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

NBER SI

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Motivation

"Comprehensive economic sanctions have an indiscriminate impact on a country and can entail severe negative humanitarian consequences for the civilian population and third countries." (State Secretariat for Economic Affairs SECO, Switzerland)

- "Smart sanctions" - hurt the elites and not the average citizen.
- The US has over 70 countries under such sanctions today (Felbermayr et al. 2020).
- But: little evidence on how targets respond and on collateral damage on the rest of the economy.
- Evidence on targeted sanctions - sanctions against specific strategic firms in 2014-2020 in Russia. Data on 600,000 Russian firm balance sheets.

Motivation

- Sanctions target strategic, "important" firms $\Rightarrow$ the impact of sanctions on the rest of the country is ex-ante non-trivial:

Strategic firms are productive Shrink after sanctions -> Country TFP declines	vs	Strategic firms are **not** productive Shrink after sanctions -> Country TFP increases

- Government may respond endogenously to protect targeted firms, reallocating resources towards targets
- The sanctions episode 2014-2020 in Russia - an ideal setting

This Paper

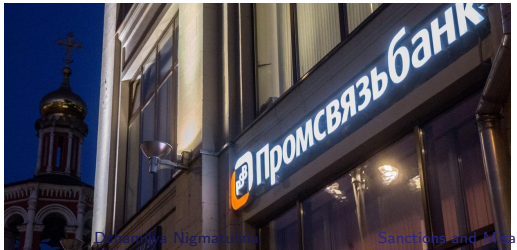
- How sanctions affect the sanctioned firms and (the TFP of) the overall economy?
- **D-i-D** The role of sanctions+government response on firms.
  - A natural experiment of US sanctions, rolled out in 2014 - 2020
- **Misallocation framework** Use a framework to get 1) sufficient statistic for being "over-" or "under-resourced" for each firm
- **D-i-D + Framework** Feed back the estimates from the D-i-D into two different frameworks to estimate the aggregate effect of sanctions on country's TFP: (use Hsieh and Klenow (2009), Levinsohn and Petrin (2012), and Baquaee and Farhi (2020))

Findings

- US sanctions targeted over-resourced firms.
- Sanctioned firms saw a **boost** in capital, revenue, and assets after sancitons, linked to increased subsidies, contracts, and short-term loans.
- Instead of correcting resource misallocation, sanctions worsened allocation (due to government protection measures).
- The combination of sanctions and government intervention led to a GDP reduction of up to 1%.

Examples: Stroigazmontazh and Promsvyazbank

- Case 1:
  - 2014: Arakdy Rotenberg is sanctioned
  - 2015: Stroigazmontazh (owned by Rotenberg) wins the government contract of 223,1 bln roubles to build the bridge to Crimea.
- Case 2:
  - Promsvyazbank re-purposed to compensate the losses from sanctions of Russia's defence sector.





Contributions to the Literature

- **The effects of economic sanctions** (Ahn & Ludema 2020, Tuzova & Qayum 2016, Crozet & Hinz 2016, Haidar 2017, Draca et al. 2019, Stone 2016, Gold et al. 2019, Mamonov and Pestova 2022).
  - Quantify the effect of sanctions on the economy through aggregate TFP
- **Effects of political connections for firm-level outcomes** (Hsieh & Song 2015, Berkowitz et al. 2017, Brandt et al. 2018, Bussolo et al. 2019, Brown et al. 2006).
  - Highlight a novel mechanism of how politically connected firms are (over-) protected from a negative shock
- **Allocative efficiency for aggregate outcomes** (Hsieh & Klenow 2009, Restuccia & Rogerson 2008, Baqaee & Farhi 2020, Busso et al. 2013)
  - One of the first papers to combine causal inference and a misallocation framework (along with Rotemberg 2019, Bau & Matray 2020)

Roadmap

1. **Modelling misallocation** to quantify pre-existing distortions
2. **Data** : 900k firms and sanctions
3. **D-i-D**: Quasi-experiment of sanctions
4. **Frameworks + D-i-D**: Aggregate effects of sanctions on TFP
5. Counterfactual exercises: how large are the aggregate effects relative to baseline misallocation?

Misallocation Framework

- An efficient, or distortion-free, allocation would be one in which the marginal value product of inputs is equalised across production units.
- **Stylized example**:
  - An industry with two firms: Rosneft (SOE, politically connected), and a private firm, Lukoil
  - Rosneft's marginal value product of capital is \$5 and Lukoil's is \$10.
  - Taking one unit of capital from Rosneft to Lukoil will increase the output in the industry by \$5.
  - Reallocate up until the marginal value product of capital is the same between Rosneft and Lukoil to attain the highest output in the industry using existing inputs.

Misallocation Framework

- I model misallocation as implicit taxes (or "wedges") on the prices of inputs

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

- The profit-maximizing firm will equalize the marginal revenue product to the marginal cost of input.

$$\{K_i\} : p_i \frac{\partial F_i(K_i, L_i)}{\partial K_i} = (1 + \tau_i^K) r \equiv MRPK_i \tag{2}$$

$$\{L_i\} : p_i \frac{\partial F_i(K_i, L_i)}{\partial L_i} = (1 + \tau_i^L) w \equiv MRPL_i \tag{3}$$

- Key idea: in the absence of wedges (τ_i^L and τ_i^K), MRPK and MRPL should equalize, since if not, the inputs would flow to the firms that would generate more value added on the margin.

Assumption to calculate MRPK and MRPL

Cobb-Douglas firm production function

- allows to use share of capital and labor in revenue to back out MRPK and MRPL directly in the data

$$\{K_i\} : \alpha_s \frac{p_i F_i(K_i, L_i)}{K_i} = (1 + \tau_i^K) r \equiv MRPK_i \tag{4}$$

$$\{L_i\} : (1 - \alpha_s) \frac{p_i F_i(K_i, L_i)}{L_i} = (1 + \tau_i^L) w \equiv MRPL_i \tag{5}$$

Firm data

- ~900k firms from Spark Database
- balance-sheet, tax, employment, ownership information and government contracts at the firm-by-year level.
- private and state-owned firms covering manufacturing, agriculture and services sectors.
- years 2012-2020
- representative panel of medium and large firms
- these firms' value added covers 61% of Russian value added (and revenues more than 1.5 times of the Russian GDP)

Coverage of the Russian economy

Sanctioned vs non-sanctioned

- The US imposed two types of sanctions in years 2014-2020 in a staggered fashion
  - **Input sanctions** or "SSI" (ban on long-term loans and other imported inputs), against firms
  - **Blocking sanctions** or "SDN" (ban on any transaction, e.g. export, import, lending, issuing stock, leasing), against individuals and firms
- **How were targets chosen?** "oligarchs who profit from [Russia's] corrupt system", those operating in Russia's arms or related materiel sector; entities owned or controlled by a senior Russian government official, entities and individuals operating in specified sectors of the Russian economy (Congressional Research Service, 2020)

Sanctions Data

- The SSI and SDN sanctions extend on any firm owned by a sanctioned individual or firm by more than 50 per cent ("OFAC rule of 50")
- A firm is sanctioned if
  - the firm is listed by the US Department of Treasury
  - the firm is a historical majority-owned subsidiary of the above
  - if the firm is owned by or a subsidiary of the firm owned by an SDN individual (using First, Middle and Last name match) with confirmed ownership at the time of imposition of sanctions
- I study both types of sanctions, input sanctions and blocking sanctions, together and separately.

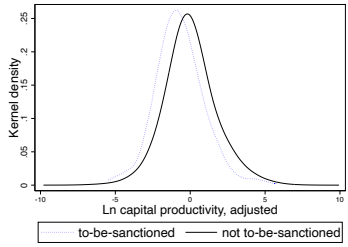
Sanctions by type and ownership

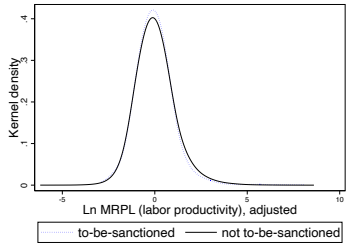
		Ownership
Sanction type	Number	Share state-owned
SDN	277	19%
SSI	397	12%
SSI and SDN	458	17%
Total	1,132	16%

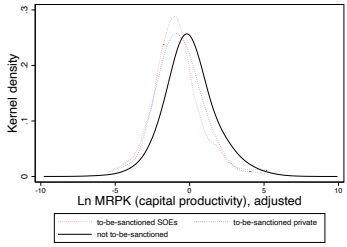
Table: 1. Sanctions by ownership

In the overall firm sample, only 4% of all firms are SOEs.

Existing distortions. Sanctioned vs non-sanctioned firms







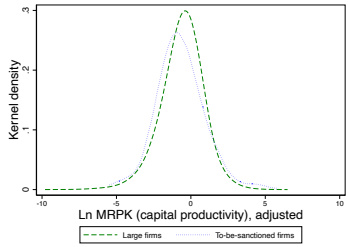


Figure: Firms before 2015 (time-invariant component, de-meaned by 4-digit industry)

Estimating Equation

$$Y_{ijt} = \phi_i + \gamma_{jt} + \theta_{st} + \beta_1 Sanction_{it} + u_{ijt} \tag{6}$$

- Y_{it} is $ln(MRPK_{ijt})$, $ln(K_{ijt})$, $ln(ValueAdded_{ijt})$, $ln(Revenue_{ijt})$ and other firm-level variables.
- $Sanctions_{it}$ is the time-variant sanctions dummy at firm-level
- ϕ_i is firm FE
- γ_{jt} is a 4-digit industry-year FE
- θ_{st} size-by-year fixed effects

- Cluster the errors two-way: by firm and 4-digit-industry-by-year.

Sanctions raised inputs

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

Clustering: Firm and industry-by-year

Table: 2. Average effects of firm-specific sanctions on inputs

Pre-trends: capital | Pre-trends: materials | Pre-trends: labor
Pre-trends within treated: capital | Pre-trends within treated: materials | Pre-trends within treated: labor
De Chaisemartin and d'Haultfoeuille estimator: capital

Sanctions raised outputs

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

Clustering: Firm and industry-by-year

Table: 3. Average effects of firm-specific sanctions on outputs

Pre-trends: revenue
Pre-trends within treated: revenue
De Chaisemartin and d'Haultfoeuille estimator: revenue

Sanctions worsened misallocation of capital

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

Clustering: Firm and industry-by-year

Table: 4. Average effects of firm-specific sanctions on misallocation

Pre-trends: MRPK
Pre-trends within treated: MRPK
De Chaisemartin and d'Haultfoeuille estimator: MRPK

Channels: contracts and subsidies increased

	(1) Ln Subsidy Volume	(2) Got a Subsidy	(3) Ln Contract Volume	(4) Become a Supplier
Any Sanction	1.146*	0.010***	0.337***	0.051***
	(0.646)	(0.003)	(0.122)	(0.013)
Firm FE	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓
Size-year trends	✓	✓	✓	✓
Firms	173	686641	140152	686641
Sanctioned firms	12	935	591	878
Industries	27	862	704	862
Observations	632	3944233	605914	3944233
R-squared	.703	.446	.762	.502

Clustering: Firm and industry-by-year

Pre-trends: Contracts
Pre-trends: Subsidies

Channels: short-term loans increased

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

Clustering: Firm and industry-by-year

Pre-trends: Loans

Robustness Checks

- Main results, gradually adding FE result
- Firm exit result
- Spillovers result
- SSI versus SDN sanctions result
- Heterogeneity of effects result
- Heterogeneity of effects by strategic status result
- Effect on A_i (or $TFPQ_i$) result
- Raw mean changes, treatment and control result

Aggregate effects?

- Use two frameworks to aggregate the effects from the D-i-d and be able to compare to other papers:
  - Hsieh and Klenow model as baseline (shortcut and full model)
  - Levinsohn and Petrin (2012), as reformulated by Baquaee and Farhi (2019)
  - Full Baquaee and Farhi (2020)

- I calibrate the frameworks to the Russian economy (and Russian distortions, corrected for measurement error)
- I plug the estimates from the regressions on inputs and change in MRPK (proxy for wedges) to get ΔTFP.
- **Why not get ΔGDP?** Empirically, it is impossible to causally separate the aggregate K changing in Russia due to sanctions (from the oil price shock, currency devaluation, other Macro effects)

Hsieh and Klenow: Intuitive Shortcut

Shortcut (for intuition): if A_i and $TFPR_i$ are jointly lognormally distributed (and the physical productivity (A_i) of the firms stays the same):

$$\Delta logTFP_s = -\frac{\sigma}{2} * VAR(logTFPR_i + \alpha \Delta logMRPK_i) \tag{7}$$

- $\Delta logMRPK_i$ is taken from **Table 4, column 1**.
- $logTFPR_i \equiv log(\frac{p_i F_s(K_i, L_i)}{K_i^{\alpha_s} L_i^{1-\alpha_s}}) \propto log(MRPK_i^{\alpha_s} * MRPL_i^{1-\alpha_s})$ is obtained by regressing $logTFPR_{it}$ on year and firm fixed effects using the pre-period sample.
- ΔTFP is a geometric average of TFP_s using sectoral shares of value added in total GDP (θ_s) as weights.

Full model

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- ΔTFP is a geometric average of TFP_s using sectoral shares of value added in total GDP (θ_s) as weights.

Full model

Baquaee and Farhi (2019) and Levisohn and Petrin (2012)

Like Bau and Matray (2023), I adapt their version of the expression to aggregate the changes of capital inputs between distorted producers. (I assume that the change in A_i is 0)

$$\Delta log(TFP_s) \approx \sum_{i \in s} \lambda_i \alpha_i^K \frac{\tau_i^K}{1 + \tau_i^K} \Delta \log K_i \tag{8}$$

where $i \in s$ is a set of firms and s is the set of industries.

Aggregate results

Framework	ΔTFP
Hsieh and Klenow, jointly log-normal assumption	-0.33%
Hsieh and Klenow, full model	-0.10%
Levinsohn and Petrin (2012)	-1.02%
Baquaee and Farhi (2020)	-0.10%

Table: Change in aggregate TFP due to the joint effect of sanctions and government support

How does the $\Delta logTFP_s$ compare to the existing TFP gaps?

How I quantify TFP gaps

- Measure overall TFP gap: 51.1 percentage points
- Measure the TFP gap between the sanctioned and non-sanctioned firms: 30.5% of the overall TFP gap Counterfactual result

Conclusion

- Sanctions, combined with shielding have led the targeted firms to gain 38% more capital and 21% more revenue relative to a non-sanctioned firm.
- Allocation of resources worsened.
- Subsidies and contracts were likely allocated at the expense of everyone else.

Result:

- **Did sanctions bring collateral damage?** Nothing but collateral damage (but, it was self inflicted)
- Were sanctions "effective"? No: elites became empowered, rather than "split"

VoxEU summary



Paper & updates



Full model of the economy

- **Level 1**

$$Y_{si} = A_{si} K_{si}^{\alpha_s} L_{si}^{1-\alpha_s} \tag{9}$$

- **Level 2**

$$Y_s = \sum_i \left(Y_{si}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{10}$$

- **Level 3**

$$Y = \prod_{s=1}^{S} Y_s^{\theta_s} \tag{11}$$

where $\sum_i^S \theta_s = 1$

back

TFP from the model structure

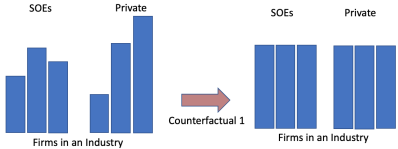
- Country TFP is the Cobb-Douglas average of the Solow residual in each sector after accounting for total inputs used in each sector.

$$Y = \prod_{s=1}^{S} (TFP_s K_s^{\alpha_s} L_s^{1-\alpha_s})^{\theta_s} \tag{12}$$

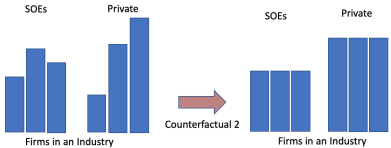
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Counterfactuals: Measuring the contribution of wedges between groups of firms to misallocation

- **Counterfactual 1** Equalize MRPK and MRPL within each four-digit industry, keeping total industry capital and labour fixed, calculate the TFP in each industry. formula



- **Counterfactual 2** I equalize MRPL and MRPK only within ownership-by-industry groups formula



- Compare the resulting aggregate TFP's.

back

Counterfactual Results: TFP gap due to SOEs

TFP*: Equalize all wedges within industries
TFPc: Equalize wedges within status-industry groups

Measures	Count	TFP/TFP*	TFPc/TFP*	Gap due to between-group wedge
To-be-sanctioned versus not	57,279	49.9%	84.7%	30.5%

Table: Counterfactual exercises

- The sanctioned vs non-sanctions wedge explains [(100-84.7)/(100-49.9)=30.5%] of the distance to the frontier.
- Sanctions explain about 1% of the "sanctioned group"-driven distance to the frontier

back

Event study on capital

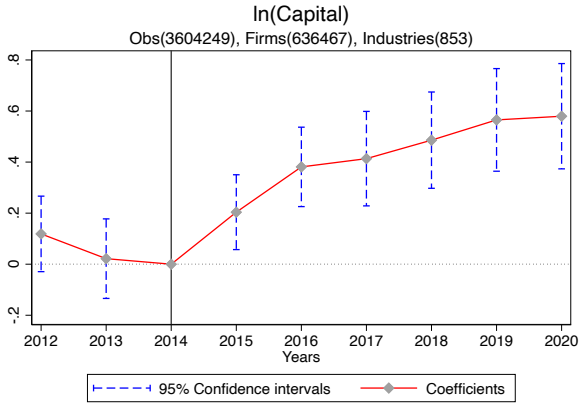


Figure: Event study relative to year 2014: capital.

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Event study on MRPK

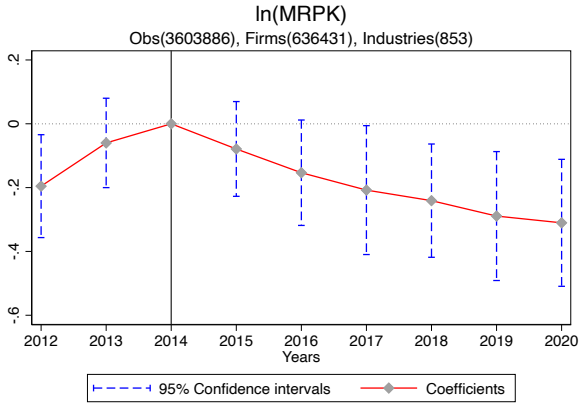


Figure: Event study relative to year 2014: MRPK.

back

Event study on MRPK, within sanctioned

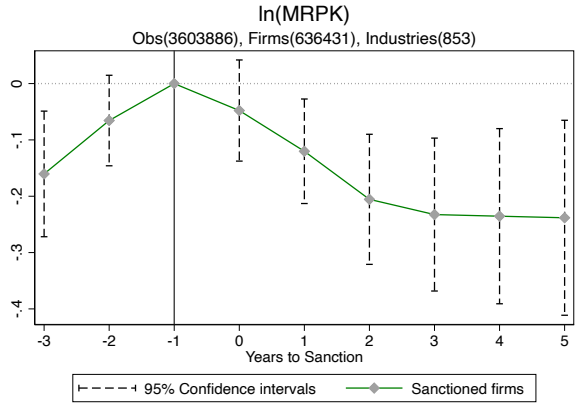


Figure: Event study relative to the year of treatment: MRPK.

back

Event study on Contracts

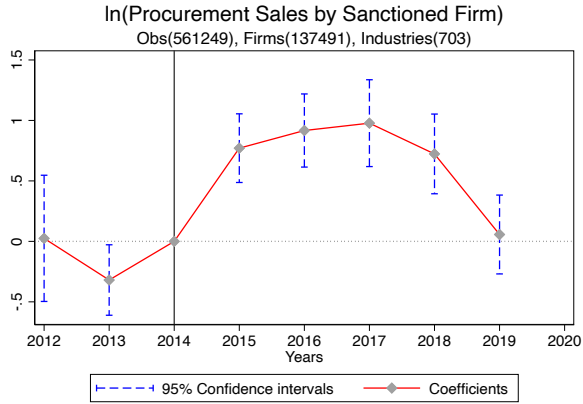


Figure: Event study relative to year 2014: Contracts.

back

Event study on Subsidies

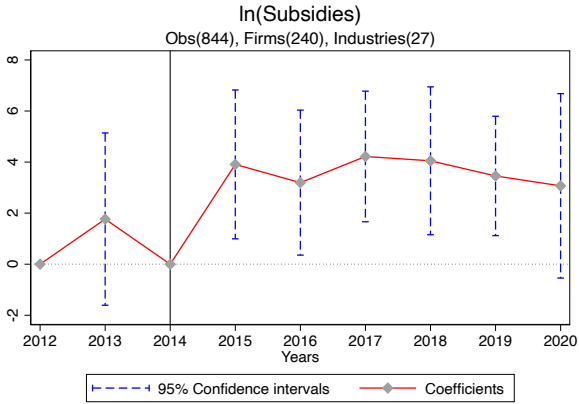
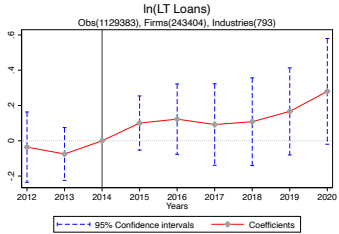
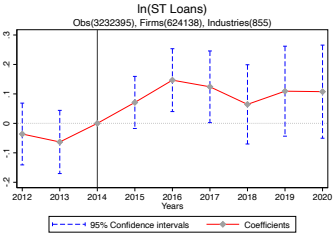


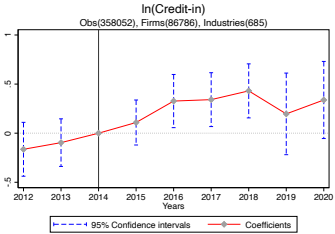
Figure: Event study relative to year 2014: Subsidies.

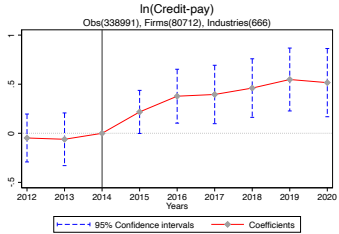
back

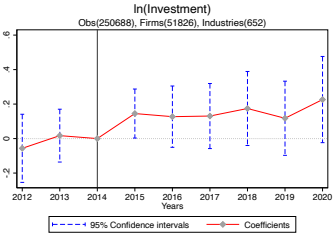
Event study on Loans











back

SSI sanctions versus SDN sanctions

back

	(1) Ln Book Value of Capital	(2) Ln Revenue	(3) Ln MRPK	(4) Ln Book Value of Capital	(5) Ln Revenue	(6) Ln MRPK
SSI Sanction	0.350***	0.201**	-0.112	0.293***	0.233***	-0.050
	(0.077)	(0.083)	(0.088)	(0.084)	(0.087)	(0.098)
SDN Sanction	0.350***	0.168***	-0.160**	0.334***	0.124**	-0.169**
	(0.074)	(0.057)	(0.064)	(0.080)	(0.062)	(0.074)
SDN Sanction × SSI Sanction	-0.144	0.006	0.132	-0.141	0.058	0.198
	(0.114)	(0.131)	(0.125)	(0.126)	(0.149)	(0.140)
SSI Sanction × SOE				0.399**	-0.220	-0.398**
				(0.172)	(0.255)	(0.172)
SDN Sanction × SOE				0.092	0.239*	0.041
				(0.164)	(0.136)	(0.122)
SDN Sanction × SSI Sanction × SOE				-0.117	-0.219	-0.253
				(0.262)	(0.314)	(0.265)
Firm FE	✓	✓	✓	✓	✓	✓
Year FE						
2-digit industry-yr FE						
4-digit industry-yr FE	✓	✓	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓	✓	✓
Firms	678994	635156	628068	678994	635156	628068
Sanctioned firms	928	916	910	928	916	910
Industries	862	842	842	862	842	842
Observations	3852607	3577822	3502744	3852607	3577822	3502744
R-squared	.889	.858	.842	.889	.858	.842

Clustering: Firm and industry-by-year

Table: ?? Average effects of sanctions by sanction type

Robustness to different fixed effects

	(1) Ln Book Value of Capital	(2) Ln Revenue	(3) Ln Book Value of Capital	(4) Ln Revenue	(5) Ln Book Value of Capital	(6) Ln Revenue	(7) Ln Book Value of Capital	(8) Ln Revenue
Any Sanction	0.266***	0.173***	0.297***	0.153***	0.241***	0.113**	0.209***	0.122**
	(0.056)	(0.051)	(0.057)	(0.051)	(0.055)	(0.050)	(0.056)	(0.051)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE			✓	✓				
2-digit industry-yr FE					✓	✓		
4-digit industry-yr FE							✓	✓
Size-year trends								
Firms	1126137	1140294	1126137	1140294	1126134	1140290	1126077	1140215
Sanctioned firms	1244	1277	1244	1277	1244	1277	1244	1277
Industries	919	910	919	910	917	908	872	862
Observations	5369531	5270905	5369531	5270905	5369511	5270885	5369158	5270507
R-squared	.883	.848	.883	.848	.884	.85	.885	.85

Clustering: Firm and industry-by-year

Table: **??**. Robustness of the main results to the different fixed effects

back

Event study on materials

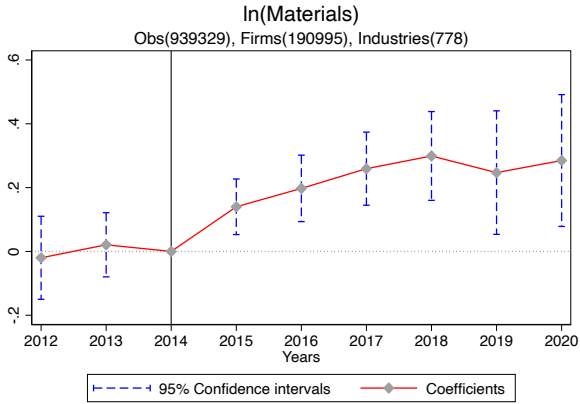


Figure: Event study relative to year 2014: materials.

back

Event study on labor

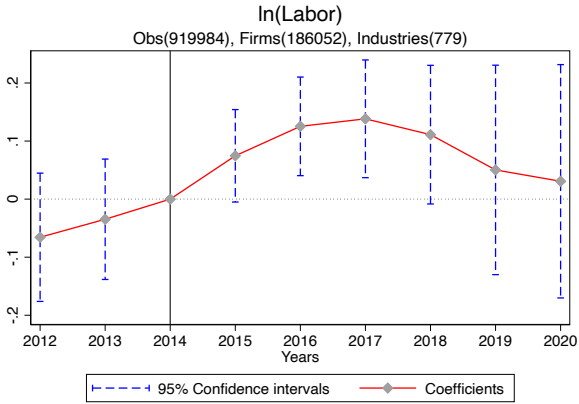


Figure: Event study relative to year 2014: labor.

back

Event study on capital, within sanctioned

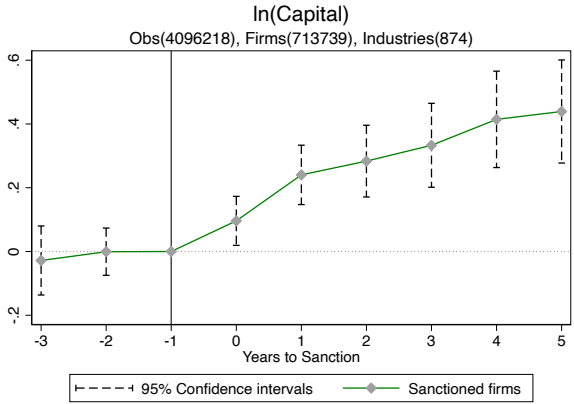


Figure: Event study relative to year 2014: capital.

back

Event study on materials, within sanctioned

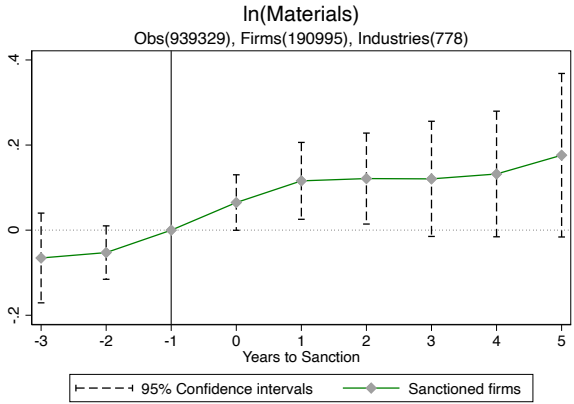


Figure: Event study relative to year 2014: materials.

back

Event study on labor, within sanctioned

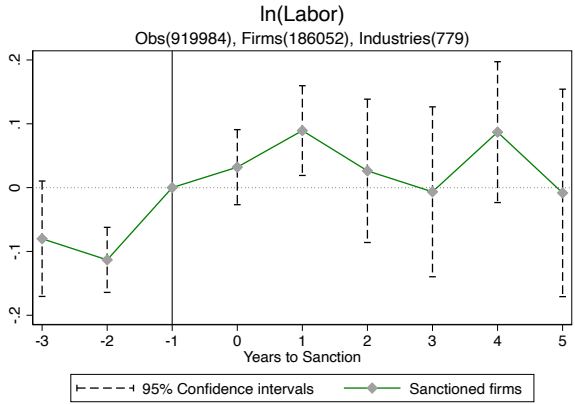


Figure: Event study relative to year 2014: labor.

back

Event study on Capital, De Chaisemartin and Haultfoeuille estimator

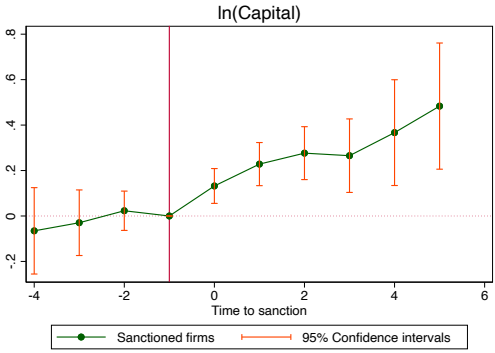


Figure: Event study relative to the year of sanctioning: capital.

back

Event study on Revenue, De Chaisemartin and Haultfoeuille estimator

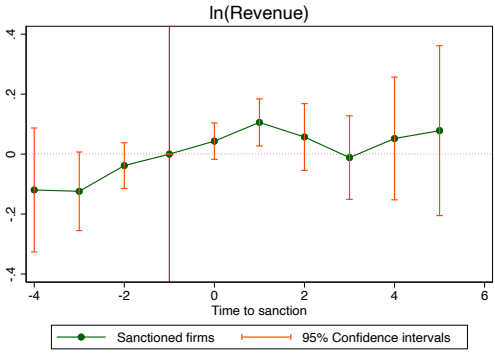


Figure: Event study relative to the year of sanctioning: revenue.

back

Event study on MRPK, De Chaisemartin and Haultfoeuille estimator

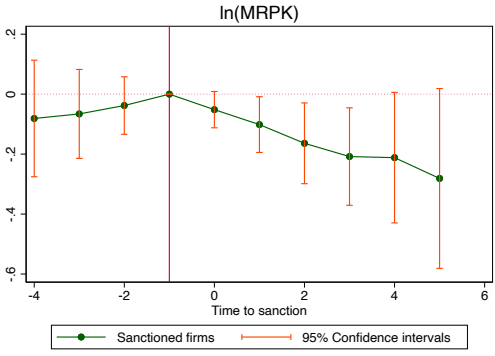


Figure: Event study relative to the year of sanctioning: MRPK.

back

Event study on revenue

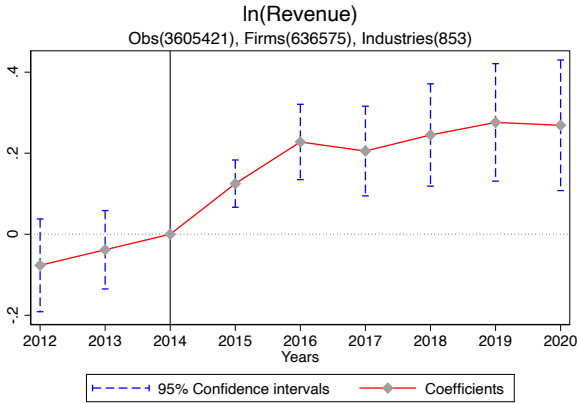


Figure: Event study relative to year 2014: labor.

back

Event study on revenue, within sanctioned

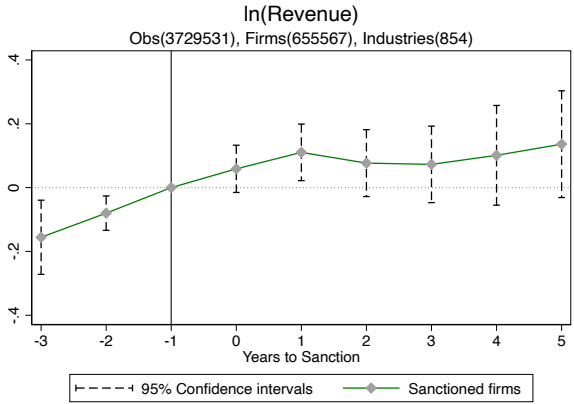


Figure: Event study relative to year 2014: revenue.

back

TFPR formula

Assuming Cobb-Douglas production function (with the same exponents within an industry s), I also define a summary measure of the wedges with respect to both inputs:

$$TFPR_i \equiv \frac{p_i F_s(K_i, L_i)}{K_i^{\alpha_s} L_i^{1-\alpha_s}} \propto MRPK_i^{\alpha_s} * MRPL_i^{1-\alpha_s} \tag{13}$$

back

Wedges between SOEs and private firms

- One can derive group wedges by equalizing all wedges within a group and only keeping the wedges across groups.
- This is equivalent to redistributing group capital and labor efficiently within the group

$$TFPR_{priv} = \frac{\left(\sum \left(\frac{A_i}{\kappa}\right)^{\frac{1-\eta}{\eta}}\right)^{\eta}}{\left(K_{priv}\right)^{\alpha\eta}\left(L_{priv}\right)^{(1-\alpha)\eta}} \tag{14}$$

Where $\eta = 1/\sigma$

back

Framework

- Model a-la Hsieh and Klenow: misallocation across firms within industry

$$\pi_i = P_i Q_i - (1+\tau_i^L) w L_i - (1+\tau_i^K) r K_i \tag{15}$$

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

$$\{L_i\} : (1-\alpha) \left(\frac{\sigma-1}{\sigma} \right) \frac{P_i Q_i}{L_i} = (1+\tau_i^L) w \equiv MRPL_i \tag{16}$$

$$\{K_i\} : \alpha \left(\frac{\sigma-1}{\sigma} \right) \frac{P_i Q_i}{K_i} = (1+\tau_i^K) r \equiv MRPK_i \tag{17}$$

back

Framework

- One can define a summary statistic of both labor and capital wedges, name it "TFPR"

$$TFPR_i \equiv \frac{P_i Q_i}{K_i^{\alpha} L_i^{1-\alpha}} \propto MRPK_i^{\alpha} * MRPL_i^{1-\alpha} \tag{18}$$

- Knowing the elasticity of substitution, one can get an expression for the firm TFP (or productivity) object, the "TFPQ":

$$TFPQ_i \equiv TFP_i \equiv A_i \propto \frac{(P_i Q_i)^{\frac{\sigma}{\sigma-1}}}{K_i^{\alpha} L_i^{1-\alpha}} \tag{19}$$

Where $\eta = 1/\sigma$ back

Framework

@hookitemize

The overall industry productivity depends on the variance of MRPK and MRPL (or the variance of the TFPR).

The lower is the variance, the higher is the aggregate industry TFP

$$TFP_s = \left(\sum_i \left(A_i \left(\frac{\overline{MRPL}}{MRPL_i} \right)^{1-\alpha} \left(\frac{\overline{MRPK}}{MRPK_i} \right)^{\alpha} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{20}$$

$$TFPe_s = \left(\sum_i \left(A_i^{\sigma-1} \right) \right)^{\frac{1}{\sigma-1}} \tag{21}$$

back

In which sectors SOEs are more productive

Out of 80 sectors, TFPR is higher for SOEs in the following sectors only:

- Manufacture of textiles
- Provision of services in the field of elimination of the consequences of pollution
- Film, video and television program production, sound recording and sheet music
- Activities auxiliary to financial services and insurance

back

Regression Results, Entry and Exit

back

	(1) Exit share	(2) Stop Report Share	(3) Exist dummy	(4) Report dummy
Any Sanction	-0.018***	-0.047***	0.002*	0.055***
	(0.002)	(0.004)	(0.001)	(0.007)
Firm FE			✓	✓
Industry-year FE	✓	✓	✓	✓
Size-year FE			✓	✓
Firms			721884	721884
Sanctioned firms			936	936
Industries	247	247	874	874
Observations	3508	3508	4196031	4196031
R-squared	.568	.566	.514	.693

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

Table: Average effects of sanctions: endogenous exit

Heterogeneity

	(1) Ln Revenue	(2) Ln Book Value of Capital	(3) Ln Revenue	(4) Ln Book Value of Capital	(5) Ln Revenue	(6) Ln Book Value of Capital	(7) Ln Revenue	(8) Ln Book Value of Capital	(9) Ln Revenue	(10) Ln Book Value of Capital
Any Sanction	0.218***	0.346***	0.180**	0.285***	0.257***	0.377***	0.225***	0.376***	0.152**	0.328***
	(0.062)	(0.067)	(0.082)	(0.073)	(0.065)	(0.066)	(0.061)	(0.063)	(0.065)	(0.070)
Any Sanction × Direct sanction dummy	-0.028	-0.002								
	(0.113)	(0.121)								
Any Sanction × SDN Sanction			0.052	0.103						
			(0.096)	(0.089)						
Any Sanction × (max) minority					-0.142	-0.158*				
					(0.089)	(0.086)				
Any Sanction × energy							-0.104	-0.197		
							(0.109)	(0.148)		
Any Sanction × exporter									0.236**	0.071
									(0.093)	(0.102)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firms	635156	678994	635156	678994	635156	678994	635156	678994	635156	678994
Sanctioned firms	916	928	916	928	916	928	916	928	916	928
Industries	842	862	842	862	842	862	842	862	842	862
Observations	3577822	3852607	3577822	3852607	3577822	3852607	3577822	3852607	3577822	3852607
R-squared	.858	.889	.858	.889	.858	.889	.858	.889	.858	.889

Clustering: Firm and industry-by-year

Table: Heterogeneity

back

Strategic Firms

	(1) Ln Revenue	(2) Ln Book Value of Capital	(3) Ln Revenue	(4) Ln Book Value of Capital	(5) Ln Revenue	(6) Ln Book Value of Capital	(7) Ln Revenue	(8) Ln Book Value of Capital	(9) Ln Revenue	(10) Ln Book Value of Capital
Any Sanction	0.202***	0.321***	0.160**	0.309***	0.166***	0.318***	0.152**	0.294***	0.165**	0.279***
	(0.060)	(0.062)	(0.063)	(0.066)	(0.056)	(0.059)	(0.065)	(0.068)	(0.068)	(0.073)
Any Sanction × military	0.066	0.204*								
	(0.096)	(0.113)								
Any Sanction × military supplier			0.279***	0.204**						
			(0.097)	(0.101)						
Any Sanction × system-forming					0.619***	0.396**				
					(0.161)	(0.186)				
Any Sanction × strategic							0.264***	0.236**	0.248**	0.111
							(0.102)	(0.109)	(0.110)	(0.109)
Any Sanction × SOE									-0.098	0.126
									(0.187)	(0.162)
Any Sanction × SOE × strategic									0.111	0.320
									(0.226)	(0.256)
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Industry-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Size-year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firms	635156	678994	635156	678994	635156	678994	635156	678994	635156	678994
Sanctioned firms	916	928	916	928	916	928	916	928	916	928
Industries	842	862	842	862	842	862	842	862	842	862
Observations	3577822	3852607	3577822	3852607	3577822	3852607	3577822	3852607	3577822	3852607
R-squared	.858	.889	.858	.889	.858	.889	.858	.889	.858	.889

Clustering: Firm and industry-by-year

Table: Heterogeneity: Strategic Firms

Data coverage of the economy in 2018

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

Table: Sample used for analysis

back

None or minor spillovers to procurement sellers after sanctions

	(1) ln(Contract Volume)	(2) Become a Buyer	(3) Contract Count
Any Sanction	-0.033	-0.001	-0.004
	(0.046)	(0.000)	(0.002)
Buyer FE	✓	✓	✓
Seller FE	✓	✓	✓
Buyer Industry-year FE	✓	✓	✓
Buyers	8655	8667	8667
Sellers	71890	72249	72249
Sanctioned buyers	576	576	576
Industries of buyers	406	406	406
Observations	526162	530079	530079
R-squared	.595	.233	.216

Clustering: Buyer and Industry of buyer-by-year

back

How I calculate the change in practice.

- Create sanctioned and non-sanctioned groups within each industry, equalizing wedges between firms in the group.
- Allocate capital to the sanctioned group, reducing its MRPK by 10.3% (Table 4).
- Assign remaining capital to the non-sanctioned group.
- Re-calculate new aggregate TFP for each industry and overall, comparing it to the TFP with initial wedge between sanctioned and non-sanctioned firms.
- Observed decline in TFP is approximately -0.1%.

back

Effect on $TFPQ_i$

	(1) ln_Ai	(2) ln_Ai
Any Sanction	-0.047	-0.009
	(0.040)	(0.042)
Any Sanction × SOE		-0.179*
		(0.101)
Firm FE	✓	✓
Industry-year FE	✓	✓
Size-year trends	✓	✓
Firms	134323	134323
Sanctioned firms	811	811
Industries	715	715
Observations	603840	603840
R-squared	.739	.739

Raw mean changes (no time fixed effects)

back

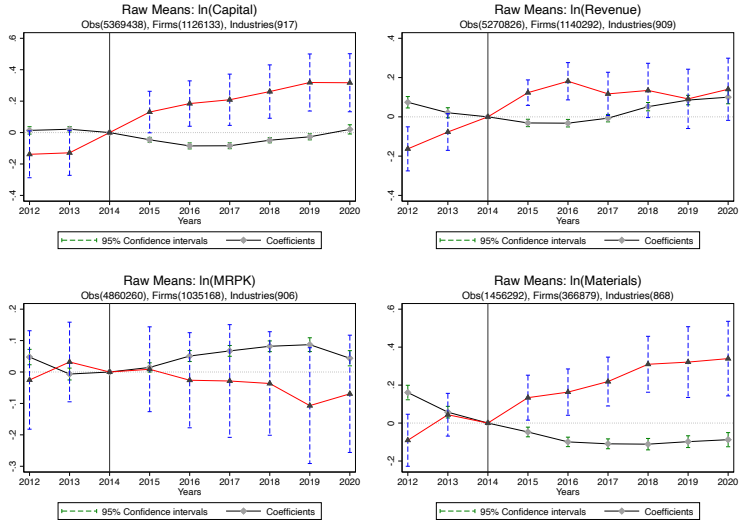


Figure: Raw means: no time controls, just firm FE

Hsieh and Klenow: Full model

- "Horizontal economy", representing each sector s
- TFP_s can be expressed as a function of MRPK and MRPL of each company.

$$TFP_s = \left(\sum_i \left(A_i \left(\frac{\overline{MRPL}}{MRPL_i} \right)^{1-\alpha_s} \left(\frac{\overline{MRPK}}{MRPK_i} \right)^{\alpha_s} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{22}$$

- Plug the changes of $MRPK_i$ from Table 4 and calculate the $\%\Delta TFP_s$

Parameter	Source
α_s	1-labor share in value added for each s
σ	7 (Hsieh and Song 2016)

Full model | Expression for country TFP | Profit maximization | A_i | How I calculate the TFP change in practice

back

Hsieh and Klenow: Full model

- "Horizontal economy", representing each sector s
- TFP_s can be expressed as a function of MRPK and MRPL of each company.

$$TFP_s = \left(\sum_i \left(A_i \left(\frac{\overline{MRPL}}{MRPL_i} \right)^{1-\alpha_s} \left(\frac{\overline{MRPK}}{MRPK_i} \right)^{\alpha_s} \right)^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \tag{22}$$

- Plug the changes of $MRPK_i$ from Table 4 and calculate the $\%\Delta TFP_s$

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Full model | Expression for country TFP | Profit maximization | A_i | How I calculate the TFP change in practice.

back