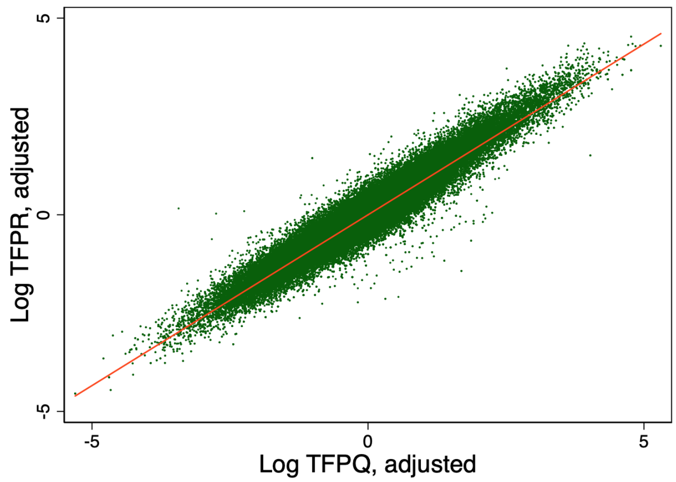
(d) Labor productivity on TFPQ

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 $TFPQ_i = \kappa \frac{(P_i Q_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha} L_i^{1-\alpha}}$. The MRPK, MRPL 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 1: Factor allocations by firm productivity

productivity. These patterns point at large institutional and economic frictions that prevent the flow of labour and capital resources to the most productive firms.

Both capital and labour distortions to a firm can be summarised with a $TFPR_i$, the revenue productivity measure, defined in equation 4. This measure will help us see whether firms that face high capital wedges, also face high labour wedges. As described in section 5, just like I do for $TFPQ_i$, I adjust the $TFPR_i$ for each firm with year and firm fixed effects and further regress the residuals on the 4-digit industry dummies. Figure 2 shows firm $TFPQ_i$ on X-axes and firm $TFPR_i$ on Y-axes. The very strong correlation of $TFPR_i$ and firm physical productivity tells us that more productive firms face higher wedges in *both* labour and capital. This confirms our findings above. Firms that experience high productivity do not have a



Notes: Each observation is a firm. $TFPR_i$, or revenue productivity, is a summary measure of distortions faced by each firm, with higher $TFPR_i$ implying higher distortions. The TFPR measure is adjusted for measurement error with firm and year fixed effects and de-meaned by 4-digit industry using the firm panel 2012-2018.

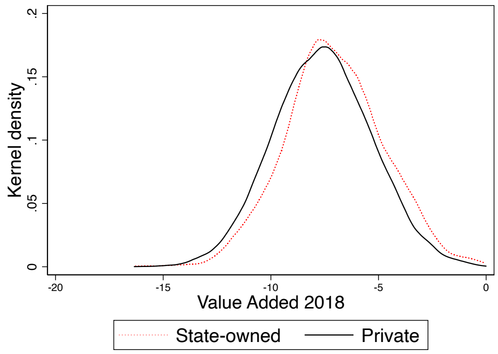
Figure 2: Firm-specific distortions and productivity (TFPR on TFPQ)

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. 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 lo less productive SOEs.

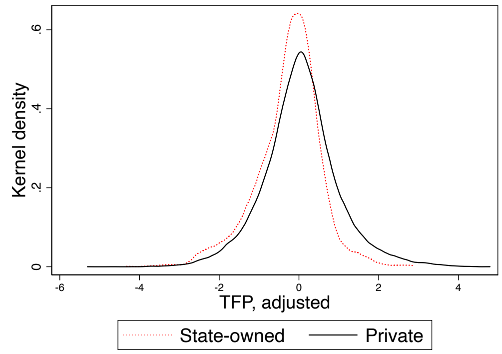
Above were the descriptives of the firm characteristics of the whole economy. So far we have not seen any information about the state-owned sector versus the private sector. Is there any misallocation across ownership groups? Could such distortions explain, at least in part, the barriers faced by more productive firms? Figure 3 below compares the density distributions of the firm-level value added, TFPQ, capital and labour productivity and TFPR between state-owned firms and private firms. These measures of TFPQ, MRPK, MRPL and TFPR are adjusted for measurement error using firm and year fixed effects as explained in Section 5.

These figures demonstrate that the state-owned firms have much lower TFPR than the private sector, especially at the high end of the distribution. Lower revenue productivity arises due to both too much capital allocated to state-owned firms and too much labour, as evidenced by subplots (c) and (d). Private firms also appear to be more productive, as shown in subplot (b). Therefore, I again witness that the more productive firms face larger ”correlated” distortions. I also note that the state-owned firms are relatively large in terms of value added, compared to private firms (subplot a). Such allocation of capital and labour, excessive from the efficiency perspective, can come from the soft budget constraint of the SOEs. As for the excess labour, since labour is complementary to capital to some extent, more labour could be employed as a result of excessive capital. On top of that, some 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].

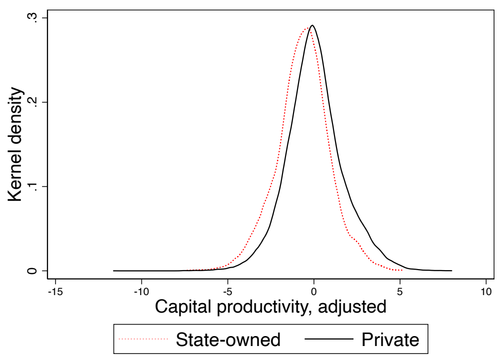
[21] The labour hoarding may be desirable from the equity perspective, but just not from the efficiency perspective.



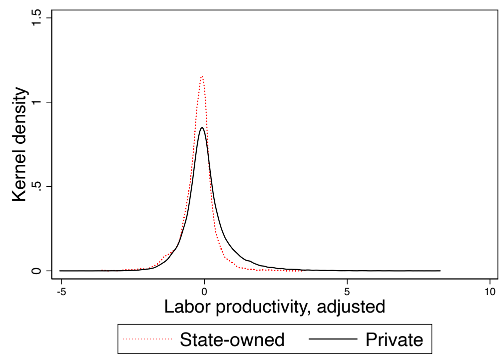
(a) Value added



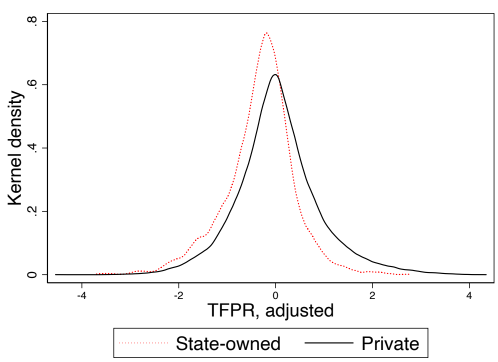
(b) TFPQ



(c) MRPK



(d) MRPL



(e) TFPR

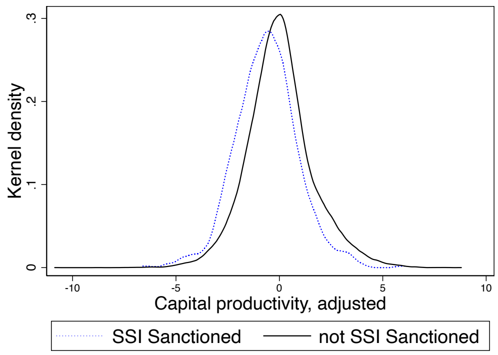
Notes: The plots show the kernel density of natural logs of value added, TFPQ, MRPK, MRPL and TFPR. The red dotted lines are the kernel densities for the SOEs sample. The black lines are the kernel densities for the sample of private firms. Labor productivity (or $MRPL_i$) refers to value added per unit 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 $TFPQ_i = \kappa \frac{(P_i Q_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha} L_i^{1-\alpha}}$. The MRPK, MRPL and TFPQ 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 2012-2018.

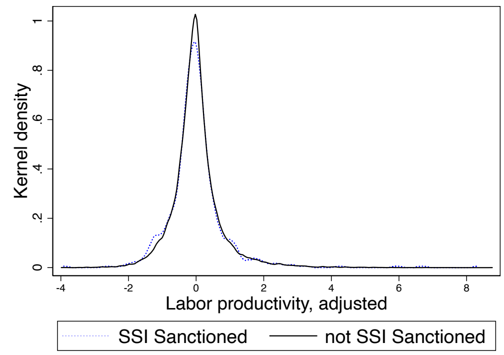
Figure 3: Allocations of SOEs versus the private sector, variables adjusted for measurement error

Linking these observations with the section on sanctions, I also show the differences in Capital and Labor productivity between SOEs and private firms before the sanctions episode, again, applying the measurement error adjustment procedure from section 5 and confirm that the SOEs were already ”too large” before the sanctions. Moreover, the sanctioned firms (that experienced input sanctions) taken together also were ”too large” from the efficiency perspective before the treatment, at least in terms of capital[22]. 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.

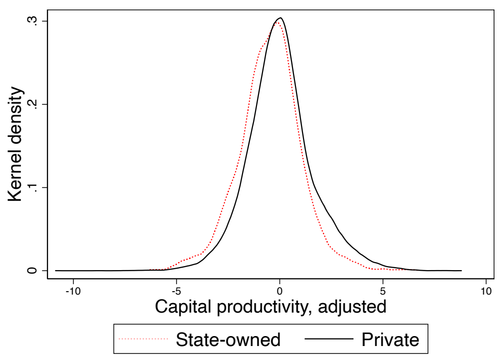
[22]The graph is similar for firms that experienced any sanctions, including the blocking ones



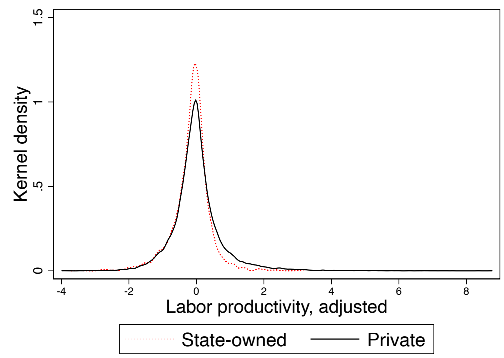
(a) MRPK of sanctioned versus other firms pre-2015



(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

Notes: The plots show the kernel density of natural logs of MRPK and MRPL. The blue dotted lines are the kernel densities for the SSI sanctioned sample. The black lines in the top two graphs are the kernel densities for the sample of non-SSI sanctioned firms. The red dotted lines are the kernel densities for the SOEs sample. The black lines in the bottom two graphs are the kernel densities for the sample of private 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 4: Allocations before 2015

7 Counterfactuals

To measure efficiency gains of reallocating resources across ownership groups I conduct two counterfactual exercises. First, I equalize all wedges (or TFPR) across firms within each four-digit industry, keeping total capital and labour fixed within industries. I then compare the aggregate TFP as measured in the data to this new efficient TFP, call it "TFPe". This comparison will give a full distance to the efficient frontier from the current status quo in Russia. Second, I equalize wedges only within ownership-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 across SOEs and private firms.

1) TFPe: Equalize all wedges within industries

2) TFPc: Equalize wedges within ownership-industry groups

Measures	Count	TFP/TFPe	TFPc/TFPe
Raw	71,180	8.7%	91.2%
FE-corrected	57,279	49.9%	94.7%
Raw, same sample as corrected	57,279	8.1%	94.5%

Notes: Column 1 reports the sample sized used for the counterfactual calculation. Column 2 reports the shares of the existing aggregate output (TFP) in the efficient output (TFPe), or TFP/TFPe. Column 3 reports the shares of the counterfactual aggregate output (TFPc), after equalising the wedges within ownership-industry groups, or TFPc/TFPe. "Raw" refers to the the raw data in 2018. "FE-corrected" refers to the fixed effects estimates from the panel regression. "Raw, same sample as corrected" refers to the TFP shares for the same sample as used to get the the fixed effects estimates, but without the actual correction.

Table 5: Counterfactual exercises

Table 5 shows the results of the counterfactual exercises. The first row uses the data for the year 2018, without adjusting for measurement error. The resulting overall distance to the frontier is very large: the current TFP is more than 10 times smaller than the frontier TFP. The remaining distance to the frontier due to wedges across the SOEs and private firms is roughly 9% (100%-91.2%), so according to this result, the current TFP will double (8.7%+9%) if an SOE versus private wedge was removed while all other distortions remained. However, most of the variation is unexplained by the SOEs-private wedge.

The overall distance to the frontier gets smaller when I correct for measurement error on the second row of Table 5. Now the Russian TFP will slightly more than double if all wedges were equalized. Now, the wedges across ownership groups appear smaller and will add roughly 11% (5.3%/49.9%=11%) to the current TFP if they are removed. Again, the bulk of wedge variation that keeps Russia at a distance from its efficient frontier remains unexplained and the ownership wedge only explains 5.3%/51.1%=10.4% of the distance to the frontier. This is not surprising: many factors, such as different forms of corruption or supplier to SOE status can contribute to misallocation of resources above and beyond the simple ownership wedge and in a companion paper I explore to what extent these factors help to further explain the distance to the frontier in Russia.

8 Sanctions as a test of the SOE protection

	Ownership		
Sanction type	Private	State-owned	Total
SDN	81%	19%	277
SSI	88%	12%	397
SSI and SDN	83%	17%	458
Total	84%	16%	1,132

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 6: Sanctions by ownership

	Sector			
Sanction type	Manufcaturing	Services	Agriculture	Total
SDN	102	174	1	277
SSI	134	254	9	397
SSI and SDN	178	268	12	458
Total	414	696	22	1,132

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 7: Sanctions by sector

Table 8 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. However, it is also important to look at the whole distribution of this variable, rather than the simple average, which masks substantial heterogeneity which we saw in figure 4.

	(1)				
	Not sanctioned	SDN	SSI	SSI and SDN	Total
Sanctioned as a subsidiary dummy	0	0.850	0.649	0.890	0.00957
	(0)	(0.357)	(0.477)	(0.313)	(0.0973)
Private firm dummy	0.965	0.785	0.874	0.836	0.964
	(0.184)	(0.411)	(0.332)	(0.370)	(0.187)
SOE dummy	0.0349	0.215	0.126	0.164	0.0365
	(0.184)	(0.411)	(0.332)	(0.370)	(0.187)
Direct sanction dummy	0	0.150	0.351	0.110	0.00245
	(0)	(0.357)	(0.477)	(0.313)	(0.0495)
Ln value added	10.47	13.08	13.32	13.26	10.50
	(1.969)	(2.193)	(2.548)	(2.492)	(1.998)
Ln revenue	11.67	13.92	14.01	14.03	11.70
	(2.185)	(2.562)	(2.939)	(2.843)	(2.209)
Ln book value of capital	9.167	12.06	12.48	12.56	9.206
	(2.781)	(3.022)	(3.559)	(3.205)	(2.810)
Ln payment to labor	9.474	12.21	12.12	12.21	9.507
	(2.014)	(2.137)	(2.346)	(2.327)	(2.039)
Ln materials	11.19	13.32	13.21	13.32	11.22
	(2.355)	(2.638)	(2.873)	(2.828)	(2.372)
Labor count, latest year	162.6	1109.4	942.4	1253.3	173.9
	(543.7)	(1884.3)	(1822.7)	(1876.9)	(586.6)
Firm age, yrs	15.99	19.76	19.47	20.36	16.04
	(7.285)	(7.179)	(7.125)	(7.758)	(7.300)
Foreign-owned firm dummy	0.000237	0	0	0	0.000234
	(0.0154)	(0)	(0)	(0)	(0.0153)
Suppliers to state and SOEs dummy	0.302	0.679	0.674	0.743	0.307
	(0.459)	(0.467)	(0.469)	(0.437)	(0.461)
Ln firm MRPK	1.288	0.882	0.579	0.442	1.279
	(2.467)	(2.278)	(2.456)	(2.229)	(2.466)
Ln firm MRPL	0.814	0.637	0.908	0.776	0.814
	(1.221)	(1.116)	(1.481)	(1.380)	(1.223)
Observations	602926				

Notes: This table reports summary statistics for the firms in the SPARK dataset from 2012 to 2018 by type of sanction. An observation is at the firm-year level. 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 8: Summary by sanction type

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 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[23]. Leonid Mikhelson has been reported to request the government to help fund the creation of deepwater drilling equipment to replace the U.S. imports[24]. Promsvyazbank was nationalized and then re-purposed to compensate the losses from sanctions of Russia's defence sectors[25]. 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.[26] 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.[27]. 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.

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

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

[25]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

[26]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

[27]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 run the following regression:

$$Y_{it} = \gamma_{jt} + \phi_i + \theta_{st} + \beta_1 * InputSanctions_{it} + X_{it}\delta + u_{ijt} \tag{18}$$

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 18, 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:

$$Y_{it} = \gamma_{jt} + \phi_i + \theta_{st} + \beta_1 * InputSanctions_{it} + \beta_2 * InputSanctions_{it} * SOE_i + X_{it}\delta + u_{ijt} \tag{19}$$

In Specification 19, I repeat the specification 18 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 19 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 8, 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 estimation of β_1 in Specifications 18 and 19 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 19 requires that SOEs are trending in parallel to private firms. Such differential trends can be controlled for. In the Appendix Table 2.A5, I control for the SOE-by-year fixed effects to absorb the bias from SOEs trending differently to private firms. In effect, Specification 19 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.

8.1 Event studies

As mentioned above, to identify β_1 in Specifications 18 and 19 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 20) 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 (21)[28].

$$Y_{it} = \gamma_{jt} + \phi_i + \theta_{st} + \alpha_s * \sum_{s=-4,s\neq 0}^{s=3} InputSanctions_i * 1_{t=s} + X_{it}\delta + u_{ijt} \quad (20)$$

Specification 20 is identical to the regression 18, 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}.

$$Y_{it} = \gamma_{jt} + \phi_i + \theta_{st} + \alpha_s * \sum_{s=2012,s\neq 2015}^{s=2018} InputSanctions_i * 1_{t=s} + X_{it}\delta + u_{ijt} \quad (21)$$

Specification 21 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.

[28]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

9 Results

9.1 Regression results

Table 9 shows my baseline results for specifications 18 and 19. The first thing to note is in columns (1) and (2) we see that the MRPK went down differentially for the SSI-sanctioned SOEs relative to SSI-sanctioned private firms and 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 4 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 subsidies.

Does this negative MRPK result come from the input increase (denominator) or the output reduction (numerator)? One could argue that de-risking against Russian sanctioned firms could have lead to a simple reduction in sales, especially the sales abroad. Columns (3), (4), (5) and (6) give us the answer: the sales and value added did not decrease, but the inputs increased. First, in column (3) we see an average net increase in capital by 16% after SSI sanctions for sanctioned firms relative to non-sanctioned firms. Capital increased for sanctioned firms on average. Then, in column (4), we see the heterogeneity of this effect. The private sanctioned firms' capital rose, but not significantly, so we can consider this effect as 0 to be conservative. But the sanctioned SOEs have seen their capital increase by 25% more than the sanctioned private firms. All this leads to one conclusion: all sanctioned firms were protected and have seen full shielding of their assets, but the sanctioned SOEs have seen "too much" shielding. The complete shielding of assets would have kept misallocation at the same level as pre-sanctions, but the excessive shielding has, in fact, worsened it. From columns (5) and (6) we see that the value added was not significantly affected by sanctions.

Columns (7) and (8) show the effects of sanctions on revenue. These results provided because revenue is a direct measure reported in the balance sheets, rather than the constructed value added, and therefore may have lower mis-measurement.

These results show that the revenues grew on average for sanctioned firms, which again means that the negative MRPK result in column (2) arises not because the revenues have been dampened by sanctions or de-risking trends.

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 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 Table 9 differ somewhat 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 only observe results till 2016, so mainly for only one effective year of sanctions. Second, they measure the combined effect of blocking and SSI 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.

	(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	-0.043	-0.006	0.163**	0.124	0.038	0.028	0.160***	0.170***
	(0.074)	(0.084)	(0.071)	(0.078)	(0.050)	(0.057)	(0.058)	(0.064)
SDN dummy	-0.041	-0.037	0.104*	0.100*	0.067	0.066	0.103**	0.104**
	(0.056)	(0.056)	(0.057)	(0.057)	(0.047)	(0.047)	(0.049)	(0.049)
SSI dummy × SOE		-0.233*		0.250*		0.060		-0.064
		(0.139)		(0.136)		(0.102)		(0.139)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓	✓	✓
Size-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. 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

9.2 Event studies results

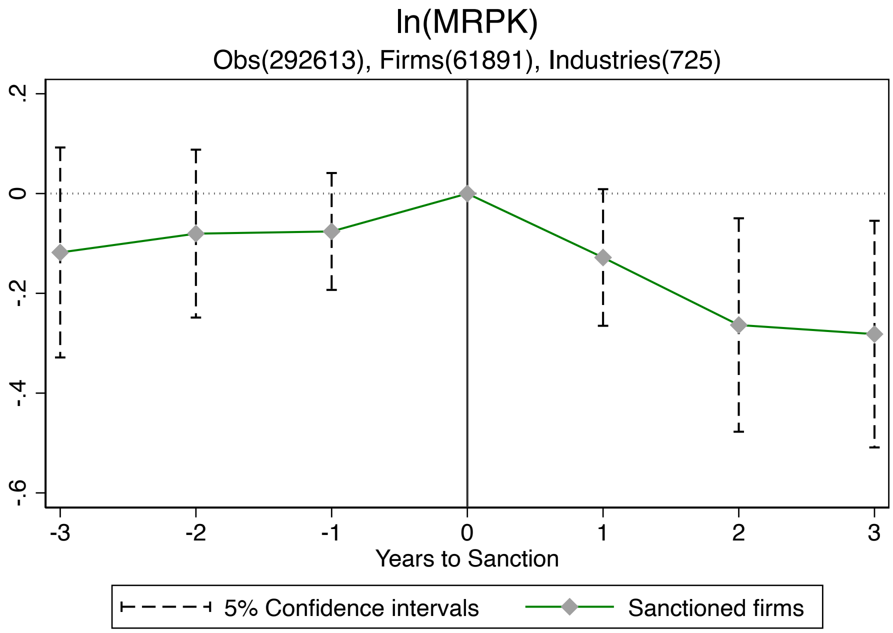
The identification in Table 9 is subject to one possible problem. What if the sanctioned firms are on different trends to the other firms and the sanction variables just pick such trends up? In Figure 5, I show the event study with ln(MRPK) as an outcome variable and confirm that the positive effects persist even if I identify them within the group of sanctioned firms, for which 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[29]. 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.

Furthermore, in Figure 6, I show an event study, in which the control group is not just to-be-sanctioned firms, but also the never-sanctioned firms. I also cannot reject that the group of sanctioned firms was on the same trends as the group of non-sanctioned firms before 2015 in Figure 6. If anything the treated firms were on the upward trend before the sanctions, so the regression results I find in Table 9 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. I do not find significant effects prior to 2015, which is consistent with the sanctioned and non-sanctioned firms being on the same trend, but I do find a significant drop in MRPK soon after 2015[30].

It is important to note that these results are for the SSI (input) sanctions, where I always control for the SDN blocking sanctions in the background.

[29] I do not have enough power to identify the effect of the interactions with SOEs, and therefore I do not include the interacted event studies.

[30] The fact that I find a significant average MRPK result in the event study based on specification 6, but not in the regression based on the specification 18, could have happened because the $InputSanction_{it}$ dummy in the regression is not just "post 2015". The dummy varied across years since the input sanctions happened in waves. We, therefore, are not comparing two almost identical specifications.



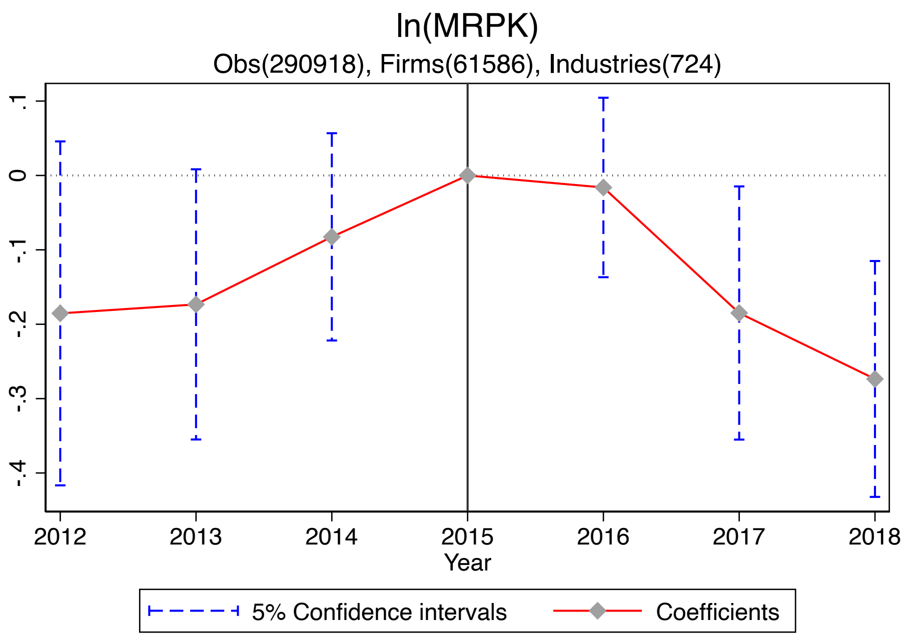
Notes: This figure reports event study graphs for the average effects of the sanctions on sanctioned firms. The effect is identified within sanctioned firms: sanctioned firms are compared to not-yet sanctioned firms. The first year of firm sanction is normalized to take place in year 0. Each dot is the 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 MRPK dependent variable is in logs. The confidence intervals are at the 95% level.

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

9.3 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[31]. This assumption is used fro convenience, to get a simple expression 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:

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



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 and 2018, and being sanctioned with SSI 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 MRPK dependent variable is in logs. The confidence intervals are at the 95% level.

Figure 6: Pre-post 2015 event study with never-sanctioned firms in the control group

$$\Delta logTFP_s = -\frac{1}{2\eta} * VAR(logTFPR_i + \alpha \Delta logMRPK_i) \tag{22}$$

The value of $\Delta logMRPK_i$ is taken from Table 9 as the coefficient on the interaction term in column (4). 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 2.A6) 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).

10 Conclusion

Using structural and reduced-form evidence, I show that SOEs are a large source of allocative inefficiency, both in terms of how inputs are allocated to SOEs at a given point in time, and in terms of how SOEs 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 model of heterogeneous firms to quantify how misallocation of capital and labour between state and private firms contributes to aggregate TFP. Then, 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 the model and quantify the effects of sanctions on misallocation and, in turn, on the aggregate TFP.

I find that the SOEs 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 11% if the wedges between state-owned and private firms were removed. My empirical estimation validates the finding that the SOEs are inefficiently large and demonstrates one channel through which the SOEs get so large: SOEs differentially respond to negative input shocks by getting subsidies that over-shoot the negative shocks. The sanctions, combined with shielding have led the SOEs to gain 25% more capital relative to a private sanctioned firm and 35%

more capital relative to a non-sanctioned firm. These results are estimated for the type of sanctions that specifically negatively shock the capital inputs of the target firms. I quantify that this joint sanctions and shielding effect reduced the aggregate TFP by 0.33%, which varied between 0% and 3% reductions in different sectors.

This paper has important policy implications. First, as this text is being written, more US sanctions are being promised by the Biden administration. Due to the evidence of excessive shielding that I find, the 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 spilt over to the rest of the economy and allocative efficiency worsened in Russia. 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, it shines a light on state ownership as one of the strong drivers of misallocation. Misallocation due to ownership status can be improved by allocating fewer resources to SOEs by limiting the soft budget constraint. This can be achieved by monitoring how the subsidies and tax breaks are granted, and specifying the rulebooks in advance on what subsidies and capital transfers the SOEs can receive under what circumstances, and what public goals these favours fulfil.

Future research will study further the channels of how misallocation across ownership lines is amplified due to the political connections of private firms to the SOEs and by which means the incentive issues of the SOEs trickle down to the rest of the economy.

Public support for state ownership has grown according to the EBRD Enterprise surveys and just under 50% of people favour an increase in state-ownership (EBRD 2020). State-owned enterprises have played important functions in emerging economies, such as China, Russia and other post-Communist countries: they stabilized employment and facilitated a more equal provision of public services and financial inclusion. However, these functions have come at a cost of ineffective management, lack of transparency and subsidies that created inefficient allocation of resources in the economy. This paper quantified this cost to be sizeable and found that TFP (and therefore, output) is lower by at least 11%.

References

Adamopoulos, T., Brandt, L., Leight, J. & Restuccia, D. (2017), Misallocation, selection and productivity: A quantitative analysis with panel data from china, Technical report, National Bureau of Economic Research.

Ahn, D. P. & Ludema, R. D. (2020), 'The sword and the shield: the economics of targeted sanctions', *European Economic Review* **130**, 103587.

Asker, J., Collard-Wexler, A. & De Loecker, J. (2014), 'Dynamic inputs and resource (mis) allocation', *Journal of Political Economy* **122**(5), 1013–1063.

Baqaee, D. R. & Farhi, E. (2020), 'Productivity and misallocation in general equilibrium', *The Quarterly Journal of Economics* **135**(1), 105–163.

Bartelsman, E., Haltiwanger, J. & Scarpetta, S. (2013), 'Cross-country differences in productivity: The role of allocation and selection', *American economic review* **103**(1), 305–34.

Bau, N. & Matray, A. (2020), Misallocation and capital market integration: Evidence from india, Technical report, National Bureau of Economic Research.

Berkowitz, D., Ma, H. & Nishioka, S. (2017), 'Recasting the iron rice bowl: The reform of china's state-owned enterprises', *Review of Economics and Statistics* **99**(4), 735–747.

Bils, M., Klenow, P. J. & Ruane, C. (2020), Misallocation or mismeasurement?, Technical report, National Bureau of Economic Research.

Brandt, L., Jiang, F., Luo, Y. & Su, Y. (2018), 'Ownership and productivity in vertically-integrated firms: Evidence from the chinese steel industry', *Review of Economics and Statistics* pp. 1–49.

Brown, J. D., Earle, J. S. & Telegdy, A. (2006), 'The productivity effects of privatization: Longitudinal estimates from hungary, romania, russia, and ukraine', *Journal of political economy* **114**(1), 61–99.

Buera, F. J., Kaboski, J. P. & Shin, Y. (2011), 'Finance and development: A tale of two sectors', *American economic review* **101**(5), 1964–2002.

Busso, M., Madrigal, L. & Pagés, C. (2013), 'Productivity and resource misallocation in latin america', *The BE Journal of Macroeconomics* **13**(1), 903–932.

Bussolo, M., De Nicola, F., Panizza, U. & Varghese, R. (2019), 'Political connections and financial constraints: Evidence from transition countries', *World Bank Policy Research Working Paper* (8956).

Crozet, M. & Hinz, J. (2016), 'Collateral damage: The impact of russia sanctions on sanctioning countries' exports cepii working paper'.

David, J. M., Hopenhayn, H. A. & Venkateswaran, V. (2016), 'Information, misallocation, and aggregate productivity', *The Quarterly Journal of Economics* **131**(2), 943–1005.

David, J. M. & Venkateswaran, V. (2019), 'The sources of capital misallocation', *American Economic Review* **109**(7), 2531–67.

Draca, M., Garred, J., Stickland, L. & Warrinnie, N. (2019), On target? the incidence of sanctions across listed firms in iran, Technical report, LICOS Discussion Paper.

EBRD (2020), The state strikes back, Technical report, European Bank of Reconstruction and Development.

Gold, R., Hinz, J. & Valsecchi, M. (2019), To russia with love? the impact of sanctions on elections, Technical report.

Gollin, D. & Udry, C. (2021), 'Heterogeneity, measurement error, and misallocation: Evidence from african agriculture', *Journal of Political Economy* **129**(1), 000–000.

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L. & Villegas-Sanchez, C. (2017), 'Capital allocation and productivity in south europe', *The Quarterly Journal of Economics* **132**(4), 1915–1967.

Haidar, J. I. (2017), 'Sanctions and export deflection: evidence from iran', *Economic Policy* **32**(90), 319–355.

Hopenhayn, H. A. (2014), 'Firms, misallocation, and aggregate productivity: A review', *Annu. Rev. Econ.* **6**(1), 735–770.

Hsieh, C.-T. & Klenow, P. J. (2009), 'Misallocation and manufacturing tfp in china and india', *The Quarterly journal of economics* **124**(4), 1403–1448.

Hsieh, C.-T. & Song, Z. M. (2015), 'Grasp the large, let go of the small: The transformation of the state sector in china', *Brookings Papers on Economic Activity* .

Jones, C. I. (2011), Misallocation, economic growth, and input-output economics, Technical report, National bureau of economic research.

Kowalski, P., Büge, M., Sztajerowska, M. & Egeland, M. (2013), 'State-owned enterprises: Trade effects and policy implications'.

Megginson, W. L. (2016), 'Privatization, state capitalism, and state ownership of business in the 21st century', *Foundations and Trends in Finance, forthcoming* .

Midrigan, V. & Xu, D. Y. (2014), 'Finance and misallocation: Evidence from plant-level data', *American economic review* **104**(2), 422–58.

Pellegrino, B. & Zheng, G. (2021), Measuring the cost of red tape: A survey data approach, Technical report, Working Paper.

Peters, M. (2020), 'Heterogeneous markups, growth, and endogenous misallocation', *Econometrica* **88**(5), 2037–2073.

Restuccia, D. & Rogerson, R. (2008), 'Policy distortions and aggregate productivity with heterogeneous establishments', *Review of Economic dynamics* **11**(4), 707–720.

Restuccia, D. & Rogerson, R. (2017), 'The causes and costs of misallocation', *Journal of Economic Perspectives* **31**(3), 151–74.

Rotemberg, M. (2019), 'Equilibrium effects of firm subsidies', *American Economic Review* **109**(10), 3475–3513.

Rotemberg, M. & White, T. K. (2017), Measuring cross-country differences in misallocation, Technical report.

Song, Z., Storesletten, K. & Zilibotti, F. (2011), 'Growing like china', *American economic review* **101**(1), 196–233.

Stone, M. (2016), 'The response of russian security prices to economic sanctions: Policy effectiveness and transmission', *US Department of State Office of the Chief Economist Working Paper* .

Tuzova, Y. & Qayum, F. (2016), 'Global oil glut and sanctions: The impact on putin's russia', *Energy Policy* **90**, 140–151.

Zilibotti, F. (2017), 'Growing and slowing down like china', *Journal of the European Economic Association* **15**(5), 943–988.

11 Appendix

12 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.

$$Q_i = A_i K_i^{\alpha} L_i^{1-\alpha} \tag{23}$$

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:

$$Q = \left(\sum_{i=1}^{N} Q_i^{1-\eta} \right)^{\frac{1}{1-\eta}} \tag{24}$$

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

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

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

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

$$P Q^{\eta} Q_i^{*1-\eta} = P_i Q_i^{*} \tag{25}$$

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:

$$\max_{L_i, K_i} \pi_i = P Q^{\eta} Q_i^{*1-\eta} - (1+\tau_i^L) w L_i - (1+\tau_i^K) r K_i$$

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.

$$\{L_i\} : (1-\alpha)(1-\eta)\frac{PQ^{\eta}(A_i K_i^{\alpha} L_i^{1-\alpha})^{1-\eta}}{L_i} = (1+\tau_i^L)w \tag{26}$$

The optimal labor allocation will satisfy this equation:

$$\{L_i\} : (1-\alpha)(1-\eta)\frac{P_i Q_i}{L_i} = (1+\tau_i^L)w \equiv MRPL_i \tag{27}$$

$$\boldsymbol{\{L_i\} : \ L_i = (1-\alpha)(1-\eta)\frac{P_i Q_i}{MRPL_i}} \tag{28}$$

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

$$\{K_i\} : \ \alpha(1-\eta)\frac{P_i Q_i}{K_i} = (1+\tau_i^K)r \equiv MRPK_i \tag{29}$$

$$\boldsymbol{\{K_i\} : \ K_i = \alpha(1-\eta)\frac{P_i Q_i}{MRPK_i}} \tag{30}$$

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

$$TFPR_i \equiv \frac{P_i Q_i}{K_i^{\alpha} L_i^{1-\alpha}} = \left(\frac{MRPK_i}{\alpha}\right)^{\alpha}\left(\frac{MRPL_i}{1-\alpha}\right)^{1-\alpha}\frac{1}{(1-\eta)} \tag{31}$$

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

$$P_iQ_i = PQ^\eta (A_i K_i^\alpha L_i^{1-\alpha})^{1-\eta} = PQ^\eta \left(A_i \left[\frac{(1-\alpha)(1-\eta)}{(1+\tau_i^L)w} \frac{P_iQ_i}{} \right]^{1-\alpha} \left[\frac{\alpha(1-\eta)}{(1+\tau_i^K)r} \frac{P_iQ_i}{} \right]^\alpha \right)^{1-\eta} \tag{32}$$

$$P_iQ_i = PQ^\eta (P_iQ_i)^{1-\eta} (1-\eta)^{1-\eta} \left(A_i \left[\frac{(1-\alpha)}{(1+\tau_i^L)w} \right]^{1-\alpha} \left[\frac{\alpha}{(1+\tau_i^K)r} \right]^\alpha \right)^{1-\eta} \tag{33}$$

$$P_iQ_i = P^{\frac{1}{\eta}} Q \left((1-\eta) A_i \left[\frac{(1-\alpha)}{(1+\tau_i^L)w} \right]^{1-\alpha} \left[\frac{\alpha}{(1+\tau_i^K)r} \right]^\alpha \right)^{\frac{1-\eta}{\eta}} \tag{34}$$

$$P_iQ_i \propto \left(\frac{A_i}{(1+\tau_i^L)^{1-\alpha}(1+\tau_i^K)^\alpha} \right)^{\frac{1-\eta}{\eta}} \tag{35}$$

Combine 27 , 29 and 35 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

$$L_i \propto \frac{1}{1+\tau_i^L} \left(\frac{A_i}{(1+\tau_i^L)^{1-\alpha}(1+\tau_i^K)^\alpha} \right)^{\frac{1-\eta}{\eta}} \tag{36}$$

$$K_i \propto \frac{1}{1+\tau_i^K} \left(\frac{A_i}{(1+\tau_i^L)^{1-\alpha}(1+\tau_i^K)^\alpha} \right)^{\frac{1-\eta}{\eta}} \tag{37}$$

Equivalently,

$$1+\tau_i^L \propto \frac{P_iQ_i}{wL_i} \tag{38}$$

$$1+\tau_i^K \propto \frac{P_iQ_i}{K_i} \tag{39}$$

Expressing 35 in terms of how we can measure each of the distortions:

$$P_iQ_i \propto \left(\frac{A_i}{(\frac{P_iQ_i}{L_i})^{1-\alpha}(\frac{P_iQ_i}{K_i})^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \qquad (4) \tag{40}$$

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 productivityA_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:

$$PQ^{\eta}(A_iK_i^{\alpha}L_i^{1-\alpha})^{1-\eta} = P_iQ_i \tag{41}$$

$$A_i = (PQ^{\eta})^{\frac{-1}{1-\eta}} \frac{(P_iQ_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha}L_i^{1-\alpha}} \tag{42}$$

$$A_i = \kappa \frac{(P_iQ_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha}L_i^{1-\alpha}} \tag{43}$$

$$\kappa = (PQ^{\eta})^{-\frac{1}{1-\eta}} \tag{44}$$

Aggregation

$$P_iQ_i = P^{\frac{1}{\eta}}Q \left((1-\eta)A_i \left[\frac{(1-\alpha)}{(1+\tau_i^L)w} \right]^{1-\alpha} \left[\frac{\alpha}{(1+\tau_i^K)r} \right]^{\alpha} \right)^{\frac{1-\eta}{\eta}} \tag{45}$$

$$PQ = \sum P_iQ_i \tag{46}$$

Use the exact expressions for optimal L_i and K_i

$$L_i = \frac{(1-\alpha)(1-\eta)P^{\frac{1}{\eta}}Q\left((1-\eta)A_i\left[\frac{(1-\alpha)}{(1+\tau_i^L)w}\right]^{1-\alpha}\left[\frac{\alpha}{(1+\tau_i^K)r}\right]^{\alpha}\right)^{\frac{1-\eta}{\eta}}}{(1+\tau_i^L)w} \tag{47}$$

$$K_i = \frac{\alpha(1-\eta)P^{\frac{1}{\eta}}Q\left((1-\eta)A_i\left[\frac{(1-\alpha)}{(1+\tau_i^L)w}\right]^{1-\alpha}\left[\frac{\alpha}{(1+\tau_i^K)r}\right]^{\alpha}\right)^{\frac{1-\eta}{\eta}}}{(1+\tau_i^K)r} \tag{48}$$

$$L = \sum L_i = (1-\alpha)(1-\eta)\sum \frac{1}{(1+\tau_i^L)w}P_iQ_i = \tag{49}$$

$$L = (1-\alpha)(1-\eta)PQ\sum \frac{1}{(1+\tau_i^L)w}\frac{P_iQ_i}{PQ} \tag{50}$$

$$L = (1-\alpha)(1-\eta)PQ\frac{1}{\overline{MRPL}} \tag{51}$$

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

$$K = \alpha(1-\eta)PQ\frac{1}{\overline{MRPK}} \tag{52}$$

Let's define the aggregate TFP the following way:

$$TFP \equiv \frac{Q}{K^{\alpha}L^{1-\alpha}} \tag{53}$$

$$TFP = \frac{Q}{\left(\alpha(1-\eta)PQ\frac{1}{\overline{MRPK}}\right)^{\alpha}\left((1-\alpha)(1-\eta)PQ\frac{1}{\overline{MRPL}}\right)^{1-\alpha}} \tag{54}$$

$$TFP = \frac{\overline{TFPR}}{P} = \frac{1}{P(1-\eta)}\left(\frac{\overline{MRPK}}{\alpha}\right)^{\alpha}\left(\frac{\overline{MRPL}}{1-\alpha}\right)^{1-\alpha} \tag{55}$$

To get P, aggregate the expression 55

$$PQ = \sum_i P^{\frac{1}{\eta}} Q \left((1-\eta) A_i \left[\frac{(1-\alpha)}{(1+\tau_i^L) w} \right]^{1-\alpha} \left[\frac{\alpha}{(1+\tau_i^K) r} \right]^{\alpha} \right)^{\frac{1-\eta}{\eta}} = \tag{56}$$

$$PQ = P^{\frac{1}{\eta}} Q \left((1-\alpha)^{1-\alpha} \alpha^{\alpha} \right)^{\frac{1-\eta}{\eta}} \sum_i \left(\frac{(1-\eta) A_i}{\left((1+\tau_i^L) w\right)^{1-\alpha} ((1+\tau_i^K) r)^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \tag{57}$$

$$P^{\frac{\eta-1}{\eta}} = \left((1-\alpha)^{1-\alpha} \alpha^{\alpha} \right)^{\frac{1-\eta}{\eta}} \sum_i \left(\frac{A_i (1-\eta)}{(MRPL_i)^{1-\alpha} (1+\tau_i^K)^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \tag{58}$$

$$P = \frac{1}{(1-\eta)} \left((1-\alpha)^{1-\alpha} \alpha^{\alpha} \right)^{-1} \left(\sum_i \left(\frac{A_i}{(MRPL_i)^{1-\alpha} (MRPK_i)^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{\eta-1}} \tag{59}$$

Plug 59 into 55.

$$TFP = \frac{1/(1-\eta) \left(\frac{\overline{MRPK}}{\alpha} \right)^{\alpha} \left(\frac{\overline{MRPL}}{1-\alpha} \right)^{1-\alpha}}{1/(1-\eta) \left((1-\alpha)^{1-\alpha} \alpha^{\alpha} \right)^{-1} \left(\sum_i \left(\frac{A_i}{(MRPL_i)^{1-\alpha} (MRPK_i)^{\alpha}} \right)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{\eta-1}}} \tag{60}$$

Aggregate TFP if you have decentralized allocation with wedges.

$$TFP = \left(\sum_i \left(A_i \left(\frac{\overline{MRPL}}{MRPL_i} \right)^{1-\alpha} \left(\frac{\overline{MRPK}}{MRPK_i} \right)^{\alpha} \right)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{1-\eta}} \tag{61}$$

Aggregate TFP if you have efficient allocation without wedges.

$$TFP^e = \left(\sum_i (A_i)^{\frac{1-\eta}{\eta}} \right)^{\frac{\eta}{1-\eta}} \tag{62}$$

Distance of aggregate TFP to the efficient (frontier)

$$\frac{TFP^e}{TFP} - 1 \tag{63}$$

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)

$$\frac{\left(L_{priv}\right)^{\eta}\left(\frac{L_{priv}}{K_{priv}}\right)^{\alpha(1-\eta)}}{(1-\alpha)(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}} = \frac{1}{MRPL_{priv}} \tag{64}$$

2)

$$\frac{\left(K_{priv}\right)^{\eta}\left[\frac{Kpriv}{L_{priv}}\right]^{(1-\alpha)(1-\eta)}}{\alpha(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}} = \frac{1}{MRPK_{priv}} \tag{65}$$

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):

$$1/TFPR_{priv} = \left[\frac{\left(K_{priv}\right)^{\eta}\left[\frac{Kpriv}{L_{priv}}\right]^{(1-\alpha)(1-\eta)}}{\alpha(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}}\right]^{\alpha}\left[\frac{\left(L_{priv}\right)^{\eta}\left(\frac{L_{priv}}{K_{priv}}\right)^{\alpha(1-\eta)}}{(1-\alpha)(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}}\right]^{1-\alpha} = \tag{66}$$

$$= \frac{\left(K_{priv}\right)^{\alpha\eta}\left(L_{priv}\right)^{(1-\alpha)\eta}}{(1-\alpha)^{1-\alpha}\alpha^{\alpha}(1-\eta)PQ^{\eta}\left(\sum\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}} \tag{67}$$

$$TFPR_{priv} = \frac{\left(\sum\left(\frac{A_i}{\kappa}\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}}{\left(K_{priv}\right)^{\alpha\eta}\left(L_{priv}\right)^{(1-\alpha)\eta}} \tag{68}$$

$$\kappa = \left(PQ^{\eta}\right)^{-\frac{1}{1-\eta}} \tag{69}$$

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.

$$TFP = \left(\sum_{o\in\{priv,so\}}\left(\frac{\overline{MRPL}}{MRPL_o}\right)^{1-\alpha}\left(\frac{\overline{MRPK}}{MRPK_o}\right)^{\alpha}\sum_{i\in o}\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\frac{\eta}{1-\eta}} \tag{70}$$

or, equivalently:

$$TFP = \left(\sum_{o\in\{priv,so\}}\left(\frac{\overline{TFPR}}{TFPR_o}\right)\sum_{i\in o}\left(A_i\right)^{\frac{1-\eta}{\eta}}\right)^{\frac{\eta}{1-\eta}} \tag{71}$$

13 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) ln_gr_pr18	(2) ln_gr_pr18	(3) ln_net_pr18	(4) ln_net_pr18
SSI dummy	0.106	0.081	0.054	0.033
	(0.067)	(0.071)	(0.091)	(0.097)
SDN dummy	0.048	0.045	0.379***	0.377***
	(0.055)	(0.055)	(0.093)	(0.092)
SSI dummy × SOE		0.169		0.122
		(0.162)		(0.240)
Firm FE	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓
Firms	77477	77477	68553	68553
Sanctioned firms	1019	1019	890	890
Industries	751	751	724	724
Observations	350296	350296	287723	287723
R-squared	.995	.995	.985	.985

Notes:

Table 2.A2: Average effects of sanctions on profits

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln MRPK	Ln MRPK	Ln MRPK	Ln MRPK	Ln MRPK	Ln MRPK
SSI dummy	-0.229**	-0.241**	0.035	0.105	0.164	0.204
	(0.095)	(0.102)	(0.099)	(0.115)	(0.174)	(0.252)
SDN dummy	0.124	0.119	-0.118*	-0.118*	-0.217	-0.196
	(0.081)	(0.081)	(0.070)	(0.070)	(0.314)	(0.358)
SSI dummy × SOE		0.129		-0.389**		-0.098
		(0.224)		(0.179)		(0.342)
Firm FE	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓	✓	✓
Firms	19307	19307	51425	51425	6960	6960
Sanctioned firms	320	320	650	650	22	22
Industries	320	320	382	382	47	47
Industry Group	Manufcaturing	Manufcaturing	Services	Services	Agriculture	Agriculture
Observations	95736	95736	218591	218591	33195	33195
R-squared	.85	.85	.899	.899	.801	.801

Notes:

Table 2.A3: Average effects of sanctions by industry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ln MRPK	Ln MRPK	Ln MRPK	Ln MRPK	Ln MRPK	Ln MRPK	Ln MRPK	Ln MRPK
SSI dummy	-0.485***	-0.349***	-0.356***	0.031	-0.439***	-0.319**	-0.324**	0.068
	(0.117)	(0.123)	(0.126)	(0.072)	(0.132)	(0.133)	(0.136)	(0.082)
SDN dummy	-0.603***	-0.762***	-0.789***	-0.004	-0.599***	-0.759***	-0.785***	-0.001
	(0.097)	(0.117)	(0.117)	(0.054)	(0.098)	(0.117)	(0.117)	(0.054)
SSI dummy × SOE					-0.297	-0.193	-0.204	-0.230*
					(0.240)	(0.211)	(0.213)	(0.138)
Constant	1.283***				1.283***			
	(0.006)				(0.006)			
Firm FE				✓				✓
Industry FE		✓				✓		
Year FE		✓				✓		
Industry-year FE			✓	✓			✓	✓
Size-year FE								
Firms	170308	169199	169105	110950	170308	169199	169105	110950
Sanctioned firms	1335	1334	1334	1179	1335	1334	1334	1179
Industries	888	865	815	772	888	865	815	772
Observations	497910	493108	492621	434375	497910	493108	492621	434375
R-squared	.000401	.278	.284	.866	.000405	.278	.284	.866

Notes:

Table 2.A4: Average effects of sanctions on MRPK, gradually adding fixed effects

	(1) Ln Book Value of Capital	(2) Ln Book Value of Capital	(3) Ln Book Value of Capital	(4) Ln Book Value of Capital	(5) Ln Book Value of Capital	(6) Ln Book Value of Capital	(7) Ln Book Value of Capital	(8) Ln Book Value of Capital
SSI dummy	2.485***	1.803***	1.841***	0.074	2.498***	1.807***	1.842***	0.036
	(0.176)	(0.181)	(0.187)	(0.069)	(0.192)	(0.193)	(0.197)	(0.076)
SDN dummy	2.259***	1.912***	1.928***	0.064	2.261***	1.912***	1.928***	0.060
	(0.134)	(0.164)	(0.165)	(0.059)	(0.134)	(0.165)	(0.165)	(0.059)
SSI dummy $\times$ SOE					-0.089	-0.027	-0.005	0.241*
					(0.436)	(0.368)	(0.374)	(0.135)
Constant	9.192***				9.192***			
	(0.007)				(0.007)			
Firm FE				✓				✓
Industry FE		✓				✓		
Year FE		✓				✓		
Industry-year FE			✓	✓			✓	✓
Size-year FE								
Firms	194069	192876	192788	131866	194069	192876	192788	131866
Sanctioned firms	1475	1474	1473	1343	1475	1474	1473	1343
Industries	897	875	828	791	897	875	828	791
Observations	602866	597289	596823	535829	602866	597289	596823	535829
R-squared	.00573	.25	.255	.929	.00573	.25	.255	.929

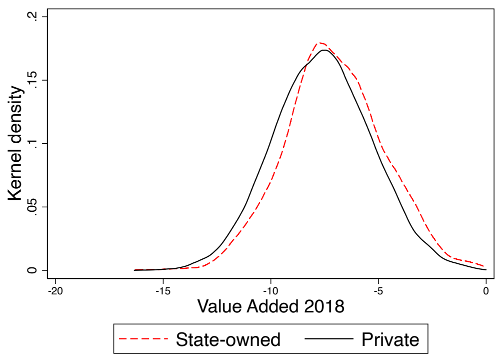
Notes:

Table 2.A5: Average effects of sanctions on capital, gradually adding fixed effects

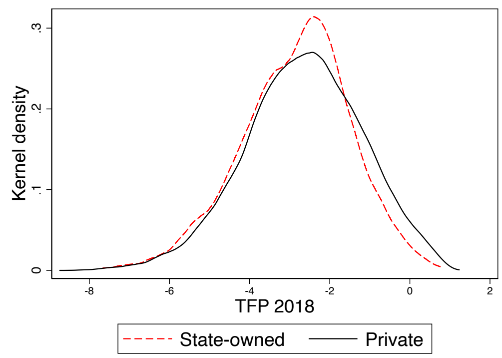
Sector	% change in TFPs	Sector	% change in TFPs
Manufacture of computers and peripheral equipment	-3.36	Production of drugs and materials used for medical purposes	-0.15
Transportation of gas and products of its processing through pipelines	-3.23	Wholesale trade of solid, liquid and gaseous fuels and similar products	-0.14
Electricity production by thermal power plants, including activities to ensure the operability of power plants	-2.34	Provision of drilling services related to oil, gas and gas condensate production	-0.13
Activities in the field of communication based on wired technologies	-1.81	Activities in the field of architecture	-0.13
Production of petroleum products	-1.28	Mechanical processing of metal products	-0.11
Market research	-1.25	Other scientific research and development in the field of natural and technical sciences	-0.10
Communication equipment manufacturing	-0.96	Investments in securities	-0.10
Supporting activities related to air and space transport	-0.93	Electrical work	-0.09
Transportation of crude oil by sea-going tankers of foreign voyages	-0.92	Activities of health resort organizations	-0.06
Extraction of crude oil	-0.46	Manufacture of electric motors, generators and transformers	-0.05
Manufacture of parts for electronic tubes, tubes and other electronic components, not elsewhere classified	-0.45	Printing newspapers	-0.04
Retail sale of motor fuel in specialized stores	-0.44	Research and development in the field of natural and technical sciences	-0.04
Production of parts for railway locomotives, tram and other motor cars and rolling stock; production of track equipment and devices for traffic control of railway, tram and other tracks, mechanical and electromechanical equipment for traffic control	-0.36	Cultivation of cereals	-0.02
Construction of railways and metro	-0.35	Activities for the provision of cash loans secured by real estate	-0.01
Distribution of gaseous fuels through gas distribution networks	-0.31	Lease and management of own or leased real estate	-0.01
Manufacture of other electrical equipment.	-0.31	Topographic and geodetic activities	-0.01
Technical inspection of vehicles	-0.23	Holding company management activities	0.00
Manufacture of parts of devices and instruments for navigation, control, measurement, control, testing and other purposes	-0.22	Production of building metal structures, products and their parts	0.00
Tool production	-0.20	Breeding of dairy cattle, production of raw milk	0.00
Storage and warehousing of grain	-0.19	Real estate management on a fee or contract basis	0.00
Activities related to the use of computers and information technology, other	-0.19	Computer software development	0.01
Repair and maintenance of aircraft, including spacecraft	-0.17	Wholesale and retail trade; repair of motor vehicles and motorcycles	0.01
Electricity transmission and technological connection to distribution grids	-0.17	Manufacture of bricks, tiles and other building products from baked clay	0.02
Other types of printing activities	-0.16	Activities in the field of communication based on wired technologies	0.07
Other auxiliary activities related to transportation	-0.16	Manufacture of television receivers, including video monitors and video projectors	4.10

Notes: The table shows aggregate effects on output (TFP) in each industry with sanctioned firms. The effect comes from the combined effect of sanctions and government response on misallocation.

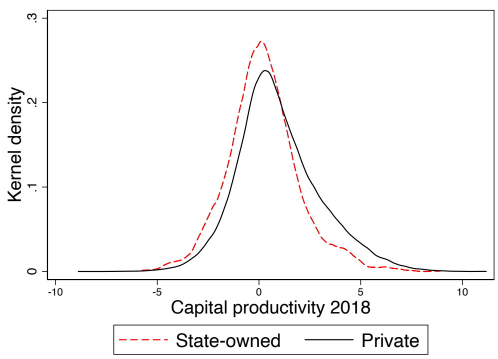
Table 2.A6: TFPs Results (aggregate effects of sanctions by industry)



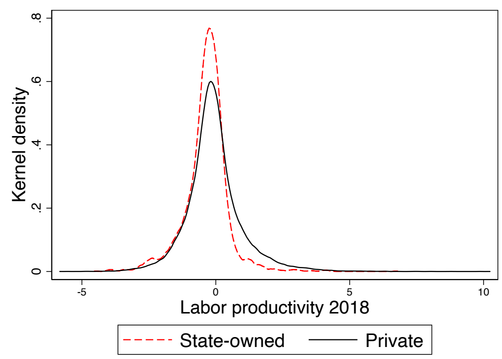
(a) Value Added



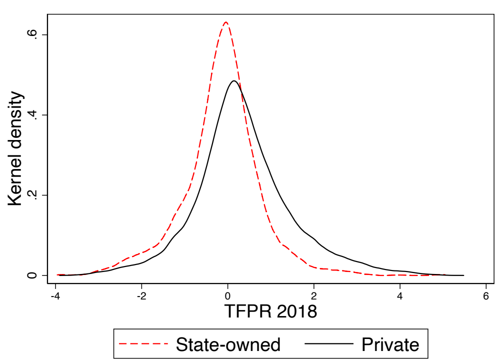
(b) TFPQ



(c) MRPK



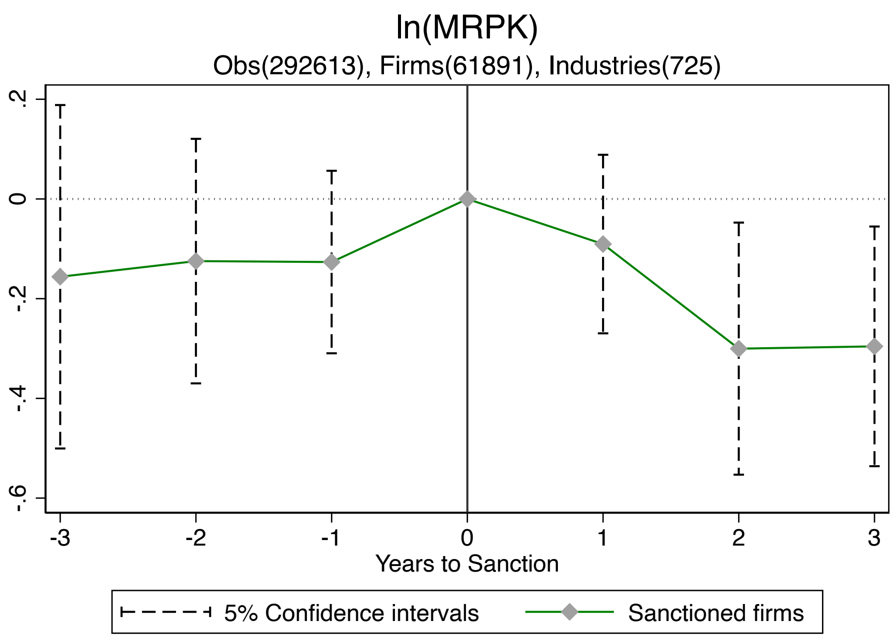
(d) MRPL



(e) TFPR

Notes: The plots show the kernel density of natural logs of value added, TFPQ, MRPK, MRPL and TFPR. 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. Labor 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 $TFPQ_i = \kappa \frac{(P_i Q_i)^{\frac{1}{1-\eta}}}{K_i^{\alpha} L_i^{1-\alpha}}$. Each measure is directly calculated from the raw data in 2018.

Figure 2.A1: Allocations of SOEs versus the private sector



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 sample used in this regression is constant and includes firms that are observed three years prior and three years after the sanctions announcement. 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 MRPK dependent variable is in logs. The confidence intervals are at the 95% level.

Figure 2.A2: Constant sample SSI event study

14 Appendix C. 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.