The Aggregate Costs of Political Connections

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Abstract

This paper quantifies the aggregate costs of political connections using a general equilibrium model in which politically connected firms benefit from output subsidies and endogenously spend resources on rent-seeking activities. The model is structurally estimated using rich firm-level data for the Indonesian manufacturing sector and a firm-level measure of political connectedness based on a natural experiment from the authoritarian rule of Suharto at the end of the 1990s. A major innovation is to flexibly identify the distribution of output subsidies from relative total factor productivity (TFPQ) distributions across connected and non-connected firms. While only 1.3% of firms are connected, I find that connections impose large costs, with permanent consumption losses of 7.4% and output losses of 2.7%. 2/3 of costs are driven by too much dispersion in subsidies across connected firms, while 1/3 are driven by an excessive level of subsidies.

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1 Introduction

What are the economy-wide costs of a few corrupt elites? There is strong anecdotal and quantitative evidence that autocrats and their inner circles obtain special economic privileges for their businesses to amass large fortunes. For example, wealth in excess of one-quarter of GDP was attributed to Putin's inner circle in Russia (Aslund 2019) and Tunisia's former dictator Ben Ali (Rijkers, Freund, and Nucifora 2017). This accumulation of wealth in the hands of a few politically connected elites and their businesses comes, among others, from corruption, unfair competition and systematic property rights violations and therefore is the sign of larger distortions that matter in the aggregate.

This paper systematically quantifies the costs that a few connected firms can pose for the entire economy. A motivating example makes the costs of political connections that this paper quantifies more explicit. In 1996, the Indonesian government decided to promote its national car industry by offering a generous combination of various tax and tariff exemptions to selected firms. Seemingly by coincidence, one day before the policy announcement, Suharto's son created a local car manufacturing company that ended up becoming the sole beneficiary of the government tax exemptions. These tax exemptions were awarded despite the company not operating a single car assembly line. Eventually, another presidential decree by Suharto allowed his son's company to import cars instead and sell these at an effective tax rate that was about 90% lower than that faced by competitors (for details, see Hale 2001). Additionally, the government further supported the company by directly buying its cars. This example illustrates two main economy-wide costs of political connections. First are *misallocation* costs: direct and indirect subsidies led the connected car manufacturer to increase its operations and demand more inputs, pushing up input prices and crowding out productive capital and labor from other firms in the economy. These *misallocation* costs depend crucially on (1) how the government selects connected firms, (2) the extent of the subsidies and (3) whether the subsidies alleviate other distortions in the economy. The second main costs of political connections are *opportunity costs of public funds*: direct and indirect subsidies to connected firms are costly because these resources could be spent on other objectives.

In Indonesia, only 1.3% of firms are connected, but they are disproportionately large, making up 15% of total (value-added) revenue. The average connected firm is around twelve times larger than the average non-connected firm, which also holds within narrowly defined industries. I show this by drawing on detailed annual firm-level manufacturing census data and previous micro-empirical work by Mobarak and Purbasari (2006), who identify connected firms in Indonesia under the authoritarian rule of Suharto at the end of the 1990s using a natural experiment.[1] A key question to quantify

[1] The natural experiment follows Fisman (2001) and identifies all stock-listed firms that benefit from connections by looking at stock-price fluctuations in response to plausibly exogenous shocks to the health of dictator Suharto.

economy-wide distortions from political connections is how much of this size difference is due to political connections and how much is due to other firm fundamentals that we may simply call *productivity*. I use a structural model to disentangle the role of selection from the benefits of political connections and quantify the costs of favors to connected firms. The model is in the tradition of Hsieh and Klenow (2009) with entry and exit dynamics and endogenous rent-seeking. Firms in the model differ in their productivity and their degree of connections, and they spend resources on rent-seeking activities to obtain an output subsidy that can be seen as a reduced-form net transfer from the government.[2] The major methodological innovation of this paper is to identify the unobserved distribution of subsidies from differential distributions in total factor productivity across connected and non-connected firms.

The identification of subsidies is difficult because they do not just enter as "wedges" that distort model-based first-order conditions as usually studied in the misallocation literature, but they also directly distort observed revenue. This means that in the language of Hsieh and Klenow (2009), subsidies – in contrast to wedges – will show up in measured TFPQ rather than TFPR. The methodological contribution of this paper is to show how the relative TFPQ distribution across connected and non-connected firms – the TFPQ quantile ratio – flexibly identifies (i) the technology through which rent-seeking by connected firms leads to subsidies and (ii) the joint distribution of firms' heterogeneous connections and productivity. I find that the TFPQ quantile ratio is strongly hump-shaped, which my model explains through two main features. First, firm productivity and political connections are strongly negatively correlated, in line with evidence from other contexts (e.g. Gonzalez and Prem 2019; Schoenherr 2019). And second, there are not only decreasing returns from rent-seeking, but also costs from public oversight that are increasing in rent-seeking. The economic intuition is that firms optimally trade-off spending rent-seeking activities to obtain subsidies with trying to stay below the radar of public oversight.

Despite noise in the observed TFPQ quantile ratio, the model fits the hump-shaped distribution almost perfectly, with an R^2 of 85%. To further validate the model estimates, I use two sets of untargeted moments. First, I show that while rent-seeking is not directly observable in the Indonesian data, through the lens of the model it can be indirectly inferred from differential spending

Mobarak and Purbasari (2006) then find the remaining connected firms by exploiting a highly concentrated ownership network and link all connected firms to the micro-data.

[2] This subsidy captures many of the channels through which political connections matter, such as lower taxes due to tax avoidance and evasion (Johnson and Mitton 2003; Do, Nguyen, and Tran 2017), output and input subsidies, preferential access to government contracts, state-owned land and natural resources (Brugués, Brugués, and Giambra 2018; Chen and Kung 2018; Schoenherr 2019; Straub 2014; Szucs 2017) as well as preferential access to institutions and infrastructure (Fisman and Wang 2015). While the identification of benefits allows for any combination of these factors, subsequent estimates of aggregate costs rely on the government paying for the benefits and them entering through revenue, as is the case for tax evasion, government subsidies and government demand.

on intermediates by connected firms. I find that the model correctly predicts average differential intermediate shares and that in line with the rent-seeking channel, connected firms in the data spend higher shares on other expenditures such as "royalty fees" and "management fees to third parties". Second, I directly validate the model-implied distribution of rent-seeking, differential profits and subsidy rates using rare quantitative evidence on high-level rent-seeking activities from a different context: the Odebrecht corruption scandal in Latin America (see Campos et al. 2021). These untargeted moments confirm the model-implied combination of high subsidy rates (on average about 44%), relatively low rent-seeking shares (between 2-5% of total sales) and high profit margins for connected firms.

I then use the estimated model to quantify the aggregate costs of political connections by considering a counterfactual economy without political connections where any additional tax revenue is redistributed lump-sum to households. While there is a rationale to subsidize connected firms given the baseline level of a distortive value-added tax, I find that political connections have sizable aggregate costs, with permanent consumption losses of 7.4% and output losses of 2.7%. About 2/3 of the aggregate costs of connections stem from the misallocation induced by the dispersion in subsidies across connected firms, while 1/3 of the costs stem from an excessive level of subsidies that misallocates resources from non-connected to connected firms. Political connections also distort entry and exit. However, the costs of political connections depend on what the government would do in their absence. For example, if the government could spend saved subsidies instead on reducing distortive taxes for everyone, the aggregate costs of connections can be even larger, with output costs more than doubling. To consider more feasible government policy to curb the influence of connections, I finally look at government oversight such as auditing. I find that the current (estimated) level of auditing is far from optimal and that the government could easily double all resources to corruption-related auditing, even under very conservative estimates for their costs.

The structure of the paper is as follows: Below, I discuss the related literature and contribution. Section 2 discusses the data, while Section 3 presents the model, estimation and validation. Section 4 quantifies economy-wide costs. In Section 5, I consider two key extensions. The first combines subsidies and wedges, showing that subsidies explain more than 90% of the costs of connections. The second extension considers industry heterogeneity and linkages through the production network. In line with Liu (2019), I find that the observed concentration of connected firms in upstream industries slightly decreases the aggregate costs of connections. The last section concludes.

Literature

The key contribution of this paper is to provide quantitative estimates of the aggregate costs of political connections in general equilibrium. A growing micro-empirical literature has documented how favors to connected firms drain government resources[3] and lead to large allocative inefficiencies.[4] However, quantifying the aggregate costs of political connections has remained an elusive quest.[5]

Garcia-Santana et al. (2020) consider costs of political connections in general equilibrium but do not have firm-level evidence of political connections, forcing them to draw on sectoral estimates of corruption. The firm-level data allows to estimate firm-level subsidies directly. To the best of my knowledge, this paper is the first to propose a method that allows to test the functional form used for the rent-seeking technology.[6] Flexible identification matters; I find robust evidence for a hump-shaped TFPQ quantile ratio, which the decreasing returns to scale (DRS) rent-seeking technology that is commonly assumed in the literature struggles to explain (e.g. Garcia-Santana et al. 2020; Arayavechkit, Saffie, and Shin 2018; Huneeus and Kim 2021). More importantly, I find that incorrectly assuming the DRS technology leads to very different quantitative results. The DRS technology overestimates consumption losses from political connections by 50% and output losses by more than a factor of two. The reason is that the DRS technology overestimates the amount of subsidies at the left and right tail, precisely because it fails to capture the hump-shaped TFPQ quantile ratio.

Contemporaneous work by Arayavechkit, Saffie, and Shin (2018) and Huneeus and Kim (2021) studies the aggregate costs of lobbying in the US, which they infer from firm-level lobbying expenditures

[3]E.g. Chen and Kung (2018) find that connected firms in China pay between 55-60% less for state-owned land.

[4]Haselmann, Schoenherr, and Vig (2018) show extensive misallocation of bank credit between connected firms and banks in Germany and Schoenherr (2019) finds that politically connected firms in Korea win a larger number of government contracts and that they execute these contracts systematically worse and at higher costs than non-connected firms. Schoenherr (2019) estimates that three quarters of the costs of contract misallocation are due to selecting the wrong firms to give contracts to. Similarly, Brugués, Brugués, and Giambra (2018) find that connected firms are more likely to win discretionary government procurement contracts in Ecuador and that these firms charge higher prices and are less efficient. Szucs (2017) shows that connected firms in Hungary sort into government procurement contracts that are allocated with higher bureaucratic discretion and finds evidence that these connected firms are of lower productivity. In contrast, Bertrand et al. (2018) does not find evidence that connected firms receive higher benefits from the state in France.

[5]Few papers looked at aggregate costs, e.g. Faccio (2006); Fisman (2001); Gonzalez and Prem (2019); Martinez-Bravo, Mukherjee, and Stegmann (2017); Straub (2014); Gonzalez, Prem, and Urz'ua (2018); Chen and Kung (2018); Fisman and Wang (2015); Haselmann, Schoenherr, and Vig (2018); Schoenherr (2019). Notable recent exceptions are Akcigit, Baslandze, and Lotti (forthcoming), Bai, Hsieh, and Song (2020), Garcia-Santana et al. (2020), Arayavechkit, Saffie, and Shin (2018) and Huneeus and Kim (2021). Brugués, Brugués, and Giambra (2018), Szucs (2017) and Koren et al. (2015) also look at costs of rent-seeking focussing exclusively on partial equilibrium effects.

[6]This technology is similar to the idea of a "concealment technology" (Cremer and Gahvari 1994) or evasion technology (e.g. Slemrod and Yitzhaki 2002) used in the tax evasion literature. It is closer to the idea of tax avoidance (see Slemrod and Yitzhaki 2002; Slemrod 2001) in that I model political connections without risk, firms know how much taxes they have to pay and are only uncertain about future tax payments as political connections may change. This seems to be more in line with how connections work in developing countries (e.g. see Hoang 2018; Chen and Kung 2018).

and size distortions. The novelty in both papers is that they directly observe lobbying activity. I study the aggregate costs of rent-seeking in a context that is corruption-rife and non-democratic and where lobbying data is not available and would only capture a small portion of overall rent-seeking behavior. To quantify the aggregate costs of rent-seeking, one requires knowledge on the returns from rent-seeking as well as the extent of rent-seeking. My approach – using only information on standard firm inputs and output as well as whether a firm is connected or not – allows to flexibly identify returns and infer unobserved rent-seeking activities. Given the lack of data on rent-seeking activities – especially in corruption-rife contexts where rent-seeking activities are likely the most harmful – the approach in my paper is applicable across many different contexts.

The paper is also complementary to Bai, Hsieh, and Song (2020) and Akcigit, Baslandze, and Lotti (forthcoming) in that I provide quantitative estimates on the costs and benefits of political connections that help to better understand welfare implications. Bai, Hsieh, and Song (2020) show how bureaucrats in China favor firms to help them avoid bad institutions and growth distorting regulation. I find that costs greatly outweigh benefits on aggregate. Akcigit, Baslandze, and Lotti (forthcoming) show important evidence for dynamic losses from political connections through a lack of innovation. I abstract from such dynamic losses because the data, unfortunately, does not allow me to study how connections change at the firm-level over time. Since I abstract from dynamic losses, I see my estimates as lower bounds on the costs of political connections.

At last, the paper strongly relates to the misallocation literature in emphasizing the difference between subsidies and wedges. While most quantitative empirical work has followed the wedge approach in Hsieh and Klenow (2009) (this also includes Garcia-Santana et al. (2020) and Huneeus and Kim (2021)), I show that (1) subsidies are identified from fundamentally different variation in the data than wedges, and that (2) subsidies can matter far more than wedges. In a main extension of the model that includes both subsidies and wedges, I show that more than 90% of the aggregate costs of political connections are driven by subsidies and not wedges. A key reason for this difference is that subsidies pose real opportunity costs of public funds as they show up in the government budget constraint, in contrast to wedges. This poses as a forceful reminder of the limitations of only focussing on pure misallocation losses.

2 Political Connections in Indonesia

The starting point is a good measure of political connections for which I draw entirely on Mobarak and Purbasari (2006). I first introduce their measure and the firm data and then briefly highlight key empirical regularities that will inform subsequent modelling choices.

Identifying connected firms in Indonesia

Indonesia under the rule of dictator Suharto at the end of the 1990s was characterized by a vast patronage network that extended from the capital city of Jakarta down to the village level (Fisman 2001; Martinez-Bravo, Mukherjee, and Stegmann 2017). By allocating public contracts, concessions, credit, and extra-budgetary revenues, a network of elites closely connected to the state administration was able to amass large amounts of wealth (see Hadiz and Robison 2013; Robison and Hadiz 2004). Such economic systems of patronage are, unfortunately, still widely prevalent around the world (e.g. Aslund 2019; Chen and Kung 2018; Diwan, Malik, and Atiyas 2019). Based on comparative statistics such as Transparency International's Corruption Index, today's Indonesia is similarly corrupt as countries such as Russia, Vietnam, Mexico and Brazil.

There is also strong evidence that political and economic elites held onto power after the fall of the Suharto regime in the aftermath of the Asian Financial Crisis in 1997/8 (see Robison and Hadiz 2004; Martinez-Bravo, Mukherjee, and Stegmann 2017). Still, recent empirical work finds that the eventual democratisation process led to productivity improvements and reductions in frictions among firms (Abeberese et al. 2021) and that this was at least in part driven by an increase in competition after the fall of previously connected firms (Hallward-Driemeier, Kochanova, and Rijkers 2021). In this paper, I will be able to quantify a number of economic mechanisms through which these effects played out.

At the same time, Indonesia is exceptional for providing several rich data sources that have allowed scholars to identify politically connected firms and link these to detailed annual firm-level panel data. Specifically, this paper draws on the Annual Manufacturing Survey (Survei Tahunan Perusahaam Industri Pengolahan) collected by Indonesia's Central Bureau of Statistics (Badan Pusat Statistik), which covers all formal manufacturing establishments with more than 20 employees. Based on the GGDC 10-sector database, these account for about 30% of all value-added manufacturing output in Indonesia (Fentanes and Gathen 2022). The survey contains detailed industry information (up to 5-digit), employment, production, and other firm characteristics and has been used extensively in the Economics literature (e.g. Amiti and Konings 2007). I combine this with the measure of political connections from Mobarak and Purbasari (2006), who identified politically connected firms and already linked these to firms in the survey.

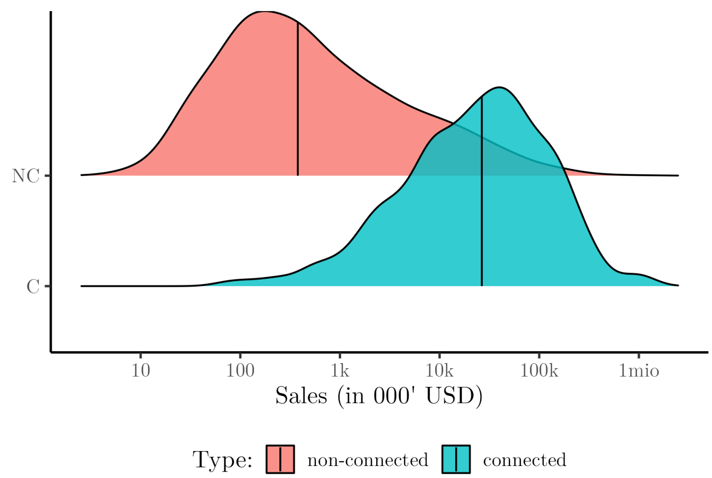
Mobarak and Purbasari (2006) identify connected firms in two different ways. In this paper, I use the union of the two sets of firms as my main measure of whether a firm is politically connected. The first set of firms is identified by tracing firms that were directly owned and founded by blood relatives of Suharto. This set excludes firms whose owners might have strategically married into the Suharto family. For the second and more comprehensive set of firms, Mobarak and Purbasari (2006) draw on the natural experiment in Fisman (2001). Fisman (2001) uses news about plausibly exogenous health issues of dictator Suharto in various periods between 1995-1996 and looks at responses to firms' stock prices on the Jakarta Stock Exchange around these events. The idea is that news about the deteriorating health conditions of the dictator should negatively affect the stock price of firms that benefit from being politically connected to the dictator. The added benefit of the Indonesian context is that the Indonesian regime was highly centralized around the dictator, so shocks to the dictator's health should affect any listed connected firm. Mobarak and Purbasari (2006) then link the identified listed connected firms to non-listed connected firms by tracing all other firms that share ownership and management through conglomerate structures. As Claessens, Djankov, and Lang (2000) and Carney and Child (2013) show, most firms belong to larger conglomerate structures owned by specific families and ownership and control is rarely separated in Southeast Asian firms, including Indonesia. At last, Mobarak and Purbasari (2006) link the set of identified connected firms to the manufacturing census, leaving a sample of 241 firms, of which 89 firms are identified as being owned and founded by blood connections of Suharto.

I provide more detailed information on each of the steps in Appendix A.1. However, it is important to highlight three key features of this data. First, the definition of political connections captures "high-level" political connections and does not capture more local connections of firms to local authorities in the bureaucracy or police. The reason is that the approach only captures firms linked to conglomerate structures that either belong to Suharto's blood family or include at least one listed firm that is identified via the natural experiment. Second, the measure of political connections is different from state-owned enterprises, but there is some overlap. About 16% of connected firms in the data have some state ownership, compared to only 3% among non-connected firms. To ensure that results in the paper are not driven by state ownership, I subsequently control for state ownership in all main results. At last, the approach identifies a snapshot of the connected manufacturing firms in 1994-1997, the accounting years right before the Asian Financial crisis in 1997/8. Throughout, I consider only data before the Asian Financial Crisis, because I do not observe changes in connections after the crisis.

Differences between connected and non-connected firms

Figure 1 shows firm-size differences in total firm sales between connected and non-connected firms for the cross-section of Indonesian manufacturing firms in 1997, the accounting year before the crisis. The average connected firm is about twelve times larger than the average non-connected firm, but there is also considerable overlap in output across the two distributions, as non-connected

Figure 1: Sales Distributions: Connected vs. Non-connected firms



Notes: Sales are annual (deflated) firm gross sales in 000's 2010 USD. Data is for cross-section of Indonesian firms in 1997 based on Statistik Industri, the manufacturing firm census. Connected vs. non-connected firms are identified as in Mobarak & Purbasari (2006). Non-connected firms: N = 18,317. Connected firms: N = 241.

Table 1: Within-industry size ratios of average connected over average non-connected firms

		Within industry			
	unconditional	2-digit	3-digit	4-digit	5-digit
Ratio	11.77	12.62	11	9.44	15.08
# industries	1	9	31	115	302
# industries w/ connected firm	1	9	26	62	103

Details: Size is measured as real gross sales for cross-section of Indonesian manufacturing firms in 1997 based on Statistik Industri. Size ratios are computed based on ratio of average size for connected vs. average size of non-connected firms within each industry and then averaged across industries using the number of connected firms in each industry as weight. Non-connected firms: N = 18,317. Connected firms: N = 241.

feature both the smallest and largest firms in the economy. The size distribution of non-connected firms is visibly more right-tailed and more dispersed. As a measure of the differences in dispersion, the coefficient of variation – the normalized standard deviation – is more than twice as large for non-connected versus connected firms (7.9 vs 3.2).

Table 1 documents average within-industry size differences between connected and non-connected firms, taking a weighted average across industries using as weight the number of connected firms within an industry. Column 1 reports the average size ratio without industry heterogeneity, and Columns 2-5 report ratios looking respectively within 2-, 3-, 4- and 5-digit industries. Even within narrowly defined industries, the average connected firm is between 9 to 15 times larger than the average non-connected firm, suggesting that selection into specific industries does not drive size differences.[7] One key reason is that connected firms are widely distributed across industries. Only

[7] Outliers do not drive this pattern. As shown in Appendix A.2, similar results hold for firms' value-added.

about 1.3% of firms are connected, but connected firms are present in all nine 2-digit, 26 out of 31 3-digit and about one-third of all 302 5-digit industries.

3 Quantifying the role of connections: A structural approach

This section develops a standard model of heterogeneous firms under monopolistic competition to shed light on the large size differences between connected and non-connected firms. In the model, size differences are driven by fundamental differences in idiosyncratic productivity and idiosyncratic political connections that allow firms to obtain output subsidies. The main difference to the standard firm misallocation setup in Hsieh and Klenow (2009) is that the model endogenizes firm-level subsidies through firms' strategic spending on rent-seeking activities and selection into rent-seeking, similar to Garcia-Santana et al. (2020), Huneeus and Kim (2021) and Akcigit, Baslandze, and Lotti (forthcoming). To study the aggregate costs of political connections, I embed the model in a standard general equilibrium model of firm dynamics that features endogenous entry and exit. Finally, I take the model to the data. I show how differences in distributions of productivity (TFPQ) across connected and non-connected firms are key to identify a flexible technology that maps rent-seeking activities into government subsidies, which in turn governs the aggregate costs of rent-seeking.

3.1 Modeling political connections

3.1.1 Household

The household side of the model is kept as simple as possible, featuring a representative household maximizing lifetime discounted utility from consuming an aggregate consumption good:

$$\sum_{t=0}^{\infty} \beta^t U(C_t) \quad \text{with:} \quad U'(.) > 0, U''(.) < 0$$

subject to a per period budget constraint:

$$P_t A_{t+1} + P_t C_t = (1+r) P_t A_t + w_t L_t + P_t T_t$$

where P_t is the price of the consumption good, households provide labor L_t inelastically at potentially time-varying wage w_t, rent assets A_t in the form of capital to firms at lending rate r, and demand consumption goods fully elastically. I assume Indonesia is a small open economy in which the international interest rate net of capital depreciation is exogenously given by $R = r + \delta$. Households further receive net revenue T_t from the government. In line with evidence that firm ownership is highly concentrated in Indonesia (Claessens, Djankov, and Lang 2000; Carney and Child 2013), I assume that firm profits Π_t do not go to households but to absentee owners instead.[8] Throughout, I normalize the price of the consumption good to one.

3.1.2 Production & Firms

On the production side, I start by describing the "within-period" production decisions and move to firm dynamics after. For expositional purposes, I suppress the indexing of time in this subsection. In each period, there exists a competitive final goods producer who uses a continuum of different varieties i to produce an aggregate good Y according to:

$$Y = \left[\int_0^N y_i^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}} \qquad \text{with:} \quad \sigma > 1 \tag{1}$$

where σ captures the elasticity of substitution across varieties. Each variety is produced by a different firm, with a total (endogenous) mass of firms given by N. The aggregate good can be used for final consumption, as capital or as intermediate goods in production. A firm's gross revenues Rev_i are given by:

$$\text{Rev}_i = (1+\tau_i)p_i y_i \quad \text{with} \quad y_i = z_i k_i^{\alpha} l_i^{\beta} m_i^{\gamma} \quad \text{and} \quad \underbrace{(\alpha+\beta+\gamma)}_{\equiv\eta}\left(\frac{\sigma-1}{\sigma}\right) \equiv \tilde{\eta} \in (0,1) \tag{2}$$

z_i captures firm-specific productivity, k_i, l_i & m_i denote the firm's input choices and (α, β, γ) give the output elasticities of capital, labor and intermediates respectively.[9] Throughout, I denote revenue elasticities with a tilde (i.e. $\tilde{\alpha} \equiv \alpha\frac{\sigma-1}{\sigma}$ and correspondingly for β, γ and the joint elasticity η). Crucially, firms face idiosyncratic subsidies τ_i that depend on political connections. Idiosyncratic subsidies τ_i capture in a reduced-form way many of the channels through which connected firms benefit from interactions with the government that were mentioned in the introduction. For the subsequent quantification of the costs of political connections, I treat subsidies as being directly paid by the government, as is the case for a public mark-up – higher output prices that the government pays for. Subsidies also implicitly capture preferential tax cuts or tax evasion. I return to how I model the statutory Indonesian tax system below.

In the model, idiosyncratic subsidies τ_i are endogenous. To make this clear, I also refer to τ as the *Political Connections Technology*. In line with different models of rent-seeking used in the literature

[8]This choice only affects consumption losses from political connections and has no effect on the supply side of the economy.

[9]As is standard for CES setups, z_i captures firm-level productivity and – isomorphically – any firm-level demand shifters (see Appendix A.3.1.). I cannot separately identify the two and for ease of exposition refer to them as productivity throughout.

(e.g. Garcia-Santana et al. 2020; Huneeus and Kim 2021), the *Political Connections Technology* depends on two key inputs: rent-seeking activities m_{Ri} and firm's idiosyncratic level of political connection ε_i. Rent-seeking resources m_{Ri} capture direct bribes to obtain or renegotiate government contracts, push for favorable legislation and subsidies, or receive tax breaks. They also capture two other common forms of rent-seeking activities in developing countries: (1) payments to third parties who specialize in facilitating rent-seeking and corruption (see Hoang 2018), and (2) the total costs incurred by an in-house rent-seeking department in charge of lobbying, tax evasion and bribery (see Campos et al. 2021).

Idiosyncratic connections ε_i capture firms' productivity at obtaining subsidies (or "rent-seeking productivity"), which is potentially correlated with productivity z_i. Access to political connections is given by $\mathbb{P}(\varepsilon > 0) = \pi_C$, which I assume to be a constant probability across firms as in Akcigit, Baslandze, and Lotti (forthcoming). Both access and the degree of political connections are exogenous, capturing the luck involved in having political connections. As in Akcigit, Baslandze, and Lotti (forthcoming) & Huneeus and Kim (2021), the model features endogenous selection into political connections via heterogeneity in ε_i and a fixed cost $F_C \geq 0$ for establishing and maintaining relations with the government. Intuitively, the fixed cost makes it harder for small unproductive firms to become connected (conditional on their ε), while π_C and a low ε_i can explain why many of Indonesia's largest firms are not connected. Throughout, I denote *potential connected firms* as firms with $\varepsilon > 0$ and *connected firms* as *potential connected firms* who also choose to use their connections (i.e. $m_R > 0$) and who I measure as being connected in the data.

How do firms make production and rent-seeking decisions given the *Political Connections Technology* $\tau(m_{Ri}, \varepsilon_i)$? While productivity z_i and connections ε_i may vary across periods, within each period firms take (z_i, ε_i), aggregate prices and quantities (w, R, P, Y), and their downward sloping demand curve as given to choose their inputs (k_i, l_i, m_i), their rent-seeking activities m_{Ri}, and their firm-level price p_i to maximize within-period profits π^*. Firms also face two types of taxes that capture the main features of the Indonesian corporate tax system: a value-added tax τ^V and a corporate income tax τ^C levied on profits π^*.[10] Profits $\pi^*(z_i, \varepsilon_i)$ are given by:

$$\begin{aligned} &\max_{k,l,m,m_R} \left\{ (1-\tau^V) \Big[(1+\tau(m_R,\varepsilon_i)) p y(z_i,k,l,m) - P(m+m_R) - \mathbb{1}_{m_R>0} F_C \Big] - wl - Rk \right\} \\ &\text{subject to:} \quad \pi^{\text{net}} = (1-\tau^C)\pi^*(z_i,\varepsilon_i) \quad \& \quad p = P \cdot Y^{\frac{1}{\sigma}} y(z_i,k,l,m)^{-\frac{1}{\sigma}} \quad \text{(CES demand)} \end{aligned} \tag{3}$$

The following proposition summarizes optimal choices by firms and formalizes that higher subsidies

[10] I set $\tau^V = 0.1$, given the official rate. For the corporate income tax rate, I follow Fentanes & Gathen (2024) in setting $\tau^C = 0.2$, a rate that is representative for the selection of firms in this paper while abstracting from further variation in marginal rates. Note that τ^C does not distort within-period decisions.

(similar to higher productivity) incentivize firms to scale up their production.

Proposition 3.1 (Optimal firm choices)**.** *Assuming firms optimally invest in rent-seeking activities to obtain subsidies τ_i^*, firms' optimal production choices imply revenues and profits that are increasing and convex functions of productivity and subsidies:*[11]

$$
\begin{aligned}
&Rev_i = \tilde{z}_i(1+\tau_i^*)^{\frac{1}{1-\tilde{\eta}}} \quad \& \quad \pi_i^* = (1-\tau^V)\left\{(1-\tilde{\eta})\,\tilde{z}_i(1+\tau_i^*)^{\frac{1}{1-\tilde{\eta}}} - Pm_{Ri}^* - \mathbb{1}_{m_R>0}F_C\right\} \\
&\textit{with: } \tilde{z}_i \equiv [z_i^* x^*]^{\frac{1}{1-\tilde{\eta}}} \;\; \& \;\; z_i^* \equiv z_i^{\frac{\sigma-1}{\sigma}} PY^{\frac{1}{\sigma}} \;\; \& \;\; x^* \equiv \left((1-\tau^V)\frac{\tilde{\alpha}}{R}\right)^{\tilde{\alpha}} \left((1-\tau^V)\frac{\tilde{\beta}}{w}\right)^{\tilde{\beta}} \left(\frac{\tilde{\gamma}}{P}\right)^{\tilde{\gamma}}
\end{aligned}
\tag{4}
$$

As long as an interior solution holds, firms invest in rent-seeking activities m_R^* until marginal costs P equate the marginal benefits of receiving additional subsidies:

$$
P = \frac{\partial \tau_i(m_R^*, \varepsilon_i)}{\partial m_R^*}\tilde{z}_i(1+\tau_i^*)^{\frac{\tilde{\eta}}{1-\tilde{\eta}}} \tag{5}
$$

Proof. The proof including corresponding firm-level prices and input choices are in Appendix A.3.2.

3.1.3 Firm dynamics, entry & exit

Firm dynamics in the model are described by changes in firm-specific productivity z_i and connections ε_i, and by firms' entry and exit decisions. At the beginning of a period, incumbent firms draw their new productivity z_i and new connections ε_i. After observing both, firms make within-period production choices. At the end of the period, firms draw a preference shock for staying in operation and decide whether to exit. Potential entrants have to pay an entry cost to enter and draw their productivity and connections, upon which they act as incumbents.

Dynamics of productivity and connections Both productivity z_i and connections ε_i are persistent, which I model in the following way. Productivity follows a standard persistent AR(1) process according to: $log(z_{i,t}) = \rho_z log(z_{i,t-1}) + \zeta_{i,t}$ with persistence parameter ρ_z and innovation $\zeta_{i,t}$ which is normally distributed with parameters $(\mu_\zeta, \sigma_\zeta^2)$. After drawing productivity z_i, firms draw their new connections ε_i based on the joint distribution of productivity and connections, which I assume to have the following form:[12] $(log(z), \varepsilon) \sim \mathcal{N}(\mu_z, \sigma_z^2, \mu_\varepsilon, \sigma_\varepsilon^2, \rho)$ with CDF $F_{z,\varepsilon}$ and where $(\mu_\varepsilon, \sigma_\varepsilon^2)$ denote the mean and variance of political connections. Importantly, connections and productivity can be flexibly correlated as captured by ρ. The joint distribution implies that

[11] Technically, convexity in productivity only holds as long as: $(\sigma-1)/(\sigma(1-\tilde{\eta})) > 1$ for which $\sigma > 1$ is not sufficient. For the empirical value of $\tilde{\eta}$ in this paper, the condition holds for standard values of σ (i.e. $\sigma > 1.2$).

[12] This specification is identical to concurrent work by Huneeus and Kim (2021), except that I assume connections are normally, rather than log-normally distributed. Quantitatively, I find less skewness in connections to better fit the data.

persistence of ε is a function of the persistence in z, the correlation ρ and the variances $(\sigma_\varepsilon^2, \sigma_z^2)$, which is evident from the implied distribution of ε conditional on z:

$$f_{\varepsilon|z} \sim \mathcal{N}\Big(\alpha_{\varepsilon|z} + \beta_{\varepsilon|z} log(z), \sigma^2_{\varepsilon|z}\Big) \text{ with: } \alpha_{\varepsilon|z} \equiv \mu_\varepsilon - \beta_{\varepsilon|z}\mu_z \;\;\&\;\; \beta_{\varepsilon|z} \equiv \rho\frac{\sigma_\varepsilon}{\sigma_z} \;\;\&\;\; \sigma^2_{\varepsilon|z} \equiv (1-\rho^2)\sigma^2_\varepsilon \quad (6)$$

Since I can only measure political connections at a single point in time, I abstract from additional persistence in access to political connections. That is, firms face a constant $\mathbb{P}(\varepsilon > 0) = \pi_C$ each period. In Section 3.3, I discuss how results would differ with additional persistence.

Exit At the end of a period, firms draw a preference shock for staying in operation $f^F_{i,t}$, upon which they decide whether to continue producing or permanently exit. $f^F_{i,t}$ captures a variety of reasons for why firms may want to exit the market, including changing outside options for entrepreneurs. I assume it is drawn from a distribution G that is Gumbel distributed with scale and variance parameters (μ^X, σ^X). The scale parameter governs the level of exit in the economy, while a larger variance means that reasons for exit are less influenced by firms' productivity, rationalizing strong observed overlap in the productivity distributions of exiting and surviving firms in Indonesia. Firms' exit decisions and ex-ante exit probabilities (before the shock realization $f^F_{i,t}$) are given by:

$$\max\Big\{\frac{1}{1+r}\mathbb{E}_{(\varepsilon',z')|z}V(z',\varepsilon') - f^F_{i,t}, 0\Big\} \;\;\Rightarrow\;\; \mathbb{P}^{\text{Exit}}(z) = G\Big(\frac{1}{1+r}\mathbb{E}_{(\varepsilon',z')|z}V(z',\varepsilon')\Big) \quad (7)$$

where $V(z,\varepsilon)$ denotes the value function of an incumbent who starts the period with z and ε, and where I have suppressed dependence on time given the focus on stationary equilibria.

Entry There is a large pool of potential entrants who can enter by paying an entry cost f^E which I denote in the output good.[13] Upon entry, firms draw their productivity z_i and connections ε_i from the (primitive) joint distribution $F_{z,\varepsilon}$. Potential entrants face the following problem that gives rise to a free entry condition:

$$\max\Big\{\mathbb{E}_{\varepsilon,z}V(z,\varepsilon) - f^E, 0\Big\} \;\;\Rightarrow\;\; \mathbb{E}_{\varepsilon,z}V(z,\varepsilon) = f^E \quad \text{(Free entry condition)} \quad (8)$$

which follows in equilibrium from profit arbitrage as long as there is a positive mass of entrants.

3.1.4 Stationary Equilibrium

Denote by $\mathcal{I}$ the set of active firms in the economy. The focus in this paper is on a *stationary competitive equilibrium* that is described by an international interest rate R, prices $\{w, P, \{p_i\}_{i\in\mathcal{I}}\}$,

[13] I also tried denoting costs in labor as in Klenow and Li (2024) but this was unstable. Details are in Appendix B.

allocations $\{C, A, \Pi, T, Y, \{y_i, k_i, l_i, m_i, m_{Ri}\}_{i\in\mathcal{I}}\}$, aggregate labor supply L and a distribution of active firms $\mathcal{F}_{z,\varepsilon}$ with measure N so that each period:

- the household optimally chooses consumption and savings taking as given $\{P, R, w, \Pi, T\}$
- incumbent firms make optimal input and pricing decisions $\{p, y, k, l, m, m_R\}$ given (z, ε) and $\{P, R, w, Y\}$
- the labor market clears: $L = \int l(z, \varepsilon) d\mathcal{F}_{z,\varepsilon}$
- the government collects taxes, subsidizes connected firms and rebates the rest back to households:

$$\int \Big(\underbrace{\tau^V \left[(1-\tilde{\gamma})\text{Rev}(z,\varepsilon) - Pm_R(z,\varepsilon) - \mathbb{1}_{m_R>0}F_C\right]}_{\text{VAT revenue}} + \underbrace{\tau^C \pi^*(z,\varepsilon)}_{\text{CIT revenue}} - \underbrace{\tau(z,\varepsilon)p(z,\varepsilon)y(z,\varepsilon)}_{\text{Govt Subsidies}} \Big) d\mathcal{F}_{z,\varepsilon} = T$$

- for each (z', ε'), $m(z', \varepsilon')$ – the endogenous measure of firms at (z', ε') – stays constant following:

$$m(z',\varepsilon') = \underbrace{\mathcal{E}(z',\varepsilon')}_{\text{Entrants}} + \underbrace{\int \Gamma(z',\varepsilon'|z)(1-\mathbb{P}^{\text{Exit}}(z))d\mathcal{F}_{z,\varepsilon}}_{\text{Survivors who transitioned to } (z',\varepsilon')}$$

  with $\Gamma(z', \varepsilon'|z)$ giving the transition probability induced by the processes of z and ε and the mass of entrants $\mathcal{E}(z', \varepsilon')$ pinned down by the free entry condition and the primitive distribution $F_{z,\varepsilon}$.

3.2 Estimation

This section discusses model estimation, that is: what in the data allows to pin down the aggregate costs of subsidies to politically connected firms. Through the lens of the model, the aggregate implications of subsidies are ex-ante unclear. Given the baseline distortion of value-added taxes that all firms face, there is a welfare argument for subsidizing connected firms. Specifically, given a distribution of firms, it is optimal to subsidize firms at constant rates in the model studied here (up to small general equilibrium corrections), a result I show formally in Appendix A.3.3. In the end, whether subsidies to connected firms are harmful in comparison to no subsidies to connected firms depends on at least four key margins: (i) How many firms become connected, (ii) the distribution of subsidies, (iii) the extent of socially wasteful spending on rent-seeking activities, and (iv) to which extent connections distort entry and exit in the economy.

Unfortunately, only the first margin is directly observed in the data. Quantifying the remaining three margins requires an estimated model. For this, I separate model estimation into a "within-period" and an "across-period" estimation step. The "within-period" estimation step determines subsidies and rent-seeking activities and thus pins down margins (ii) and (iii). Below, I start by clarifying why estimating the extent of subsidies and rent-seeking activities is empirically challenging. I then discuss estimation of the *Political Connections Technology* and joint distribution of productivity z and connections ε, which pin down subsidies and rent-seeking. Next, I move to the "across-period" estimation step and show how to pin down productivity dynamics and the entry and exit margin from observed firm dynamics. I end the section with a careful validation of the estimates.

3.2.1 The difficulty of identifying subsidies

Why is it difficult to estimate subsidies? As a starting point, one may be tempted to back out the distribution of subsidies using the approach in Hsieh and Klenow (2009), treating subsidies simply as "wedges". The following proposition formalizes why this approach fails.

Proposition 3.2 (Why subsidies are not wedges)**.** *Define TFPR based on Hsieh and Klenow (2009): TFPR-HK*$_i$(*Revenue*) $\equiv \frac{Revenue}{k_i^\alpha l_i^\beta m_i^\gamma}$*. Then with the additional assumption of* $\eta = 1$ *(CRS), variation in TFPR-HK*$_i$ *across firms captures solely variation in subsidies only if observed revenue was reported without subsidies, that is: TFPR-HK*$_i^{CRS}(p_i y_i) = (1+\tau_i^*)^{-1}(x^*)^{-1}$*. As long as observed revenue is distorted by subsidies: TFPR-HK*$_i^{CRS}((1+\tau_i^*)p_i y_i) = (x^*)^{-1}$*, which captures no variation due to subsidies. Without CRS, TFPR-HK generally captures variation due to both* τ_i^* *and* z_i*. Applying the Hsieh and Klenow (2009) approach using distorted revenue attributes subsidies instead to what Hsieh and Klenow (2009) define as TFPQ, i.e. TFPQ-HK*$_i = (1+\tau_i^*)^{\frac{\sigma}{\sigma-1}} z_i$*.*

Proof. All proofs are in Appendix A.3.4.

In short, subsidies are not wedges in that they actually distort observed revenue – a key limitation of the Hsieh and Klenow (2009) approach that is clearly emphasized in the original paper. An alternative estimation approach to disentangle subsidies and productivity is thus needed, drawing directly on (measured) TFPQ variation.

3.2.2 Within-period estimation

I introduce the within-period estimation in three sub-steps. First, I estimate revenue elasticities. Second, I use the estimated revenue elasticities to construct an empirical measure of (residualized) TFPQ variation and formalize how this variation is key for identification. At last, I estimate the remaining "within-period" model parameters. Table 2 provides an overview of all model parameters and their estimates.

Table 2: Overview of parameter identification and estimation

Object	Description	Type	Identification idea	Value
Parameterization:				
β	HH discount rate	F	Standard	0.95
δ	Depreciation rate	F	Standard	0.10
τ^V	Value-added tax (VAT)	F	Official rate	0.10
τ^C	Corporate Income Tax	F	Official rate	0.20
Within-period Estimation:				
Sub-Step: Revenue Elasticities				
$\{\tilde{\alpha}, \tilde{\beta}, \tilde{\gamma}\}$	Capital, Labor, Inputs	F^*	Firms' FOCs	{0.13,0.17,0.54}
$\{w, P, R\}$	Equilibrium prices	E	Normalized/SS value	{1,1,0.15}
Sub-Step: Political Connections Technology				
F_C	Fixed cost of connection	F	min{TFPQ^C}	0
π_C	Probability of connection	F	Share connected firms	0.013
$\{\theta_\varepsilon, c, \theta_c\}$	DRS, cost level & elasticity	F	TFPQ-QR variation	$\{0.20, 1.07\text{e}{-8}, 1.00\}$
$\{\alpha^*_{\varepsilon\|z^*}, \beta^*_{\varepsilon\|z^*}, \sigma^2_{\varepsilon\|z^*}\}$	ε distribution conditional on z	F^*	TFPQ-QR variation	$\{0.08, -0.02, 4.86\text{e}{-7}\}$
ρ	Correlation of ε and z	F	TFPQ-QR variation	-0.999
Across-period Estimation:				
Productivity process:				
$\{\rho_z, \mu_{\zeta^*}, \sigma^2_{\zeta^*}\}$	Persistence, Mean & Var of z	F^*	TFPQ dynamics NC	{0.967,0.090,0.014}
Entry/Exit process:				
$\{\mu^X, \sigma^X\}$	Scale & Var of fixed costs	F	Exit proba over TFPQ	$\{-6.85e7, 3.29e7\}$
f^E	Entry cost	F	Free entry condition	$1.02e7$
For counterfactuals:				
L	Aggregate Labor Supply	F	SS value given $\{N, w\} = 1$	1.49e6
σ	Elasticity of substitution	F	Implied by $\tilde{\eta}$ & CRS	6.16

Details: Types are: F(undamental) and E(quilibrium object). The former stay fixed in counterfactuals, the latter change endogenously. F^* denotes fundamentals that are still functions of the elasticity of substitution and general equilibrium objects, which change endogenously in counterfactuals. The baseline economy is observationally equivalent for different values of the elasticity of substitution, but not counterfactually equivalent.

Estimating revenue elasticities To estimate standard revenue elasticities which are required to construct TFPQ, I draw on the model's first-order conditions for input choices:

$$\tilde{\alpha} = \frac{Rk^*}{(1-\tau^V)\text{Rev}_i^*} \quad \text{and} \quad \tilde{\beta} = \frac{wl^*}{(1-\tau^V)\text{Rev}_i^*} \quad \text{and} \quad \tilde{\gamma} = \frac{Pm^*}{\text{Rev}_i^*} \tag{9}$$

Importantly, I estimate revenue elasticities using input cost shares of non-connected firms as this ensures input variation is not confounded by rent-seeking activities. I use observed revenue, the official value-added tax rate τ^V and median cost shares for each input. Implicitly, I am treating observed variation in cost shares as measurement error in inputs. I use median shares to reduce the influence of outliers. For labor and materials, I use the firms' reported total input costs, which does not require to take a stand on input prices (P, w). For capital, firms report their total capital stock k, so that I additionally require a measure of the international interest rate R. I assume that $R = r + \delta = \frac{1-\beta}{\beta} + \delta$, in line with an international interest rate that is pinned down by the steady state savings behavior of foreign households with the same discount rate β. I assume a standard value of $\beta = 0.95$ and $\delta = 0.1$, implying a capital rental rate of roughly 15%. While I do not need to take a stand on the equilibrium wage w in this step, it is important for later steps to see that I draw on the wage bill as a measure of firms' effective stock of labor, which corrects for quality differences across workers. As is standard, this means that the level of an efficiency unit of labor is not identified, allowing to normalize the steady state equilibrium wage w to one without loss of generality. I enforce the implied total labor supply L for all subsequent counterfactuals, guaranteeing model consistency.

As shown in Table 2, I find an intermediate input share $\tilde{\gamma}$ of roughly 0.54, a labor cost share $\tilde{\beta}$ of 0.17 and a capital cost share $\tilde{\alpha}$ of 0.13. These estimates imply a total revenue-based returns to scale $\tilde{\eta}$ of around 0.84. A high intermediate input share and relatively low labor shares (also in relative comparison to capital) is broadly similar to manufacturing data in comparable countries (e.g. for India see Peter and Ruane 2022).

The importance of (residualized) TFPQ variation To estimate the remaining "within-period" model parameters that govern the *Political Connections Technology* and joint distribution of productivity z_i and political connections ε_i, I target the entire relative distribution of TFPQ-HK$_i$ across connected and non-connected firms. Specifically, I draw on the following monotonic transformation of TFPQ-HK$_i$:

$$TFPQ_i \equiv \left[\text{TFPQ-HK}_i(\text{Rev}_i)\right]^{\frac{\sigma-1}{\sigma}} \equiv \frac{\text{Rev}_i}{k^{\tilde{\alpha}} l^{\tilde{\beta}} m^{\tilde{\gamma}}} = (1+\tau_i^*) z_i^* \qquad \text{where:} \quad z_i^* \equiv z_i^{\frac{\sigma-1}{\sigma}} Y^{\frac{1}{\sigma}} \tag{10}$$

The measure of TFPQ can be directly constructed in the data and does not rely on taking a stance on the value of σ, nor on the (general equilibrium) level of output Y, a point I formalize further below. Importantly, as implied by Proposition 3.1, $TFPQ_i$ varies across firms solely due to variation in subsidies and productivity z_i. The next proposition makes clear why this measure of TFPQ can be seen as an "identified moment" (Nakamura and Steinsson 2018) that speaks directly to the distribution of subsidies, and hence the aggregate costs of connections.

Proposition 3.3 (Subsidy identification conditional on ε)**.** *Write optimal subsidies $\tau_i^*(\varepsilon, z_i^*)$ explicitly as a function of a firm's state over (ε, z^*) with $m_{Ri}^*(\varepsilon, z^*)$. Further assume the following two regularity conditions on the Political Connections Technology:*

1. ***(Rank-preserving in z)****. That is, $\frac{\partial\left(1+\tau_i^*(\varepsilon,z_i^*)\right)z_i^*}{\partial z_i^*} = (1+\tau_i^*) + \frac{\partial \tau_i^*(\varepsilon,z_i^*)}{\partial z_i^*} z_i^* > 0$ such that TFPQ is increasing in productivity z_i^*. Then conditional on ε, TFPQ & z_i^* have the same ranking, implying the following condition for quantiles Q: $Q_{TFPQ|\varepsilon} = \left(1+\tau_i^*(\varepsilon, Q_{z_i^*|\varepsilon})\right) Q_{z_i^*|\varepsilon}$.*
2. ***(Productivity cutoff)****. The Political Connections Technology is such that endogenous selection into connections is increasing in productivity: $\frac{\partial \mathbb{1}\{\pi^{C*}(z_i^*,\varepsilon) > \pi^{NC*}(z_i^*,\varepsilon)\}}{\partial z_i^*} > 0$, implicitly defining a selection productivity cutoff $\bar{z}(\varepsilon)$ that depends on ε.*

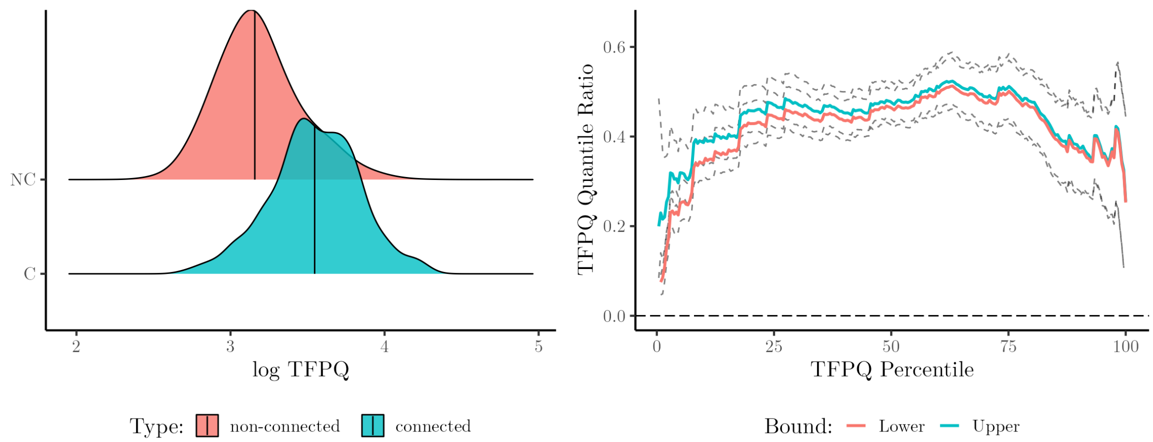
Further note that the model implies that potential connected firms and non-connected firms share the same marginal productivity distribution. Then if there is ***no variation in ε*** *across potential connected firms, the subsidy distribution is directly identified from ratios of the observed TFPQ quantiles across connected and non-connected firms:*

$$QR(p) \equiv \frac{Q^C_{TFPQ}(p)}{Q^{NC}_{TFPQ > TFPQ(\bar{z})}(p)} - 1 = \tau_i^*(Q_{z_i^*}(p)) \;\; \textit{with:} \;\; TFPQ_i(\bar{z}) \in [\min\{TFPQ^{NC}\}, \min\{TFPQ^C\})$$

Proof. The proof is in Appendix A.3.5.

The intuition for identification is simple: As long as (i) connected firms' true productivity is a random draw from a known selected productivity distribution of non-connected firms, (ii) TFPQ is monotonically increasing in productivity, and (iii) there is no further variation in ε driving differences in TFPQ, then the quantile ratio of the two distributions exactly traces out optimal subsidies. The two necessary regularity assumptions are weak restrictions on the *Political Connections Technology*. They are trivially met whenever optimal subsidies are strictly increasing in underlying productivity, as holds for the decreasing returns to scale (DRS) technology commonly used in the literature (e.g. Garcia-Santana et al. 2020; Huneeus and Kim 2021). But they are more general in that they also allow subsidies to be decreasing in productivity as long as the decrease is not faster than the corresponding increase in productivity. For example, this allows a *Political Connections*

Figure 2: Relative TFPQ distributions



(A) TFPQ distributions C vs NC (B) TFPQ quantile ratio (with bounds)

Notes: Panel A: (log) TFPQ distributions of connected vs. non-connected firms. TFPQ estimated using Equation (7) and using reported revenue. TFPQ measures for both panels are residualized on fixed effects for 4-digit industry, province, 15 firm age bins and state-ownership. Black vertical line shows respective median. Panel B: TFPQ quantile ratio as based on Proposition 3.3 using empirical quantiles. Bounds (in solid lines) use no cutoff (Upper) and cutoff implied by minimum observed TFPQ of connected firms (Lower). Grey dashed lines give bootstrapped 95 percentile confidence bands using 10,000 bootstrap samples, respectively for each bound.

Technology where subsidies decline with firm size because the probability of getting exposed increases with firm size. An important implication of Proposition 3.3 is that conditional on a guess for the *Political Connections Technology*, any deviations from the optimal implied quantile ratio needs to be explained by variation in ε and its correlation with productivity z^*.

Figure 2 plots observed TFPQ distributions across connected and non-connected firms (Panel A) and the TFPQ quantile ratio (QR) for the upper and lower bound given in Proposition 3.3 (Panel B). I construct TFPQ in the data using reported firm-level revenue as well as optimal input spendings implied by Proposition 3.1. Importantly, I use model-implied spendings on productive inputs rather than observed input spendings, isolating variation due to subsidies and productivity. It ensures that conditional on revenue elasticities and input prices, all variation in TFPQ is estimated from variation in observed revenue. This cleans the data from measurement error in input spendings, shutting down TFPR variation due to additional input wedges as studied in Hsieh and Klenow (2009) (see Proposition 3.2).[14] For connected firms, this crucially means that I do not use their reported input spendings since they capture both productive inputs and rent-seeking activities and would thus bias the TFPQ estimate. To construct TFPQ, I draw on the estimated revenue elasticities and input prices that hold in the baseline equilibrium as discussed above.

To address the important concern that observed revenue variation of connected versus non-connected

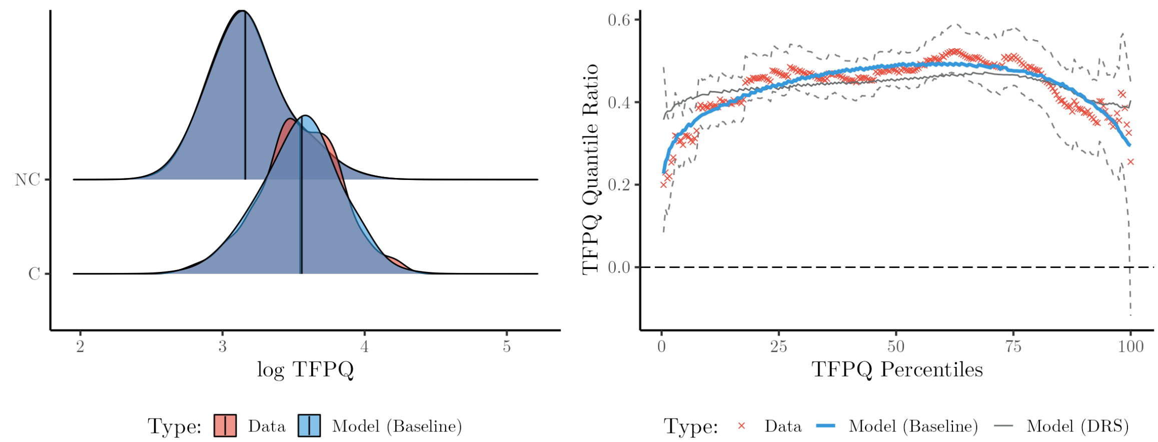
[14] Section 5 considers the extension with additional input wedges. The TFPQ quantile ratio is almost unchanged.

firms may be biased due to compositional differences that are not modelled, I residualize the TFPQ measure by a stringent set of fixed effects. These include: (1) 4-digit industry fixed effects to control for potentially differential sorting into industries that are either differentially up- or downstream or imply different input cost shares, (2) province fixed effects to control for potential geographic sorting and differential access to inputs, (3) binned firm age fixed effects to control for size differences that are driven by a firm's life cycle, and (4) a fixed effect for state-ownership to ensure this does not drive the differential size of connected firms. If not otherwise noted, all subsequent data moments shown will be residualized by the same set of fixed effects. Whenever I draw on data moments across years, I additionally residualize using year fixed effects.

There are three key take-aways from Figure 2. First, in line with the revenue distributions in Figure 1, TFPQ for connected firms shows a clear right shift. This could be either driven by sizable subsidies or simply by a high fixed cost that leads connected firms to have a restricted productivity distribution with a much higher mean. Second, the TFPQ distribution of connected firms shows a stronger left-tail than that of non-connected firms. This left tail puts strong limits on the importance of fixed costs in driving size differences. The reason is that subsidies to connected firms cannot be below zero – otherwise, the firm would simply choose not to use its connections – which means that the lowest TFPQs among connected firms give upper bounds on the productivity thresholds with which it is still worthwhile to become connected. Third, the right tail of the TFPQ distribution of connected firms is less steep than for non-connected firms, leading to a hump-shaped quantile ratio. This pattern is robust over the two bounds and using bootstrap-based 95% confidence bands. Intuitively, the relative decline in TFPQ at the right tail pins down the benefits from political connections for the largest connected firms.

Estimating the Political Connections Technology How can the model rationalize the relative TFPQ distribution of connected firms as documented in Figure 2? I show that Figure 2 is well-explained by a model that has two features: First, rent-seeking activities m_{Ri} lead to higher subsidies, but not only are there decreasing returns (DRS) from rent-seeking, there are also actual costs that are increasing in rent-seeking. These costs could for example be driven by an increasing probability of "getting caught" or that more rent-seeking activities lead to more public opposition. This first feature ensures that conditional on ε, subsidies are not increasing "too fast" in productivity. The second key feature is that there is a negative correlation between physical productivity z_i & rent-seeking productivity ε, explaining why the returns to connections for the largest connected firms are not only marginally declining but also declining in absolute terms (the absolute decline in the TFPQ quantile ratio at the right tail). Formally, I assume the following *Political Connections*

Figure 3: Main Model Fit: Relative TFPQ distributions



(A) TFPQ distributions C vs NC (B) TFPQ quantile ratio

Notes: Panel A: (log) TFPQ distributions of connected vs. non-connected firms based on the estimated model vs. data (as in Figure 2). The model fits the distribution for non-connected firms by construction, hence the perfect overlap. Black vertical line shows respective median. Panel B: TFPQ quantile ratio in data (points) vs model (blue solid line). Data is showing only "upper" bound estimate assuming a zero fixed cost. Grey dashed lines give bootstrapped 95 percentile confidence bands using 10,000 bootstrap samples. For comparison, the solid grey line gives the best fit based on a decreasing-returns-to-scale (DRS) Political Connections Technology.

Technology:

$$\tau(\varepsilon_i, m_R) = \underbrace{\varepsilon_i m_R^{\theta_\varepsilon}}_{\text{Benefits}} - \underbrace{c m_R^{\theta_c}}_{\text{Costs}} \qquad \text{with:} \quad 0 < \theta_\varepsilon < 1 \leq \theta_c \tag{11}$$

In Appendix A.5, I provide two different micro-foundations for this functional form. In the first, firms bribe and lobby politicians who need to push for regulatory changes, preferential policies and access to government contracts. In the second micro-foundation, firms bribe tax collectors to avoid taxes. In both cases, the first part ($\varepsilon_i m_R^{\theta_\varepsilon}$) captures benefits from connections. Returns to rent-seeking depend on the returns to scale as captured by θ_ε and on rent-seeking productivity ε_i. The second part of the technology captures costs of political connections. In both micro-foundations, these costs capture the risk of being detected or having some benefits overturned due to public scrutiny and lawsuits. While c captures the overall level of public oversight, θ_c captures the elasticity with which more rent-seeking activities lead to more public scrutiny. This technology captures the idea of a *window of opportunity* that political connections offer; formally, for $\varepsilon > c$, benefits from rent-seeking initially outweigh costs, but since benefits are concave and costs are convex, there is only a (potentially narrow) window in which rent-seeking is beneficial. This window widens for more connected firms that have higher ε_i, giving them more room to evade taxes or influence government policy in their favor.

To preview results, Figure 3 plots how the estimated within-period model performs on the main targeted empirical moment: the relative TFPQ distributions of connected and non-connected firms as shown in Figure 2. I now explain in more detail which parameters I estimate and how Figure 3 helps to understand identification for each parameter. First, I start by showing that one can rewrite the firms' problem in terms of z_i^* rather than z_i and focus on the conditional distribution $f_{\varepsilon|z^*}$ rather than $f_{\varepsilon,z}$ for the within-period estimation. This avoids having to take a stance on σ, aggregate Y, or the parameters of the primitive joint distribution $f_{\varepsilon,z}$. Formally, this means that the within-period estimation requires to find the following 8 parameters:[15]

$$\Omega^{\text{within}} = \left\{\pi_C, \alpha^*_{\varepsilon|z}, \beta^*_{\varepsilon|z}, \sigma^2_{\varepsilon|z}, \theta_\varepsilon, c, \theta_c, F_C\right\} \tag{12}$$

To estimate Ω^{within}, I can further simplify the estimation under the empirically relevant case where $F_C \approx 0$.[16] In this case, all firms that obtain access to political connections will also invest in rent-seeking and obtain subsidies. Technically, this implies that despite (i) unobserved variation in both productivity z_i^* and ε_i and (ii) selection on z_i^*, the marginal selected productivity distribution of connected and non-connected firms is identical. For the estimation, I can thus simply draw ε from $f_{\varepsilon|z^*}$ (given a guess for $\{\alpha^*_{\varepsilon|z}, \beta^*_{\varepsilon|z}, \sigma^2_{\varepsilon|z}\}$), enforcing the empirically observed TFPQ distribution of non-connected firms for whom $TFPQ_i = z_i^*$. The left panel in Figure 3 shows the estimated TFPQ distribution of non-connected firms, which the estimation approach fits by construction. Furthermore, for the case of $F_C \approx 0$, the best estimate for the probability of becoming connected is simply the share of politically connected firms in the data: $\hat{\pi}_C = \frac{N_C}{N}$, which is roughly 1.3%. This means that setting $F_C = 0$, we are only left with 6 parameters: $\widetilde{\Omega}^{\text{within}} = \{\alpha^*_{\varepsilon|z}, \beta^*_{\varepsilon|z}, \sigma^2_{\varepsilon|z}, \theta_\varepsilon, c, \theta_c\}$.

I estimate $\widetilde{\Omega}^{\text{within}}$ by minimizing the distance between the empirical TFPQ quantile ratio (E) and its model counterpart (M) according to:

$$\min_{\widetilde{\Omega}^{\text{within}}} \frac{\sum_p \left(QR^E(p) - QR^M(p; \widetilde{\Omega}^{\text{within}})\right)^2}{\sum_p \left(QR^E(p) - \overline{QR^E}\right)^2} \tag{13}$$

This objective function is equivalent to maximizing the model's R^2 with respect to the empirical TFPQ quantile ratio. The six remaining parameters govern the shape of the *Political Connections Technology* $\{\theta_\varepsilon, c, \theta_c\}$ and implicitly determine the joint distribution of connections and productivity

[15] Technically, two of the parameters are now functions of σ and Y and are directly related to their underlying primitives according to: $\alpha^*_{\varepsilon|z} = \alpha_{\varepsilon|z} - \beta_{\varepsilon|z}(\sigma/(\sigma-1))(1/\sigma)log(Y)$ & $\beta^*_{\varepsilon|z} = (\sigma/(\sigma-1))\beta_{\varepsilon|z}$. This says that σ and Y are not identified from the cross-sectional TFPQ variation and that different (σ, Y) still give the exact same fit as they would simply lead to a rescaling of the other primitive parameters. The practical advantage of this reformulation is that it allows to solve for optimal model-implied revenue, subsidies and rent-seeking behavior without having to compute the equilibrium output Y that directly enters firm-level demand, implicitly fixing Y at its equilibrium value.

[16] Why is $F_C \approx 0$ the empirically relevant case? As formally shown in Proposition 3.3, in a world without variation in ε, the lowest TFPQ among connected firms puts strong bounds on F_C that imply $F_C \approx 0$ (see Figure 2). In a world with variation in ε, the range of admissible F_C depends on the correlation of ε with $\tilde{z}$. As long as they are negatively correlated – again, the relevant empirical case as I discuss below – F_C will have to be even lower to explain connected firms with low observed TFPQ given higher returns to connections for low productive firms.

$\{\alpha^*_{\varepsilon|z}(\rho, \mu_\varepsilon, \sigma_\varepsilon, \mu_z, \sigma_z), \beta^*_{\varepsilon|z}(\rho, \sigma_\varepsilon, \sigma_z), \sigma^2_{\varepsilon|z}(\rho, \sigma_\varepsilon)\}$. For example, there is a one-to-one mapping between the correlation ρ and the ratio: $\beta^*_{\varepsilon|z}/\sigma_{\varepsilon|z}$. Technically, I estimate the six parameters using the entire relative TFPQ distribution of connected firms, a total of 241 empirical moments – one for each percentile given by a connected firm in the data.

Figure 3 shows that the model accounts well for the observed hump-shaped TFPQ quantile ratio, with an $R^2 = 85\%$. As shown in Table 2, it does so by estimating strongly decreasing returns to scale in rent-seeking ($\theta_\varepsilon = 0.2$), linear costs ($\theta_c = 1.0$) and an almost perfect negative correlation between connections and productivity $\rho = -0.999$. While parameters are identified jointly, one can isolate different identifying variation for different parameters. First, the negative correlation is crucial. With the assumed *Political Connections Technology* which nests the decreasing returns to scale technology commonly used in the literature, optimal subsidies are strictly increasing in productivity z^*_i for any parameter combination – a result that follows directly from applying the implicit function theorem to Equation (5). The implication is that the only way in which this class of models can rationalize a declining TFPQ quantile ratio at the right tail is for connected firms with the highest productivity to have lower ε. This force puts strong bounds on the ratio: $\hat{\beta}^*_{\varepsilon|z^*}/\sigma_{\varepsilon|z}$. Second, $\beta^*_{\varepsilon|z^*}$ and $\sigma^2_{\varepsilon|z^*}$ also depend on the variance of connections, which has opposing effects on the relative TFPQ distribution: given a negative correlation ρ, a higher variance will lead to a faster decline of the TFPQ quantile ratio at the right tail, but will simultaneously lead to higher benefits at the left tail. The observed hump-shape pins down the empirically relevant balance between these two forces.

Next, the model parameters need to be able to rationalize the observed level of the TFPQ quantile ratio, which maps directly to the level of subsidies in the economy. The level of subsidies is governed among others by the *window of opportunity* for connected firms to engage in profitable rent-seeking, which depends on the difference between $\mu_{\varepsilon|z^*}$ and c. Since $\mu_{\varepsilon|z^*} = \alpha^*_{\varepsilon|z^*} + \beta^*_{\varepsilon|z^*} log(z^*)$, conditional on the observed productivity distribution z^*, the level of the TFPQ quantile ratio jointly restrict estimates for $\{\alpha^*_{\varepsilon|z^*}, \beta^*_{\varepsilon|z^*}, c\}$. What about the distribution of subsidies? Intuitively, θ_ε captures the rate at which connected firms reach their maximally attainable subsidies; with a lower θ_ε, firms reach this point earlier, giving more strongly increasing subsidies at low levels of productivity and flatter subsidies at higher levels. The almost flat observed TFPQ quantile ratio between the 25th to the 75th percentile hence identifies the strongly decreasing returns to scale. The costs as captured by θ_c function similarly by only biting at high levels of spending, flattening optimal subsidies. This additional force given by θ_c is crucial to match the data.

To see that additional costs of investing in rent-seeking activities are needed, I compare my estimates to a model that only features benefits via decreasing returns to scale ($\tau_i^{\text{DRS}} = \varepsilon_i m_R^{\theta_\varepsilon}$), the standard

Table 3: Targeted moments: Model versus Data

Moment	Description	Data	Model
Productivity process:			
β_0^{TFPQ}	Constant in TFPQ regression	0.094	0.094
β_1^{TFPQ}	Persistence in TFPQ regression	0.966	0.966
$\text{Var}(\zeta_i^*)$	Var of error in TFPQ regression	0.015	0.015
Exit process:			
β_0^X	Constant in exit regression	0.400	0.400
β_1^X	Slope in exit regression wrt TFPQ	-0.102	-0.102

Details: For productivity process: Reports regression results of log(TFPQ) in 1998 on log(TFPQ) in 1997 for firms that are non-connected in 1997. For exit process: Reports regression results of next period exit on log(TFPQ) for non-connected firms in 1997. TFPQ and exit are both first residualized using province, state-ownership, firm age (in 15 bins) and 4-digit industry fixed effects using all firms. For the dynamic regression, TFPQ in 1998 is also residualized by a time fixed effect that controls for aggregate shocks.

assumption in the literature. The right plot of Figure 3 compares the best fit of a DRS technology with the additional convex costs specification. The DRS technology is strongly rejected in the data because it cannot capture a hump-shape TFPQ quantile ratio. The model-implied R^2 of the DRS model is only 56%, compared to the baseline model's 85%. While a strong negative correlation can induce a decrease of the TFPQ quantile ratio at the right tail, it would then counterfactually predict too high benefits at the left tail. Overall, the DRS model is not able to balance these two forces. Hence, increasing costs – and the idea of a *window of opportunity* that varies with a firms' productivity at rent-seeking ε – are crucial to fit the data. Note that the entire relative TFPQ distribution is key for disciplining the model and simply targeting the average TFPQ ratio would have failed to reject the DRS technology. In Section 4, I show that these differences in the *Political Connections Technology* matter greatly for the aggregate welfare costs of political connections.

3.2.3 Across-period estimation

The remaining model parameters relate to firm dynamics and general equilibrium counterfactuals.

Productivity process The three parameters that govern the productivity process – persistence ρ_z as well as the mean and variances $\{\mu_\zeta, \sigma_\zeta\}$ – are pinned down by observed within-plant TFPQ dynamics over time. Specifically, estimation draws on the TFPQ dynamics of firms between t and next period's t' who are initially non-connected and for whom:

$$log(\text{TFPQ}_{i,t'}) = log(1+\tau^*_{i,t'}) + \rho_z log(\text{TFPQ}^{NC}_{i,t}) + \zeta^*_{i,t'} \quad \text{w/:} \quad \zeta^*_{i,t'} \equiv \frac{1-\rho_z}{\sigma} log(Y) + \frac{\sigma-1}{\sigma}\zeta_{i,t'} \tag{14}$$

If connection status were observed over time, then $\{\rho_z, \mu^*_\zeta, \sigma^*_\zeta\}$ could be directly estimated from Eq. (14) by restricting estimation to non-connected firms that also stayed non-connected. Unfortunately, I only observe connections status with certainty in 1997. Hence, I use indirect inference, running the regression in Eq. (14) without controlling for (unobserved) subsidies both in the data and the model, finding the parameters that best match the biased regression moments.[17]

As reported in Table 2, I find strong persistence in productivity $\rho_z = 0.97$, which is pinned down by observed persistence in TFPQ. Table 3 reports model fit with respect to the targeted moments, showing that the model fits the moments perfectly. The good model fit is unsurprising given that the targeted "biased" moments – the conditional mean, persistence and variance of the shocks of TFPQ – are almost exactly equal to their productivity counterparts. The main reason is that few firms become connected and if they do, induced subsidy variation is smaller than estimated variation in productivity, implying only a small bias from looking at TFPQ. The largest correction is for the variance of the shocks, which is about 12% larger for TFPQ than for productivity (0.014 vs. 0.015), given the additional variance that political connections induce.

Exit dynamics I start by estimating the parameters of the fixed cost distribution $\{\mu^X, \sigma^X\}$ that governs firm exit. Following Eq. (7), firms' exit probabilities are a function of their expected value conditional on productivity z^*_i & the parameters of the fixed cost distribution. Formally, we can write a firm's value function before drawing ε as:

$$V(z^*_i) = \mathbb{E}_{\varepsilon|z^*_i}\left[\pi(z^*_i, \varepsilon)\right] + (1 - \mathbb{P}^{\text{Exit}}(z^*_i)) \left\{ -\mathbb{E}[f^F_i|\text{survive}(z^*_i)] + \frac{1}{1+r}\mathbb{E}_{z^{*\prime}|z^*_i}\left[V(z^{*\prime})\right] \right\} \tag{15}$$

Given a guess for $\{\mu^X, \sigma^X\}$, I solve for firms' value functions over z^*_i using Value Function Iteration to compute model-implied $\mathbb{P}^{\text{Exit}}(z^*_i, \{\mu^X, \sigma^X\})$.[18] As previously, parameter estimation draws on exit probabilities of non-connected firms in 1997, for whom $\mathbb{P}^{\text{Exit}}(z^*_i) = \mathbb{P}^{\text{Exit}}(TFPQ_i)$. I then find the parameters $\{\mu^X, \sigma^X\}$ for which empirical exit probabilities are closest to model-implied exit probabilities over observed $TFPQ^{NC}_i$. As moments, I use the constant and slope coefficients of a regression of non-connected firms' exit on their previous TFPQ: $\text{Exit}^{NC}_i = \beta^X_0 + \beta^X_1 log(\text{TFPQ}^{NC}_i) + \epsilon_i$. Estimated parameters as shown in Table 2 imply high dispersion of fixed costs that rationalize observed exit of even highly productive firms and non-exit of low productive firms. A key implication of these estimates is that while there is selection on productivity due to exit, the selection effect is

[17] Specifically, I run $log(\text{TFPQ}_{i,t+1}) = \beta^{\text{TFPQ}}_0 + \beta^{\text{TFPQ}}_1 log(TFPQ^{NC}_{i,t}) + \tilde{\zeta}^*_{i,t+1}$, targeting $\{\beta^{\text{TFPQ}}_0, \beta^{\text{TFPQ}}_1, Var(\tilde{\zeta}^*_i)\}$ for $t = 1997$. I find optimal parameters $\{\rho_z, \mu^*_\zeta, \sigma^*_\zeta\}$ by minimizing the sum of squared errors across the three moments, where error is defined as: abs(Moment(M) − Moment(E))/abs(Moment(E)). In Appendix A.4.1, I show evidence that targeted moments are unlikely to be biased by the Asian Financial Crisis that hit Indonesian manufacturing in 1998.

[18] The benefit of the Gumbel distribution is that conditional on the expected continuation value, not only the exit probability but also the expected conditional fixed costs have closed-form expressions (see Appendix A.4.2).

more muted because firms also exit for many other reasons. To put this in numbers, I find that a non-connected firm at the first quartile of TFPQ faces an exit probability of 9.7% versus only 6.2% at the 3rd quartile. As shown in Table 3 these estimates can perfectly account for the level and slope of exit rates over the observed TFPQ distribution.

Entry dynamics At last, entry dynamics are pinned down by the value of entering and the entry cost parameter f^E. Based on the model's free entry condition – which has to hold in equilibrium – entry costs are given by: $f^E = \mathbb{E}_{z^*,\varepsilon} V(z^*, \varepsilon)$ given the wage normalization in the baseline equilibrium. Using the model-implied value of entering, I find a value for f^E equal to 14% of average firm revenue, in line with comparatively high entry costs in Indonesia as found in Djankov et al. (2002).

Remaining general equilibrium parameters At last, I pin down the two remaining parameters needed for counterfactuals. For the aggregate labor supply L, I find the value that is consistent with normalizing both the wage and total mass of firms to one. This implies that the total scale of the economy is indeterminate, but given the baseline normalizations, the size of the economy can be compared across counterfactuals. For the elasticity of substitution σ, I use the estimated revenue-based returns to scale $\tilde{\eta}$ and assume constant returns to scale in production (i.e. $\eta = 1$), which implies $\sigma = 6.16$, a value well within the range of three to ten found in the literature (e.g. Broda and Weinstein 2006). Note that the constant returns to scale assumption and the value for σ are solely needed for counterfactuals, since the baseline economy is observationally equivalent for different values of σ. As I show in Appendix B.2.1, the choice of σ is conservative in that higher values give slightly higher costs of political connections, while a lower σ implies increasing returns to scale ($\eta > 1$) that has unwanted aggregation properties.

3.3 Model Validation

Before using the model to quantify the aggregate costs of political connections, I additionally validate the estimates looking at untargeted moments.

Main model mechanism I start validating the main model mechanism, showing evidence for the model-implied level and distribution of rent-seeking and subsidies. As shown in Figure A.4 in the Appendix, model-implied distributions of connected firms' rent-seeking share (m_{Ri}/Rev_i) and subsidies closely follow the hump-shaped TFPQ quantile ratio. Connected firms spend on average 4.3% of their revenue on rent-seeking and obtain average subsidy rates of 44%. Rent-seeking shares and subsidy rates are highest for medium-sized connected firms, at around 6% and 60% respectively. At the right tail of the size distribution, rent-seeking cost shares decline towards zero as benefits

Table 4: Untargeted moments: Model versus Data

Moment	Description	Data	95% CI	Model	DRS
$\mathbb{E}[\frac{m^T}{Rev}\|C] - \mathbb{E}[\frac{m^T}{Rev}\|NC]$	Avg rent-seeking share	0.057	[0.021, 0.092]	0.043	0.046
$\mathbb{V}ar[\frac{m^T}{Rev}\|C] - \mathbb{V}ar[\frac{m^T}{Rev}\|NC]$	Var of rent-seeking share	6.07e-3	[-2.01e-3, 1.43e-2]	2.35e-4	1.98e-4
$\mathbb{E}_i[\frac{m_{Ri}}{Rev_i}\|i \in$ top 25% C]	Top rent-seeking share*	0.01 - 0.03	NA	0.019	0.049
$\mathbb{E}_i[\frac{m_{Ri}}{\pi_i}\|i \in$ top 25% C]	Top rent-seeking profit ratio*	0.236	NA	0.177	0.595
$\mathbb{E}_i[\tau_i\|i \in$ top 25% C]	Top subsidy rates*	0.419	NA	0.414	0.514

Details: Row 1 reports the coefficient from a linear regression of the residualized intermediate cost share on whether a firm is connected. Confidence bands are based on clustered standard errors at the industry level. Row 2 directly computes the variances using residualized intermediate cost shares and bootstraps the confidence band. Rows 3-5 (denoted by *) report data from the Odebrecht corruption scandal from Campos et al (2021). Row 3 gives bribes as percentage of contract-value by Petrobras executives. Row 4 reports ratio of total bribes over total profits (Table 1 in Campos et al 2021). Row 5 reports mean cost after renegotiation over initial cost. For rows 3-5, model counterparts restrict to top 25 percent connected firms by reported TFPQ. Model and DRS columns report baseline and DRS model results respectively.

decline and costs increase, and subsidy rates stabilize around 30%.

While rent-seeking activities are not directly observed in the data, through the lens of the model they can be indirectly inferred from differential intermediate input cost shares, which I use for validation. Specifically, total (reported) intermediates are given by the sum of productive intermediates and any rent-seeking activities that connected firms incur ($m^T \equiv m + m_R$). Given a constant model-implied revenue share of productive intermediates (besides measurement error), the level and variance of rent-seeking are identified by:

$$\begin{aligned} \mathbb{E}_i[m_{Ri}/Rev_i|i \in C] &= \mathbb{E}_i[m_i^T/Rev_i|i \in C] - \mathbb{E}_i[m_i^T/Rev_i|i \in NC] \\ \mathbb{V}ar_i[m_{Ri}/Rev_i|i \in C] &= \mathbb{V}ar_i[m_i^T/Rev_i|i \in C] - \mathbb{V}ar_i[m_i^T/Rev_i|i \in NC] \end{aligned} \tag{16}$$

Rows 1 and 2 of Table 4 report results on both moments. The implied average rent-seeking share in the data is around 5.7%, which is only slightly higher than the model-implied 4.3%. 95% confidence bands comfortably include the model estimate. For the variance, the data reassuringly finds a higher differential variance in the intermediate input cost share of connected firms, in line with the model. Based on the point estimate, the model strongly underestimates the variance of rent-seeking, predicting a relatively low level of variation in connections ε conditional on productivity z_i. However, empirically observed intermediate input cost shares are noisy such that bootstrapped 95% confidence bands cannot actually reject the model estimates.

To further corroborate these estimates, I consider two additional pieces of evidence. First, Appendix A.6 documents differences in the composition of reported intermediate inputs. I show that connected firms spend higher shares on "other expenditures" such as "royalty fees" and "management fees to third parties" that are in line with higher rent-seeking. Second, I look at variation in connections ε, comparing firms that are connected by "blood" to Suharto (i.e. family ties) and "normally connected" firms. As reported in Appendix A.6, blood connected firms are larger on average, in line with the comparative statics of the model as long as one assumes these firms are more connected. However, the model predicts that conditional on observed TFPQ, more connected firms have larger rent-seeking shares. In the data, blood connected firms do not have larger differential intermediate shares, although these results are noisy.

To move beyond indirect evidence from intermediates, I provide additional evidence by comparing my estimates to direct measures of rent-seeking and subsidies from a large-scale corruption scandal, the *Odebrecht case*. This case implicated firms and politicians across Latin America, a region that is broadly comparable in the pervasiveness of corruption as Indonesia.[19] The case was prosecuted by the US Department of Justice and offers rare quantitative evidence of large-scale firm-level corruption. As reported in Campos et al. (2021), direct bribes paid to officials ranged from 1-3% of contract values, broadly in line with model-implied rent-seeking shares. As shown in Row 3 of Table 4, the numbers align once one restricts to the top 25% of firms (based on reported TFPQ), a reasonable comparison given the size of the firms involved in the Odebrecht case. For evidence on the returns to rent-seeking, Row 4 of Table 4 shows that the amount of bribes over total project profits was 23.6% in the Odebrecht case, while the average share of rent-seeking over firm profits in my model is around 17.7%. At last, I also construct a direct measure of subsidies, using the fact that Odebrecht firms first competed competitively for government projects (charging $p_i y_i$) and then renegotiated contracts with a markup afterwards (charging $(1+\tau_i)p_i y_i$). Row 5 of Table 4 shows that average government-paid subsidies in the Odebrecht case are close to 42%, which the model almost fits perfectly. Importantly, the model with DRS technology generally fits these untargeted moments worse than the baseline model (column 6), particularly because it overestimates rent-seeking and subsidies at the right tail.

Model shortcomings Besides the good fit for targeted and untargeted moments, there are at least three important margins which the estimated model fails to capture. First, the baseline model abstracts from further heterogeneity in input cost shares, missing for example that connected firms tend to have lower labor and capital shares that further drive up profits. To address this limitation, Section 5.1 extends the baseline model to allow for heterogeneous labor and capital wedges, showing that this further amplifies the aggregate costs of political connections. Second, while Table 1 showed that connected firms are widely spread across industries, connected firms are more likely to be in upstream industries, raising the question of whether the aggregate costs of connections also depend

[19]E.g. as based on Transparency International's Corruption Perceptions Index for 1997

on the production network. The baseline model only features roundabout production and abstracts from this mechanism, but Section 5.2 explicitly extends the model to a production network economy, also allowing for sector-specific connections technologies.

At last, the model abstracts from additional persistence in political connections over time. The key reason for this assumption is technical; it implies that the underlying marginal productivity distributions of connected and non-connected firms are identical, facilitating the "within-period" estimation. In Appendix A.6 I report evidence in line with the implication of identical underlying productivity distributions. Specifically, I look at R&D spending as a potentially direct measure of firm productivity and show evidence that connected firms do not differentially invest in R&D despite their much larger size. On the other hand, an important moment that might speak against the assumption of zero persistence is differential firm exit: in the data, non-connected firms exit at higher rates than connected firms, contrary to the model predictions. How would additional persistence affect the results? First, higher persistence in political connections generally leads to a worse selection of connected firms, as is common for models of firm dynamics (e.g. Clementi and Palazzo 2016). The reason is that persistence increases the continuation value for connected firms, lowering the exit threshold which leads less productive firms to survive. Second, I argue that such a shift in the productivity distribution of connected firms to the left will not systematically bias the results. To see this, note that taking into account the differential underlying productivity distributions shifts the selection-corrected TFPQ quantile ratio upwards. However, such upward shifts will generally be absorbed by the estimated fixed cost of using political connections.

4 Quantifying the aggregate costs of political connections

This section quantifies the aggregate costs of political connections using the estimated model. I start by quantifying total costs by comparing the baseline economy that is distorted by political connections with a counterfactual economy in which political connections are completely absent. In the second part, I study the role of government policy. Specifically, I quantify the benefits of increasing auditing to curb the influence of political connections. Throughout, I focus on costs in terms of household consumption C_t and aggregate value added output Y_t^{VA}, which I define as output net of intermediates and rent-seeking ($Y_t^{VA} \equiv Y_t - \int m_t - \int m_{Rt}$). The main text reports steady state output and consumption, the latter also holds along the transition given the open economy setup. Details on counterfactuals and full transition results are in Appendix B.

Table 5: Main results: Aggregate costs of political connections

	C	Y^{VA}	w	T	Π	N
Baseline costs: No subsidies	**+7.43%**	**+2.66%**	**-3.47%**	**+44.94%**	**-10.72%**	**+3.30%**
Costs w/ constant subsidy rate	+3.43%	+1.93%	-0.55%	+17.67%	-1.09%	+1.51%
Costs w/ 'wrong' DRS technology	+11.42%	+6.20%	-1.86%	+64.38%	-6.49%	+4.49%
Baseline costs w/out entry/exit	+5.80%	+0.82%	-5.20%	+42.35%	-4.16%	0.00%
Costs when lowering taxes	+3.39%	+5.51%	+5.39%	0.00%	+0.30%	0.00%
Wedge extension:						
No subsidies, no differential wedges	+4.65%	+0.65%	-3.50%	+28.55%	-2.65%	0.00%
No subsidies only	+4.35%	+0.38%	-3.85%	+28.20%	-2.92%	0.00%
Industry/Network extension:						
Baseline costs: No subsidies	+1.31%	-3.04%	-7.36%	+25.16%	-17.61%	0.00%
No subsidies, no IO linkage	+1.44%	-2.50%	-7.36%	+25.74%	-90.82%	0.00%

Details: Each row reports results for comparing a different counterfactual (cf) equilibrium with the baseline distorted economy. Columns report percentage deviations in household consumption (C), value-added output (Y^{VA}), the wage (w), net government transfers to households (T), aggregate firm profits (Π), and the mass of firms (N). Row 1 reports baseline general equilibrium (GE) costs comparing to an economy without political connections and where any additional tax revenue is redistributed lump-sum to households. Row 2 considers an economy where subsidy rates to connected firms are constant (using the average rate in the baseline economy). Row 3 computes costs as in Row 1 using the estimated model under the incorrect DRS technology. Row 4 reports the baseline cf without entry and exit response, fixing the mass and productivity distribution of firms. This row is highlighted because it serves as comparison for all counterfactuals without entry and exit. Row 5 gives the baseline cf without entry/exit but instead of lump-sum transfers reduces the VAT tax rate such that transfers T stay constant. Wedge extension: First row reports result for baseline cf that gives connected firms same wedge process as non-connected firms. Second row computes same cf but keeping wedge processes different. Industry/Network extension: First row reports results for baseline cf which shuts down connections. Second row starts from economy w/out IO network (inputs only sourced from own industry) and computes baseline cf.

4.1 Baseline costs of political connections

Table 5 reports the baseline costs of political connections, which I compute by considering a counterfactual economy in which political connections are shut down, taxes stay unchanged and all (additional) tax revenue is redistributed lump-sum to households. Quantitatively, I find that political connections impose large costs, with consumption losses of 7.4% and output losses of 2.7%. These are sizable effects given that only around 1.3% of firms are connected. The main reason for the gap between consumption and output losses are firm profits. As seen in Column 5, in the economy with political connections, aggregate firm profits are around 10% higher, driven by increased profits by connected firms. Given observed concentrated firm ownership, these benefits are not passed on to households and only accrue to a small elite (the absentee owners), driving a wedge between aggregate output and household consumption.

The effect on aggregate output is the net effect of two opposing forces. On the one hand, political connections alleviate existing distortions. All firms produce too little given the constant distortive value-added tax, and subsidizing connected firms undoes part of this distortion. On the other hand, political connections introduce three types of costs: (i) a pure deadweight loss of socially wasteful rent-seeking, (ii) *misallocation costs* due to heterogeneity in subsidies between connected and non-connected firms as well as heterogeneity of subsidies across connected firms, and (iii) costs that stem from an excessive level of subsidies. Quantitatively, I find that deadweight losses from wasteful rent-seeking are small. The aggregate amount of rent-seeking activities in the economy only amounts to about 0.3% of total intermediate spending, a function of the small share of connected firms and lower spending by the largest connected firms. Assuming instead that these resources are not waste implies only marginally different effects on output and consumption.

In contrast, about 50-75% of the aggregate costs of connections are driven by the dispersion in subsidies across connected firms. I derive this by looking at a counterfactual economy in which all connected firms instead faced a constant subsidy rate equal to the average rate across connected firms. As reported in Row 2 Table 5, heterogeneous subsidies across connected firms explain 46% of the consumption losses and 73% of the output losses from political connections. Differences in the contribution to consumption and output losses is explained by different effects on profits: while a constant subsidy rate only marginally decreases firm profits, the larger effect is through misallocation. These sizable costs of misallocation across connected firms stem from substantial variation in subsidies in the baseline distorted economy (see Section 3.3).[20]

[20] Note that this is in a setting in which realized subsidies still end up being positively correlated with firm productivity ($\rho_{\tau,z} \approx 0.73$), because high-productive connected firms have higher returns from investing in rent-seeking, undoing the almost perfect negative correlation between connections ε and productivity.

To additionally quantify whether there are costs from an excessive level of subsidies, I redo the previous exercise but check how output varies for different overall levels of (constant) subsidies. In line with the previous results, the current level of subsidies account for the remaining 30% of the output losses from political connections. I find that the output maximizing flat subsidy rate is much lower, at about 5.2%. Perhaps more surprisingly, as shown in Figure B.3 in the Appendix, I find that the costs of subsidies are relatively flat between 0%-20% and only start meaningfully increasing for levels of subsidy rates above 30%.

How different would the estimated costs of political connections be if I had incorrectly assumed a DRS *Political Connections Technology* as commonly used in the literature? For this, I reestimate all parameters enforcing the DRS technology assumption (details in Appendix B.2.3). As reported in Row 3 of Table 5, I find that incorrectly following the DRS technology leads to very different quantitative results. The DRS technology overestimates consumption losses from political connections by 50% and output losses by more than a factor of two. The reason is that the DRS technology overestimates the amount of subsidies at the left and right tail, precisely because it fails to capture the hump-shaped TFPQ quantile ratio. In line with Table 4, I find that the DRS model overpredicts the share of subsidies over total transfers to households by about 15 (!) percentage points (64.5 vs. 49.1). This mechanically crowds out government transfers, explaining higher consumption losses.

Next, I look at entry and exit. I show that political connections distort entry and exit by misallocating profits towards connected firms, driving up prices and discouraging entry and encouraging more exit. The baseline counterfactual shows that there are 3.3% more firms in the absence of connections. I further show that entry and exit increase the costs of connections, amplifying the costs of consumption by nearly 30% and those of output by even more. To see this, Row 4 in Table 5 reports results from the baseline counterfactual in which connections are abolished and where I additionally shut down the entry and exit margin, keeping the mass of firms and productivity distribution fixed. Shutting down subsidies to connected firms leads those firms to shrink, releasing pressure on labor markets and decreasing wages. In contrast to the economy with entry and exit, this decline in wages is not partly compensated by more entry, thus leading to a stronger wage decline (about 5.2%). In turn, lower wages make it easier to grow for non-connected firms, implying a better allocation of resources that drives output and consumption gains. Again, consumption gains are larger because of the decline in firm profits and increase in government transfers.

I want to end this section with an important insight, namely that the aggregate costs of political connections strongly depend on what the government does in their absence. To illustrate this point, suppose that instead of redistributing saved subsidies lump-sum to households, the government instead lowers distortive taxes for all firms. That is, consider a counterfactual in which government transfers stay equal to their baseline level T^0, which are used to finance a fixed set of public goods and transfer programs. I then solve for the counterfactual level of $\tilde{\tau}^V$ that ensures T^0 in an economy in which political connections are absent. For simplicity, I further shut down any entry and exit response. As reported in Row 5, I find that the aggregate costs of political connections in this alternative counterfactual are about 5.5% of output. These output costs are more than five times as large as for the comparable baseline costs without entry and exit. They are facilitated by allowing the government to reduce the value-added tax rate to 4.4%, more than half the baseline rate of 10%. Interestingly, consumption losses in this counterfactual are now smaller, the key reason is that transfers to households stay fixed and wage increases do not fully compensate households. An important take-away from this exercise is that there are sizable *opportunity costs* for subsidizing connected firms.

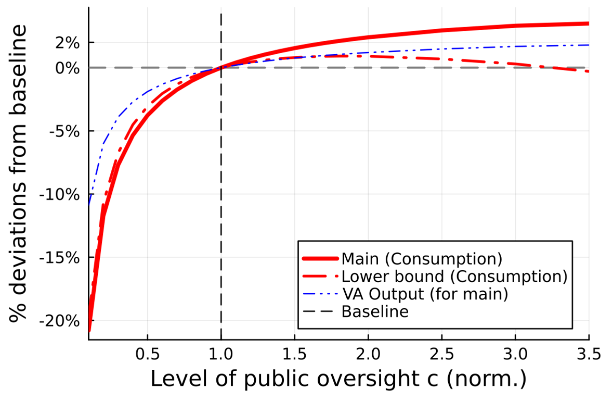
In summary, I find sizable costs of political connections. Baseline costs are about 7.5% of permanent household consumption and 2.7% of output. Political connections are costly because they discourage firm entry, misallocate resources across connected firms and provide an excessive level of subsidies that props up firm profits. Spending subsidies instead on alternative development objectives such as reducing distortive taxes for everyone further amplifies the costs of connections.

4.2 Quantifying the benefits of public oversight

The previous subsection quantified the aggregate costs of connections by considering counterfactual economies where political connections are completely absent. This subsection considers a more policy-oriented exercise: what are the gains from increasing public oversight to curb the influence of political connections? And what should the government be willing to spend on such additional oversight? To answer these questions, I consider variation in the level of public oversight as captured by parameter c in the *Political Connections Technology* (see Appendix A.5 for its microfoundation). Concretely, c captures the quantity of public oversight – things like the amount of tax audits and the number of investigative reports on corruption – and $P_c \cdot c$ denotes their total costs. The idea of the exercise is to come up with a very rough back-of-the-envelope calculation of how far the baseline level of public oversight is from its optimum.

For this, I derive an estimate of the baseline costs of public oversight ($P_c \cdot c$) drawing on the Indonesian government budget in 1996/7 (IMF 1996). Since the official budget does not directly report the share of government expenditure paid to all kinds of auditing activities on politically connected firms, I conservatively approximate this share using as numerator the total expenditures on the entire legal system and as denominator all development-related expenditures. This expenditure share is about 0.53%, which I map to the model-implied government tax revenue before paying out

Figure 4: Optimal public oversight: Consumption and output effects of different levels of oversight



Notes: Figure reports (steady state) results for counterfactual economies in which the level of public oversight is varied (relative to its baseline level). All results are reported as percentage deviations from the baseline distorted economy. VA Output denotes value-added output that is net of intermediates and rent-seeking.

subsidies ($G \equiv T +$ total subsidies). I view the 0.53% estimate as a conservative estimate given that most parts of the judicial system are unrelated to investigating favors to connected firms. But to be even more conservative, I also report results for a lower bound estimate that multiplies this share by a factor of 10, which is roughly equal to the total personnel costs of "General public services". Further details are in Appendix B.2.4.

Figure 4 shows (steady state) consumption and output effects for counterfactual economies in which the estimated cost P_c is fixed but the level of oversight c varies from 10% to 350% of the baseline level. Note that the effectiveness of public oversight is an endogenous outcome of the model as it depends on how much connected firms choose to invest in rent-seeking activities in response to changes in oversight c. Consumption and output are both expressed in terms of percentage deviations from the economy with the baseline level of oversight. In contrast to the baseline economy where I ignored the costs of public oversight (and hence implicitly assumed $P_c = 0$), I now compute aggregate consumption taking costs into account.

The main take-away is that the current level of public oversight is far from optimal. The main estimate suggests the government should more than triple all public oversight, undoing between 45%-65% of the aggregate consumption and output costs of political connections as reported in Table 5. Consumption effects are hump-shaped because costs of auditing increase, but in practice this bites at only high levels of auditing. To see this, I also show results for the very conservative lower bound according to which the optimal level of public oversight is slightly below doubling overall expenditures on auditing. To get a rough idea of magnitudes, the additional costs of doubling public oversight amount to 0.1% of GDP, which at Indonesia's GDP in 1997 already translates to a

100-fold increase in the annual global budget of Transparency International in 2019.[21]

5 Main Extensions

In this section, I consider two main extensions. The first extension studies the combination of subsidies and firm-level wedges as studied in the misallocation literature (e.g. Hsieh and Klenow 2009). The second extension considers how the costs of political connections depend on industry heterogeneity and linkages through a production network (Bigio and La'o 2020). Throughout, I relegate details to Appendix C and focus mainly on the results. To ensure tractability and comparability with the misallocation and production network literatures, the two extensions consider a static economy without firm dynamics.

5.1 Wedges & the costs of market power

The setup so far considered output subsidies as the only source of firm-specific idiosyncratic frictions in the economy. What if political connections also distort capital and labor in the form of wedges as in Hsieh and Klenow (2009)?[22] And importantly, how important are subsidies relative to wedges? To answer these questions, I introduce wedges in the firm problem as follows:

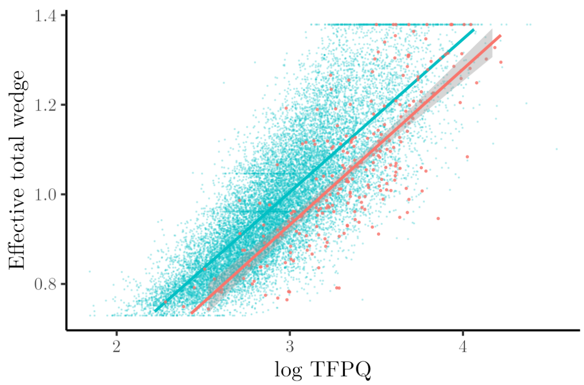
$$\begin{aligned} \max_{k,l,m,m_R} & \left\{ (1-\tau^V)\Big[(1+\tau(m_R,\varepsilon_i))py(z_i,k,l,m) - m - m_R\Big] - (1+\tau_i^L)wl - (1+\tau_i^K)Rk \right\} \\ & \text{subject to:} \qquad p = P\cdot Y^{\frac{1}{\sigma}} y(z_i,k,l,m)^{-\frac{1}{\sigma}} \quad \text{(CES demand)} \end{aligned} \tag{17}$$

where τ_i^K and τ_i^L denote capital and labor wedges. I start by showing empirical variation in wedges, given that capital and labor wedges are directly identified from observed variation in capital and labor cost shares. Again, I residualize this variation to ensure results are only driven by within-industry variation of comparable firms. In the data, I find two key patterns. First, connected firms face *higher* labor and capital wedges. For example, the median connected firm has a labor (capital) share that is 2.2 (2.6) percentage points *lower* than for the median non-connected firm, translating to roughly 15 percentage points higher wedges. Dispersion, on the other hand, is less clear. While the variance in the labor wedge is about 10% lower for connected firms, the variance in the capital wedge is roughly 30% higher. Second, I find that wedges are strongly increasing in firm-level TFPQ, in line with the idea that positively correlated distortions are common in developing countries, or – analogously –

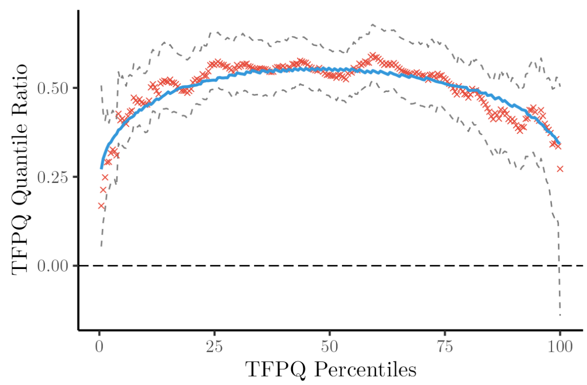
[21]See: https://www.transparency.org/en/the-organisation/our-operating-budget. Accessed on 12th May 2022.

[22]While the approach could in principle allow for wedges on all inputs (on top of the output subsidy), I abstract from a wedge on intermediates because I cannot directly back out wedges on intermediates for connected firms given that their observed intermediate spending captures both productive and rent-seeking activities. Alternatively, one could first back out the "intermediate" wedges for non-connected firms and then make an assumption on how these wedges also apply to connected firms.

Figure 5: Distribution of wedges and TFPQ



(A) Correlation: wedges and TFPQ



(B) TFPQ quantile ratio

Notes: Panel (A) plots firm TFPQ against the effective total wedge defined as: $\tau_i^T \equiv (1+\tau_i^K)^{\tilde{\alpha}}(1+\tau_i^L)^{\tilde{\beta}}$, where τ_L and τ_K are firm-level labor and capital wedges respectively. Panel (B) plots the TFPQ quantile ratio over percentiles of the TFPQ distribution. Red dots give data moments, while the blue line gives the estimated fit for the model with wedges (explained in text).

that profit shares are increasing in TFPQ. To show this, Figure 5 (A) plots wedges against TFPQ using a measure of total labor and capital wedges τ_i^T defined as: $\tau_i^T \equiv (1+\tau_i^K)^{\tilde{\alpha}}(1+\tau_i^L)^{\tilde{\beta}}$, which summarizes the distortionary effect of wedges on firm revenues and subsidies.[23] Importantly, despite higher average wedges, conditional on TFPQ, connected firms actually face slightly lower wedges because they have higher TFPQ, consistent with preferential treatment. While this does not matter for the quantification, in the following, I thus interpret higher wedges as a market power story related to firm size, rather than higher taxes on larger firms.

To quantify how wedges affect the aggregate costs of political connections, I re-estimate the baseline model extended by firm-level wedges. Specifically, I allow for firm-specific wedges that are increasing in TFPQ and potentially different for connected and non-connected firms. While I observe firm-specific wedges for all firms, the issue remains that I cannot directly disentangle productivity and connections, leaving the joint distribution of wedges, productivity and connections unidentified. To solve this identification problem, I parameterize their dependence and estimate parameters indirectly. Specifically, I assume that total wedges and productivity are jointly log-normally distributed in line with the log-log-linear relationship in Figure 5 (A). The key restriction I make is that connections ε_i and wedges τ_i^T are only dependent through their dependence on productivity z_i, which rules out quid-pro-quo benefits where subsidies are offered conditional on how connected firms choose inputs. Importantly, I do not restrict the relative distributions of labor and capital wedges conditional on τ_i^T and allow the distribution of wedges τ_i^T and the correlation of wedges and productivity to vary

[23]Further details and separate information on labor and capital wedges are reported in Appendix C.1.

across connected and non-connected firms.

While introducing wedges changes the measured TFPQ, Figure 5 (B) shows that the resulting TFPQ quantile ratio is still strongly hump-shaped and only marginally different from the baseline ratio shown in Figure 2. As for the baseline estimation, the TFPQ quantile ratio remains key for identifying the *Political Connections Technology*. Figure 5 (B) shows that the re-estimated model fits the new TFPQ quantile ratio well. Newly estimated parameters (reported in Table C.2 in the Appendix) are close to the baseline parameter estimates, with strongly concave benefits ($\theta_\varepsilon = 0.2$), slightly convex costs ($\theta_c = 1.04$) and an almost perfect negative correlation between connections and productivity (-0.998). As for the new parameters, I find higher average but equally dispersed wedges for connected firms and that wedges and productivity are less strongly correlated for connected than for non-connected firms (0.824 vs. 0.76).

With the estimated model in hand, I start quantifying the aggregate costs of political connections by considering a counterfactual economy in which political connections are absent and connected firms face the same law of motion for idiosyncratic wedges as non-connected firms. Any additional tax revenue is, again, redistributed lump-sum to households. This implies that without political connections, previously connected firms face a lower overall level of wedges, leading to higher input cost shares and lower profit shares. Building on good evidence for Indonesia that connected firms are in less competitive industries (Hallward-Driemeier, Kochanova, and Rijkers 2021) and that connected firms are much more likely to receive licenses that buy them market power (Mobarak and Purbasari 2006), I interpret this counterfactual as reducing connected firms' differential market power, on top of cutting their government-funded subsidies. As shown in Row 7 of Table 5 the overall costs are sizable and comparable to the baseline costs without entry and exit (Row 6). Consumption losses from connections are 4.65% and output losses are 0.65%. Given these sizable costs, an interesting question is how much of these costs are due to differential wedges versus subsidies. To answer this question, I consider a second counterfactual in which I abolish subsidies, but keep differential wedges (Row 8). Interestingly, I find that subsidies drive about 93.5% of the total consumption losses from political connections. That is, the costs of differential subsidies are almost a magnitude larger than the costs of differential wedges.

5.2 Industry heterogeneity and the production network

The second main quantitative extension considers industry heterogeneity and linkages through a production network. As I show in Table C.3 in the Appendix, connected firms in Indonesia tend to be more prevalent in more upstream industries such as 'Chemicals' and 'Machinery' rather than downstream industries such as 'Textiles', a pattern that mimics sectoral government intervention in historical South Korea and modern-day China (see Liu 2019). Are net subsidies to connected firms also larger in upstream industries? And to the extent that these upstream sectors act as bottlenecks for the economy, do sectorally concentrated distortions from political connections amplify or weaken the aggregate costs of political connections? To shed light on these questions, I extend the baseline model by industries, each industry is a small version of the baseline model with heterogeneous firms that face industry-specific *Political Connection Technologies*, production functions and productivity distributions. Industries are then linked through the labor market and an intermediate input production network as in Bigio and La'o (2020). Full model details are in C.2.[24]

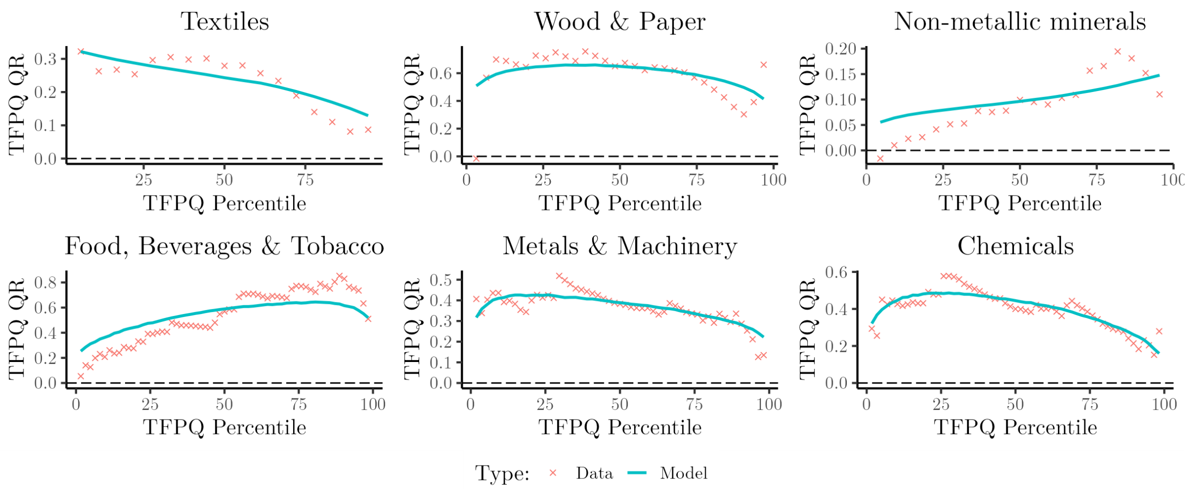
To extend the setup to multiple industries and a production network, I have to make some compromises. Given the relatively small number of connected firms and the restriction to use manufacturing census data only, I look at six relatively coarse industries: 'Textiles', 'Wood & Paper', 'Non-metallic minerals', 'Food, Beverages & Tobacco', 'Metals & Machinery' and 'Chemicals', which I can also map to the input-output table. As reported in Appendix Table C.3, by far the three largest industries based on value-added shares as well as Domar weights are 'Chemicals', 'Machinery' and 'Food'. They are also the industries with the highest share of connected firms; e.g. the share of connected firms in the upstream sector 'Chemicals' is five times larger than in the downstream sector 'Textiles', the least connected industry.

I allow industries to differ in their production function elasticities and elasticity of substitution, which – as for the baseline model – I identify from within-industry median input cost and profit shares assuming constant returns to scale. Table C.3 shows that there is considerable variation in elasticities across industries, with 'Food' and 'Chemicals' being intermediate input intensive, 'Textiles' and 'Non-metallic minerals' (e.g. pottery & glass) being labor intensive, and 'Metals & Machinery' being particularly capital intensive. Estimated elasticities of substitution for varieties within industries broadly align with economic intuition. For example, the most substitutable varieties are within 'Non-metallic minerals' (think pottery varieties) and 'Textiles', while among the least substitutable varieties are 'Chemicals' and 'Machinery'. Note that this also means that the share of connected firms tends to be higher in industries with higher profit shares.

Next, I estimate *Political Connections Technologies* by industry, drawing now on relative TFPQ distributions across connected and non-connected firms *within* industries. Figure 6 plots observed TFPQ quantile ratios and the estimated model fit by industry. Observed TFPQ quantile ratios differ across industries both in terms of their levels and in their shape, but they are hump-shaped

[24] The main differences with respect to Bigio and La'o (2020) is that the model features (i) heterogeneous firms, (ii) firm-specific distortions, rather than industry-specific distortions, and that (iii) distortions are endogeneous. The setup is also related to Liu (2019) in that connections introduce industry-specific subsidies that may undo part of the distortions that the VAT rate introduces.

Figure 6: Model fit: TFPQ Quantile Ratio distributions by industry



Notes: Figure plots for each of the six industries, the observed TFPQ quantile ratio over the TFPQ percentile distribution. Each dot is a connected firm. Lines denote the best model fit.

in at least five of the six industries. The estimated model, using the same functional form for the *Political Connections Technology* but allowing parameters to vary across industries, fits the data well. The average R^2 is around 63%, with some industries such as 'Chemicals', 'Metals & Machinery' and 'Wood & Paper' providing an almost perfect fit. The only industry for which the model struggles to fit the hump-shape is 'Non-metallic minerals', by far the smallest industry. The reason is that the industry features close to constant revenue returns to scale that lead small differences in subsidies to drive large size changes. Estimated parameters, as reported in Table C.3, are broadly similar across industries and compared to the baseline estimates, with strongly decreasing returns to scale in rent-seeking, increasing costs and an almost perfect negative correlation of connections and productivity. Finally, I find that model-implied total rent-seeking activities are still small in the aggregate, about 0.3% of total GDP, while total subsidies are still large, about 5.4% of GDP (compared to the baseline 5.9%). In line with the concentration of connected firms, 'Chemicals', 'Machinery' and 'Food' together account for roughly 85% of total rent-seeking and subsidies.

Finally, I use the estimated extended model to quantify the aggregate costs of connections. Perhaps surprisingly, I find that industry heterogeneity and the production network on net *reduce* the estimated costs of connections compared to the baseline results. I show this, again, by considering a counterfactual economy in which political connections are absent and any additional tax revenue is redistributed lump-sum to households. As reported in the first row under *Industry/Network Extension* in Table 5, consumption losses from connections are 1.3% and there are even non-negligible output *gains*. To better understand what drives these smaller aggregate effects, I decompose the effect of industry heterogeneity from the network structure. I find that almost all reductions in costs are driven by industry heterogeneity, rather than by the production network. I show this by isolating the role of the production network using the same counterfactual change of shutting down connections but instead starting from an economy without an input-output structure – that is, an economy where inputs are only sourced from the own industry (see C.2 for details). As reported in Row 2, consumption and output losses are almost unchanged. The main reason for the small effect of the production network is that most Indonesian industries – at least at this level of aggregation – already mainly use their own industry good as input. If anything I find that input-output linkages further *reduce* the aggregate consumption losses from political connections. To the extent that upstream sectors are much more heavily subsidized in Indonesia, this is in line with Liu (2019) who shows that upstream sectors become sinks of distortions that warrant subsidizing them more. In the model economy, distortions apart from connections only arise from a uniform VAT rate across industries, but which distorts industries differentially given their different labor and capital intensities in production.

6 Conclusion & Discussion

This paper has provided a structural approach to quantify the general equilibrium costs of political connections using a model where firms differ in their connections and endogenously invest in rent-seeking activities to obtain firm-specific subsidies. The key methodological innovation of the paper is to show how one can flexibly identify subsidy distributions and the joint distribution of connections and firm productivity using relative TFPQ distributions across connected and non-connected firms. Applying this methodological approach to Indonesia, I find large aggregate costs of political connections, with consumption losses of 7.4% and output losses of 2.7%.

A number of qualifications of the results are in order. While the paper has considered important extensions such as firm-specific wedges and industry heterogeneity, some issues are harder to assess. For example, due to data constraints, the focus of this paper has been on manufacturing plants. Political connections may play a different role in other sectors and at the firm-level. Furthermore, political connections will always remain elusive, making measurement of them difficult. This paper's measure of political connections is based on a natural experiment and arguably among the most credible estimates we have. One complementary avenue for future research is to collect more direct evidence on rent-seeking activities and use this to validate the model-implied distributions of firm-level subsidies and rent-seeking activities. A more serious study of the dynamics of political connections is also unfortunately beyond the scope of this paper.

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A Measurement & Model derivations

A.1 Further details on measuring political connections

Mobarak and Purbasari (2006) extend the work by Fisman (2001) by examining how the stock price of the universe of firms traded on the Jakarta Stock Exchange (JSX)[25] responded to adverse news about Suharto's health in various episodes between 1994 and 1997. Using daily stock price data for the 985 market trading days between 1994 and 1997, they run a set of regressions of abnormal stock returns for each firm on aggregate movements in the JSX, the average return for the industry category in which that firm belongs, movements in the exchange rate and interest rate, and an indicator variable for days when the news about Suharto's health was reported by the press. A firm is defined to be "politically connected" if the Suharto health news indicator has a negative coefficient which is significantly different from zero at the 95% confidence level. Using statistical significance as a threshold gives a firm-specific threshold that also takes into account the firm-specific variability of its stock price.[26] This identifies 29 stock listed firms as being politically connected and the authors used newspapers and other media to confirm that these firms were indeed connected.

The identities of the key personnel running these 29 politically connected firms allow Mobarak and Purbasari (2006) to identify, by proxy, other firms that are connected to Suharto, but not traded on the Jakarta Stock Exchange. The authors do this by locating all other firms that share ownership and management with those 29 firms. As Claessens, Djankov, and Lang (2000) and Carney and Child (2013) show, ownership and control is rarely separated in Southeast Asian firms including Indonesia and most firms belong to larger conglomerate structures that are owned by specific families. This allows to link stock-listed firms to a larger network of other firms of the same conglomerate, who are owned by the same family. Due to the prevalence of political connections being tied to interpersonal links between families, this allows to track connected firms beyond stock-listed firms. Specifically, Mobarak and Purbasari (2006) identify each member of the Board of Directors and Board of Commissioners of each of the 29 firms using the Indonesian Capital Market Directory 1998. They then use the publication *400 Prominent Indonesian Businessmen* to find the names of all conglomerates to which the individuals running the connected firms belong. Finally, they turn to *Conglomeration Indonesia* to identify all subsidiary firms of the 'connected' business

[25] The authors estimate this for 285 of the 293 firms traded on the Jakarta Stock Exchange at that time.

[26] The authors use three different definitions of firm stock returns, including the actual return, the deviation of the actual return from its average, and the abnormal return net of movements correlated with the aggregate JSX market return. They also variably define the event dates to be the day the illness occurs or the day it is reported in the press. The identities of 'politically connected' firms are roughly invariant to the particular definition of returns or event dates used. Note that using statistical significance as a filter may introduce differential bias by size. If the variability of stock prices is related to fundamentals such as firm size then statistical power will vary by size of firm and then selection will be worse for smaller firms. I have not conducted tests or simulations to assess this concern, but given that T = 985, it seems likely that power is not a relevant concern.

groups and trace all other firms and conglomerates that share ownership and management. In total, this gives them 2,126 connected firms.

The implicit assumption at this point is that all relevant political connections in Indonesia go through larger conglomerates which have at least one publicly traded firm that is identified as being politically connected. Thus, this definition of political connections captures "high-level" political connections and is unlikely to capture more local connections of firms to local authorities in the bureaucracy or police. This should be kept in mind when interpreting the results in this paper. Another key concern of using this measure of connections is that it is likely to capture only larger firms and is more likely to miss small connected firms. In the structural approach used later in the paper, results will explicitly depend on the smallest observed connected firms exactly to be robust to the idea that if all connected firms are large and successful this must not imply that connections are very beneficial, but could also be driven by the fact that we do not capture smaller and less successful connected firms in the data.

The next limitation of the data is that while the approach allows to identify a variety of connected firms, the available firm-level data to link these to is the annual manufacturing census data that captures medium- and large-sized manufacturing firms with more than 20 employees. This considerably restricts the sample: only 16 of the 29 initial stock-listed firms and 408 of the 2,126 identified connected firms are manufacturing firms, which makes up roughly 20% of firms. Based on the GGDC 10-sector database, the manufacturing sector accounted for about 34% of value-added output in 1997, which is squarely between the percentage of manufacturing firms among stock-listed firms and the percentage among all connected firms. It is unclear exactly what biases this sample selection introduces, but it may even lead to more conservative estimates of the costs of political connections given that connections are likely to play a bigger role in a number of non-manufacturing sectors such as utilities (including telecommunications and energy), mining, construction, finance and land-dependent agriculture. Of these manufacturing firms, linking them to the census is further complicated by the fact that firms are generally de-identified in the manufacturing census data. Using three broad identifying variables - province location, 5-digit industry code and (rough) number of employees - Mobarak and Purbasari (2006) can succesfully match 241 firms or 59% of connected firms to the census of manufacturing firms. Mobarak and Purbasari (2006) argue that the attrition involved in this matching step is not related to any fundamentals and should thus not differentially bias the estimates apart from underestimating the number of connected firms.[27]

[27]However, I have not been able to validate this claim and replicate this part of their analysis given that the authors could not share this part of the analysis with me. There could be a number of reasons why the matching step could introduce additional problems. For example, matching by (rough) number of employees may introduce bias against small firms as this set of firms may include more overlap in the number of employees and thus makes it less likely to find unique matches in the data. On the other hand, matching by province location may make it harder to match

In the end, this approach allows to identify 241 connected firms in the manufacturing census data. It allows to identify the snapshot of politically connected firms at the highest level for a short time period of around 1-2 years shortly before the Asian Financial crisis in 1997/8. Throughout the paper, I allow the set of connected firms to vary over time with some firms loosing their connections or seeing changes in the extent of their connections, but all results will be based on the set of connected firms in 1997 and I therefore assume that this is a representative picture of connected firms also for other years in the data. Of the 241 firms, 89 firms are identified as being owned and founded by blood connections of Suharto. 34 of these 89 firms are similarly identified as being connected by the stock market identification approach. This imperfect overlap may be due to three different problems. First, it may show that the stock market identification approach is highly imperfect in capturing all connected firms (only about 40% of connected firms are identified). This could be due to the nature of the approach only capturing firms that are linked through conglomerates that have a stock listed firm or the statistical uncertainty in the estimates, but it could also be because the approach only captures connected firms whose connections are deemed sufficiently volatile. These issues only pose a real problem for this paper if they bias the identified size distribution of connected firms, otherwise, this paper will only underestimate the costs of political connections. Second, imperfect overlap may indicate that not all blood connected firms identified in the data truly benefit from their connections. In this case, I could overestimate the costs of political connections. However, if the assumptions for the estimation of subsidies are correct, this should be picked up by the estimation approach.

A.2 Further results on size differences

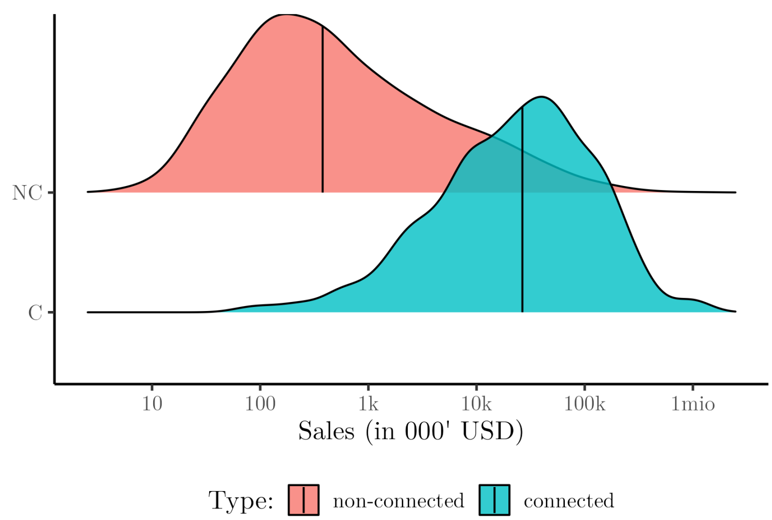
Figure A.1 shows that size distributions as measured by firms' value-added follow a similar pattern as shown for sales in Figure 1.

Similarly, the dispersion in value added differs strongly across the two distributions, with value-added of non-connected firms being roughly 4x more dispersed than that for connected firms (12.95 vs. 3.06). In a previous version of the paper, all results (and the model) were formulated in terms of value-added rather than gross output and results were very similar.

A.3 Model derivations & additional results

more successful firms in more economically active parts of the country (e.g. Java). Access to the set of all connected manufacturing firms could allow to control for potential differential misclassification in this step of the analysis.

Figure A.1: Distributions of value-added output: Connected vs. Non-connected firms



Notes: Value added is sales minus materials spending in 000's 2010 USD. Series are annual and deflated. Data is for cross-section of Indonesian firms in 1997 based on Statistik Industri, the manufacturing firm census. Connected vs. non-connected firms are identified as in Mobarak & Purbasari (2006). Non-connected firms: N = 18,317. Connected firms: N = 241.

A.3.1 Productivity vs. demand in a CES world

In this part of the Appendix, I show a standard result in the heterogeneous firm literature, namely that in models with CES demand, productivity changes and changes in demand are isomorphic with respect to observed firm-level revenue. Suppose that instead of the CES final output aggregator assumed in Equation (1), the output good is aggregated using:

$$Y = \left[\int_0^N \psi_i y_i^{\frac{\sigma-1}{\sigma}}\, di\right]^{\frac{\sigma}{\sigma-1}} \qquad \text{with:} \quad \sigma > 1 \tag{18}$$

where ψ_i captures a demand shifter, such as changes in tastes for a final output product that features more input of variety y. One can also have the aggregator directly on the household side in which case ψ_i would simply capture more taste for consumption of variety i. Then the implied firm-level demand curve for variety i is given by:

$$p_i = \psi_i y_i^{-\frac{1}{\sigma}} P Y^{\frac{1}{\sigma}} \tag{19}$$

Plugging this into the firm's problem, one can see that a change in ψ_i is isomorphic to a change in productivity z_i. In the main paper, I do not distinguish the two and simply call them "productivity" for ease of exposition. Note that distinguishing the two is only relevant for how to interpret the results in the paper, but does not affect the results itself.

A.3.2 Proposition 3.1 (Optimal firm choices)

Firms with productivity z_i and connections ε_i solve the following within-period problem:

$$\pi^*(z_i,\varepsilon_i) \equiv \max_{k,l,m,m_R} \left\{(1-\tau^V)\Big[(1+\tau(m_R,\varepsilon_i))py(z_i,k,l,m) - P(m+m_R) - \mathbb{1}_{m_R>0}F_C\Big] - wl - Rk\right\}$$
$$\text{subject to:} \qquad \pi^{\text{net}} = (1-\tau^C)\pi^*(z_i,\varepsilon_i) \quad \text{and} \quad p = P \cdot Y^{\frac{1}{\sigma}} y(z_i,k,l,m)^{-\frac{1}{\sigma}} \quad \text{(CES demand)}$$

To prove Proposition 3.1, first note that given optimal subsidies τ_i^*, optimal input choices are given by:

$$\begin{aligned}
k^* &= (1-\tau^V)(1+\tau_i^*)P \cdot Y^{\frac{1}{\sigma}}((\sigma-1)/\sigma)y_i^{\frac{\sigma-1}{\sigma}}\left(\frac{\alpha}{R}\right)\\
l^* &= (1-\tau^V)(1+\tau_i^*)P \cdot Y^{\frac{1}{\sigma}}((\sigma-1)/\sigma)y_i^{\frac{\sigma-1}{\sigma}}\left(\frac{\beta}{w}\right)\\
m^* &= \qquad\qquad (1+\tau_i^*)P \cdot Y^{\frac{1}{\sigma}}((\sigma-1)/\sigma)y_i^{\frac{\sigma-1}{\sigma}}\left(\frac{\gamma}{P}\right)
\end{aligned}$$

That is, optimal choices for capital and labor are distorted by the value-added tax, but material input choices are not. From this, we can construct optimal output y_i^*:

$$y_i^* = z_i\,(k^*)^{\alpha}\,(l^*)^{\beta}\,(m^*)^{\gamma} = \left(z_i(1+\tau_i^*)^{\eta}\,(\bar{x})^{\eta}\,(x^*)^{\frac{\sigma}{\sigma-1}}\right)^{\frac{1}{1-\tilde{\eta}}}$$

where: $\eta \equiv \alpha+\beta+\gamma$, $\bar{x} \equiv PY^{\frac{1}{\sigma}}$, and $x^* \equiv \left((1-\tau^V)\frac{\tilde{\alpha}}{R}\right)^{\tilde{\alpha}}\left((1-\tau^V)\frac{\tilde{\beta}}{w}\right)^{\tilde{\beta}}\left(\frac{\tilde{\gamma}}{P}\right)^{\tilde{\gamma}}$, and where revenue elasticities are given by a tilde (e.g. $\tilde{\alpha} \equiv \frac{\sigma-1}{\sigma}\alpha$). Plugging this into the CES demand function gives the implied optimal variety-specific price:

$$p_i^* = \bar{x}\left(z_i(1+\tau_i^*)^{\eta}\,(\bar{x})^{\eta}\,(x^*)^{\frac{\sigma}{\sigma-1}}\right)^{\frac{-1}{\sigma(1-\tilde{\eta})}}$$

And combining the two gives optimal revenue as stated in Proposition 3.1:

$$(1+\tau_i^*)p_i^*y_i^* = (1+\tau_i^*)\bar{x}\left(z_i(1+\tau_i^*)^{\eta}\,(\bar{x})^{\eta}\,(x^*)^{\frac{\sigma}{\sigma-1}}\right)^{\frac{\sigma-1}{\sigma(1-\tilde{\eta})}} = \tilde{z}_i(1+\tau_i^*)^{\frac{1}{1-\tilde{\eta}}}$$

with: $\tilde{z}_i \equiv [z_i^* x^*]^{\frac{1}{1-\tilde{\eta}}}$ and $z_i^* = z_i^{\frac{\sigma-1}{\sigma}}\bar{x}$.

Next, we can solve for optimal implied (gross) profits using the previously derived optimal revenues and input choices:

$$\pi^*(z_i,\varepsilon_i) \equiv (1-\tau^V)\Big[\underbrace{(1-\tilde{\alpha}-\tilde{\beta}-\tilde{\gamma})}_{\equiv(1-\tilde{\eta})}\tilde{z}_i(1+\tau_i^*)^{\frac{1}{1-\tilde{\eta}}} - Pm_R^* - \mathbb{1}_{m_R>0}F_C\Big]$$

Finally, we can solve for the first-order condition for optimal rent-seeking activities:

$$\frac{\partial \pi^{\text{net}}}{\partial m_R^*} = 0: \quad P = (1-\tilde{\eta})\tilde{z}_i(1-\tilde{\eta})^{-1}(1+\tau_i^*)^{\frac{\tilde{\eta}}{1-\tilde{\eta}}}\frac{\partial \tau_i(m_R^*, \varepsilon_i)}{\partial m_R^*} = \frac{\partial \tau_i(m_R^*, \varepsilon_i)}{\partial m_R^*}\tilde{z}_i(1+\tau_i^*)^{\frac{\tilde{\eta}}{1-\tilde{\eta}}}$$

A.3.3 Optimal subsidies to connected firms in the presence of distortive taxes

In this section, I formally solve for optimal subsidies to connected firms taking as given the existing mix of value-added and corporate income taxes.[28] The problem of optimal subsidies is an optimal taxation problem where the government has a fixed amount of resources $\overline{T}$ it can potentially spend or levy on connected firms in the form of firm-specific output subsidies τ_i. Note that $\tau_i < 0$ captures the case of taxes. The government's objective is to maximize total output as this is the consumption good that households care about. I formally start with the simpler case of a partial equilibrium analysis where the distribution of firms is given and input prices are unaffected by the taxes. Given that the focus is on arbitrary taxes for a few individual firms, this is generally close to the optimal taxes in general equilibrium and I discuss the general case further below.

I show that the partial equilibrium problem has a simple solution that requires setting a constant subsidy rate across (connected) firms. This means that more productive firms will receive higher total amounts of subsidies, but not at a higher subsidy rate. Formally, the optimal taxation problem can be written as:

$$\begin{aligned}
&\max_{\{\tau_i\}_i} \left[\int_0^N (y_i^*)^{\frac{\sigma-1}{\sigma}} di\right]^{\frac{\sigma}{\sigma-1}} \quad \text{s.t.} \quad \overline{T} \leq \int_0^N \tau_i p_i^* y_i^* \\
\Leftrightarrow \quad &\max_{\{\tau_i\}_i} \left\{ \left[\int_0^N (1+\tau_i)^{\frac{\tilde{\eta}}{1-\tilde{\eta}}} (z_i x)^{\frac{\sigma-1}{\sigma}\frac{1}{1-\tilde{\eta}}} di\right]^{\frac{\sigma}{\sigma-1}} + \lambda \left[\overline{T} - \int_0^N \tau_i (1+\tau_i)^{\frac{\tilde{\eta}}{1-\tilde{\eta}}} (z_i x)^{\frac{\sigma-1}{\sigma(1-\tilde{\eta})}} \bar{x} di\right] \right\}
\end{aligned} \tag{20}$$

where in the second line I have directly plugged in the optimal y_i^* and p_i^*. Technically, the government optimizes over the envelope of optimal firm decisions. The setup is under perfect information with the government setting idiosyncratic taxes based on the revealed size of the firm.

Taking first-order conditions for any τ_i, we get the following optimal tax condition:

$$\frac{\partial Y}{\partial \tau_i} = \lambda \frac{\partial \tau_i p_i^* y_i^*}{\partial \tau_i}$$

which states that the government should equalize the marginal budget benefits from setting a higher tax rate (captured by the shadow cost of public funds λ) with the negative marginal output effects from setting a higher tax rate. The budget benefits scale with the tax rate times the optimal

[28] I want to thank Matthias Meier for suggesting to do this exercise.

revenue that the firm chooses based on the tax rate. The optimal tax rate can then be expressed in closed-form as a function of the shadow cost of public funds:

$$\tau_i = \frac{\frac{\tilde{\eta}}{1-\tilde{\eta}}\frac{\sigma}{\sigma-1} - \lambda}{\frac{\tilde{\eta}}{1-\tilde{\eta}} + \lambda}$$

Importantly, idiosyncratic productivity z_i cancels out in this expression such that optimal tax rates end up being uniform across firms and their level is determined by the need of funds.

In general equilibrium, this result changes slightly. The reason is that any tax changes now also have an indirect effect on equilibrium prices as well as the equilibrium distribution of firms. Given that both general equilibrium responses do not have closed-form expressions, further analytical results for optimal taxation in general equilibrium are beyond the scope of this paper. However, it is important to note that general equilibrium corrections to the optimal taxation result in partial equilibrium are generally small given that we are looking at a problem where a few individual firms may be subsidized. (Could add limit case result with fixed distribution of firms.)

A.3.4 Proof of Proposition 3.2 (Why subsidies are not wedges)

The first part of Proposition 3.2 says that variation in TFPR-HK$_i$ across firms captures solely variation in subsidies only if observed revenue was reported without subsidies. To show this, define:

$$\text{TFPR-HK}_i(\text{Revenue}) \equiv \frac{\text{Revenue}}{k^\alpha l^\beta m^\gamma}$$

according to Hsieh and Klenow (2009) (where the only difference is that I have extended their setup to also include intermediates). Then:

$$\text{TFPR-HK}_i(p_i y_i) = \frac{\bar{x}\left[z_i(1+\tau_i^*)^\eta \bar{x}^\eta \left(x^*\right)^{\frac{\sigma}{\sigma-1}}\right]^{\frac{-1}{\sigma(1-\tilde{\eta})}} z_i k^\alpha l^\beta m^\gamma}{k^\alpha l^\beta m^\gamma} = \left(z_i\bar{x}^\eta\right)^{\frac{\sigma-(\sigma-1)\eta-1}{\sigma-(\sigma-1)\eta}} \left(1+\tau_i^*\right)^{\frac{-\eta}{\sigma-(\sigma-1)\eta}} \left(x^*\right)^{\frac{-1}{\sigma-(\sigma-1)\eta}}$$

which generally varies due to both z_i and τ_i. Under the special case of $\eta = 1$ (CRS), which is the case studied in Hsieh and Klenow (2009), this expression simplifies to:

$$\text{TFPR-HK}_i^{CRS}(p_i y_i) = \left(1+\tau_i^*\right)^{-1}\left(x^*\right)^{-1}$$

where z_i drops out and cross-sectional variation in TFPR is caused solely by variation in subsidies. However, as long as observed revenue is distorted by subsidies:

$$\text{TFPR-HK}_i^{CRS}((1+\tau_i^*)p_i y_i) = \left(x^*\right)^{-1}$$

which shows no variation due to subsidies.

Next, we can look at the alternative measure of TFPQ proposed by Hsieh and Klenow (2009) to capture variation in physical productivity that should not be affected by subsidies. Following Hsieh and Klenow (2009), define: TFPQ-HK$_i$(Revenue) $\equiv \frac{\text{Revenue}^{\frac{\sigma}{\sigma-1}}}{k^\alpha l^\beta m^\gamma}\kappa$, where κ is a constant that is a function of the general equilibrium objects P and Y. This definition is identical to Hsieh and Klenow (2009) except that I have included materials and κ is not sector-specific. The approach in Hsieh and Klenow (2009) assumes that one can use undistorted revenue to compute TFPQ, in which case one can indeed exactly recover physical productivity z_i:

$$\text{TFPQ-HK}_i(p_i y_i) = \frac{\left(PY^{\frac{1}{\sigma}} y_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}}{k^\alpha l^\beta m^\gamma}\kappa = \left(PY^{\frac{1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \kappa z_i = z_i$$

with $\kappa \equiv \left(PY^{\frac{1}{\sigma}}\right)^{\frac{-\sigma}{\sigma-1}}$. If instead, TFPQ-HK$_i$ is measured using distorted revenue that includes subsidies, the measure recovers both physical productivity and subsidies:

$$\text{TFPQ-HK}_i\left((1+\tau_i^*)p_i y_i\right) = \frac{\left((1+\tau_i^*)PY^{\frac{1}{\sigma}} y_i^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}}}{k^\alpha l^\beta m^\gamma}\kappa = \left(PY^{\frac{1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \kappa z_i = (1+\tau_i^*)^{\frac{\sigma}{\sigma-1}} z_i$$

This concludes the proof of Proposition 3.2.

A.3.5 Proof of Proposition 3.3 (Subsidy identification conditional on ε)

In the following I proof proposition 3.3.

I start by proving that the model implies that potential connected firms and non-connected firms share the same marginal productivity distribution. First, note that the productivity process of surviving firms is identical across connected and non-connected firms by assumption. This means that the only way in which marginal productivity distributions could differ across connected and non-connected firms is if the two groups differentially enter or exit. For entry, potential entrants are all ex-ante identical and have no knowledge of their connections status before entering. After entering, they draw productivity from the joint (primitive) distribution $F_{z,\varepsilon}$ and the probability of becoming connected π_C is independent of productivity and ε, implying that connected and non-connected firms both draw from the same marginal productivity distribution. For firm exit, the assumption that there is no persistence in being connected (that is, firms redraw from π_C every period) ensures that exit is only a function of productivity z_i (and aggregates) and is thus identical across connected and non-connected firms. This proves the first part.

Next, I prove that without variation in ε across potential connected firms, the subsidy distribution is directly identified from ratios of the observed TFPQ quantiles across connected and non-connected firms:

$$\text{QR}(p) \equiv \frac{Q^{C}_{\text{TFPQ}}(p)}{Q^{NC}_{\text{TFPQ}>\text{TFPQ}(\bar{z})}(p)} - 1 = \tau^*_i(Q_{z^*_i}(p)) \quad \text{with: } \text{TFPQ}_i(\bar{z}) \in [\min\{\text{TFPQ}^{NC}\}, \min\{\text{TFPQ}^{C}\})$$

Given the assumption of the **Productivity cutoff**, there exists a cutoff $\bar{z}(\varepsilon)$ such that firms that have access to the connections technology $\tau(\varepsilon, z^*_i, m_{Ri})$ and that have a weakly higher productivity choose to use their connections. Without variation in ε, this cutoff is the same across firms. Next, the assumption that the connections technology evaluated at the optimal level of rent-seeking m^*_R is **rank-preserving in z** ensures that the ranking of TFPQ and z^* is identical for a fixed level of ε. In combination with having the same marginal productivity distributions, evaluating the TFPQ distributions at the same quantiles (after restricting the TFPQ distribution of non-connected firms to firms above the productivity cutoff) means that:

$$\text{QR}(p) \equiv \frac{Q^{C}_{\text{TFPQ}}(p)}{Q^{NC}_{\text{TFPQ}>\text{TFPQ}(\bar{z})}(p)} = \frac{(1+\tau^*_i(Q_{z^*_i}(p))z^*(p)}{z^*(p)} = 1 + \tau^*_i(Q_{z^*_i}(p))$$

where I have used that non-connected firms' TFPQ is only equal to their productivity z^*. At last, one can bound the productivity cutoff $\bar{z}$ with the lower bound given by the lower bound of the marginal productivity distribution revealed by non-connected firms ($\min\{\text{TFPQ}^{NC}\}$). The upper bound is given by the lowest TFPQ among connected firms given that $(1+\tau^*(\varepsilon, z^*_i))z^* \geq z^* \;\; \forall z^*$. Exploiting the ordering properties of the quantile ratio is common for quantile estimation techniques such as quantile treatment estimators.

A.4 Further estimation details

A.4.1 Estimation of productivity process & the Asian Financial Crisis

In the following I show evidence that estimation of the productivity and firm exit process are unlikely going to be substantially affected by the Asian Financial Crisis, despite estimating these processes on the period from 1997 to 1998.

I start showing the annual evolution of aggregate output across manufacturing firms between 1990 and 2003 in Figure A.2, plotting both total sales and total value-added. One can see that despite a slight slow down in growth in 1997, the Asian Financial Crisis only hits manufacturing firms starting in the accounting year of 1998. This means that all of the within-period estimation that is based on year 1997 will not be affected by the Asian Financial Crisis.

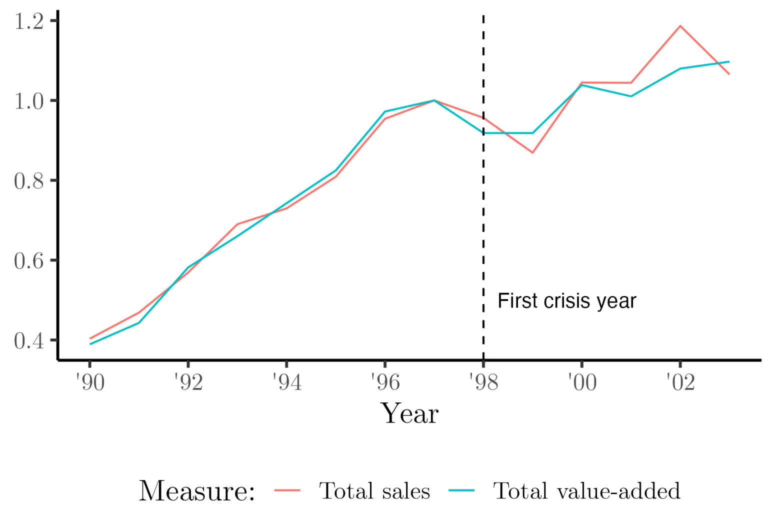


Figure A.2: Evolution of aggregate real sales and real value added for Indonesian firms based on Statistik Industri, the manufacturing firm census. Series are normalized by values in 1997 respectively.

Next, I discuss how the Asian Financial Crisis in 1998 may bias targeted moments that I use to estimate the underlying productivity process. For this, I compare the targeted moments in Table 3 with alternative moments had I instead used 1996-1997 as the comparison years (rather than the 1997-1998 years as in the main text). I use the same procedure to construct both sets of moments (i.e. the same residualization across time and cross-sectional fixed effects). Since the time fixed effects I use to residualize the data controls for any common multiplicative shocks across firms over time, the Asian Financial Crisis would only affect the estimates to the extent that the crisis affects firms heterogeneously. I do not find strong evidence for this. As reported in Table A.1, targeted moments are not very sensitive to the year chosen. Furthermore, if anything I find that choosing 1997 as the base year estimates more persistence in TFPQ, speaking against heterogeneous shocks that dilute persistence in TFPQ. On the other hand, I do find slightly more variance in the shocks, in line with the Asian Financial Crisis increasing overall volatility of firm-level shocks. In the end, it is not clear that target moments from an earlier base year would affect results meaningfully.

To make an even stronger case for this, it is important to note that the two cases are not strictly comparable. Both cases have a “bias” compared to the true primitive parameters of the productivity process, which is related to firm-level subsidies and selection into political connections. While the “bias” of the baseline targeted moment comes from selecting non-connected firms in 1997 who might become connected in 1998 without me observing so, the bias of the alternative targets comes from selecting non-connected firms in 1997 who might have been connected in 1996. In principle, both biases can be replicated using the model, making both sets of targeted moments suitable for indirect inference. Importantly, one would expect the two biases to have opposite effects on the targeted

Table A.1: Data moment targets when taking 1996-1997 as baseline (rather than 1997-1998)

Moment	Description	Data 1997 (baseline)	Data 1996 (robustness)
Productivity process:			
β_0^{TFPQ}	Constant in TFPQ regression	0.094	0.183
β_1^{TFPQ}	Persistence in TFPQ regression	0.966	0.945
$\text{Var}(\zeta_i^*)$	Var of error in TFPQ regression	0.015	0.011
Exit process:			
β_0^X	Constant in exit regression	0.400	0.299
β_1^X	Slope in exit regression wrt TFPQ	-0.102	-0.074

Details: For productivity process: Reports regression results of log(TFPQ) in 1998 on log(TFPQ) in 1997 for firms that are non-connected in 1997. For exit process: Reports regression results of next period exit on log(TFPQ) for non-connected firms in 1997. TFPQ and exit are both first residualized using province, state-ownership, firm age (in 15 bins) and 4-digit industry fixed effects using all firms. For the dynamic regression, TFPQ in 1998 is also residualized by a time fixed effect that controls for aggregate shocks. For the column 'Data 1996 (robustness)' the exact same procedures are applied, except for moving everything back by one year to 1996-1997.

parameters, thus shrinking their implied difference for the primitive parameters of the underlying productivity process. To conclude, I find little evidence for the Asian Financial Crisis to affect the productivity parameter estimates.

Next, I look at estimates for the exit process. Figure A.3 plots (raw) average firm exit rates over time, defined as the share of firms exiting *next period*. Average exit rates are relatively stable over time. I do find a small uptick in exit rates in 1997 (firms that are exiting in 1998), but these exit rates are very similar to exit rates in 1995 and 1996, making it unlikely that the Asian Financial Crisis biases the overall level of exit in the economy.

To gauge potential biases, Table 3 also reports alternative target moments had I instead used data between 1996-1997 (but otherwise construct coefficients identically). Again, regression coefficients are very similar to the baseline targeted coefficients. Not surprisingly, given the slightly lower observed exit rates, I also find lower estimated coefficients when using 1996 as the baseline year. Perhaps more surprisingly, I also find a slightly lower exit elasticity with respect to firm TFPQ, implying that exit reasons were less influenced by TFPQ in 1996 (before firms could have anticipated the Crisis) than in 1997 (where firms might have exited due to the crisis). This would imply that with alternative targeted exit moments, the model would give a slightly lower overall exit rate and exit that is less elastic to TFPQ, further muting any firm exit effects due to shutting down political connections.

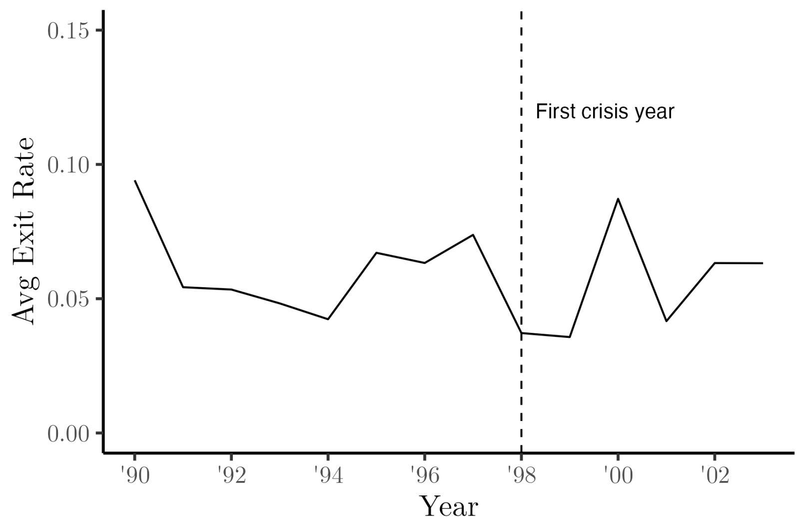


Figure A.3: Evolution of average exit rates for Indonesian firms based on Statistik Industri, the manufacturing firm census. Firm exit is measured as a firm exiting the firm census and not reentering in the future. This measure is robust to temporary firm exit, which could be due to non-reporting.

A.4.2 Gumbel distribution derivations

Here I show that the Gumbel distribution for fixed costs allows closed-form expressions for the exit probability and the conditional expectation of fixed costs.

$$\mathbb{P}^{\text{Exit}}(z_i^*) = 1 - exp\left(-exp\left(\frac{-(x(z_i^*) - \mu^x)}{\sigma^x}\right)\right) \tag{21}$$

$$\mathbb{E}[f_i^F|\text{survive}(z_i^*)] = x(z_i^*)(1 - \mathbb{P}^{\text{Exit}}(z_i^*)) - \sigma^x \Gamma\left(0, exp\left(\frac{-(x(z_i^*) - \mu^x)}{\sigma^x}\right)\right) \tag{22}$$

where $x(z_i^*) \equiv \frac{1}{1+r}\mathbb{E}\big[V(z_i^{*'}, \varepsilon')|z_i^*\big]$ and $\Gamma()$ gives the incomplete Gamma function (whose values are known).

A.5 Microfoundations of the Political Connections Technology

In the following I provide two possible microfoundations for the *Political Connections Technology* used throughout the paper that are based on two different interpretations of what political connections buy. In the first interpretation, the *Political Connections Technology* buys output subsidies, while in the second interpretation, the *Political Connections Technology* is reinterpreted as the share of taxes that connected firms pay.

A.5.1 The *Political Connections Technology* as an output subsidy

One interpretation of the *Political Connections Technology* is as a net output subsidy. The parametric form chosen for this technology is: $\tau_i = \varepsilon_i m_R^{\theta_\varepsilon} - c m_R^{\theta_c}$. To microfound this choice, suppose the government can use part of the tax revenue to buy products from firms that are then redistributed to households. As was shown before, τ_i only captures demand beyond standard demand for a similar non-connected firm. That is, the government basically offers a contract to a connected firm saying, whatever your total demand from households, we will pay $\tau_i/(1+\tau_i)$ percent of this demand or we subsidize households' demand by this percentage. The assumption here is that most government policies that directly or indirectly subsidize firms can be represented by this menu over τ_i instead of contracts that are fixed to quantities. That is, politicians directly bargain over subsidy rates and not absolute transfers. The microfoundation of the parametric form of τ_i is then linked to the political process that offers subsidy rates.

Specifically, suppose that for each connected firm there exists a continuum of relevant government bills that each may promise a unit of government demand. τ_i gives at the same time the net subsidy rate obtained by a connected firm i as well as the measure of government bills that the connected firm managed to influence in its favor. Given that there are few connected firms in this economy, this model abstracts from competition for government bills across connected firms and simply assumes that all connected firms care about their own set of government bills that they can influence. There are two terms in the *Political Connections Technology.* The first term captures the amount of bills that the firm managed to influence, while the second term captures the amount of influenced bills that are overturned via audits or other public oversight. Given the continuous measure of government bills, these audits give deterministic detection rates. Let us look at each of the terms in turn.

The first part of the technology ($\varepsilon_i m_R^{\theta_\varepsilon}$) captures the measure of bills that the connected firm manages to influence via bribing and lobbying the politician they are connected to. There are two ways to think about this term that lead to very similar parameter interpretations. First, the politician has direct access to government bills and offers the firm a linear bribe schedule ($\tilde{\tau}_i = \text{const.} * b$), but the firm faces costs of concealment or production costs to transform rent-seeking spending p into actual bribes b so that $b = \widetilde{\text{const.}} + \varepsilon_i * m_R^{\theta_\varepsilon}$ where ε_i gives the firm's productivity at concealing bribes and θ_ε is now the elasticity of this concealment technology. This captures what economic sociologists call costs of obfuscating bribes m_R as meaningful, symbolic interactions (Hoang 2018). ε_i can isomorphically be thought of as the strength of the connection as measured by the politician's efficiency at making legislative changes rather than the firms' productivity at rent-seeking.

Alternatively, political capital does not need to be converted ($m_R = p$), but the politician may face direct costs of obtaining the subsidy rates through parliamentary approval, bargaining with other politicians or filling out the paper work. For example, increasingly higher benefits to firms might require the approval of more politicians who all need to be bribed as well, explaining $\theta_\varepsilon \in (0,1)$). Then, θ_ε captures the elasticity of costs from obtaining output subsidy rates. In both cases, counterfactuals have very similar interpretations. For example, one can think of doubling ε as doubling the efficiency of the politician to transform bribes into subsidies.

For the second term, suppose the politician faces risks of audits or opposition from other politicians. Remember that subsidy rates are determined by a continuum of small amendments to laws or policies. In this case, audits can overturn a fraction of subsidies. The second term ($cm_R^{\theta_c}$) then captures the number of subsidy rates that are overruled by audits. $m_R^{\theta_c}$ captures the idea that benefits to politically connected firms are more likely to be contested by other politicians or the public as the number of distortionary policy and regulatory amendments increases. θ_c measures the elasticity of this opposing reaction. Importantly, c measures the level of audits in the economy.

A.5.2 The *Political Connections Technology* as a tax evasion technology

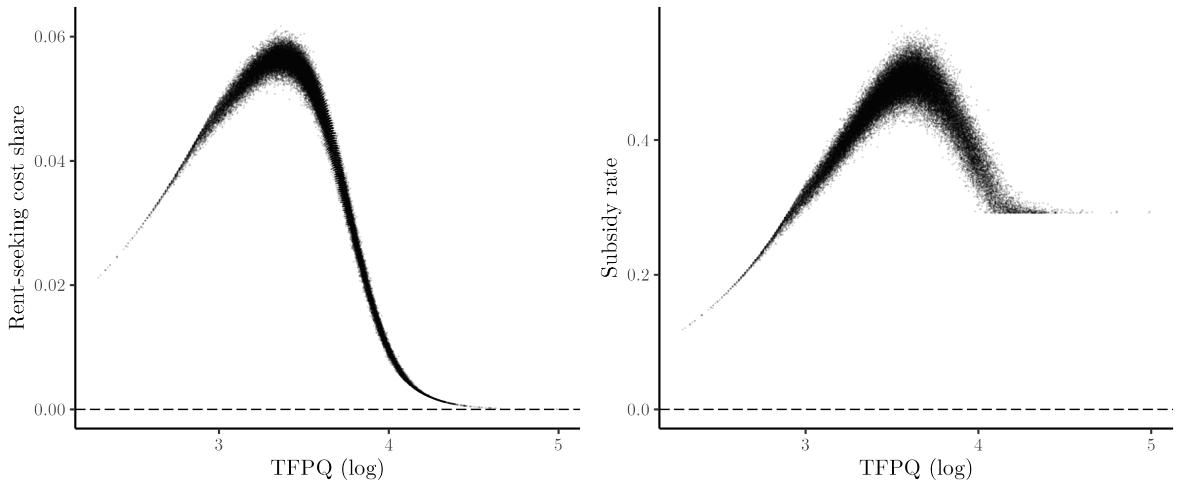
We can also redefine the *Political Connections Technology* as a tax evasion technology. For this, write the share of taxes that connected firms pay as: $\phi_i \equiv 1 - \tau_i\left(\frac{1-\bar{\tau}}{\bar{\tau}}\right)$ where $\bar{\tau}$ gives the official revenue tax rate. Plugging in the parametric form chosen for the *Political Connections Technology*, this can be rewritten as:

$$\phi_i = 1 - \varepsilon_i m_R^{\theta_\varepsilon}\left(\frac{1-\bar{\tau}}{\bar{\tau}}\right) + cm_R^{\theta_c}\left(\frac{1-\bar{\tau}}{\bar{\tau}}\right)$$

The share of taxes that a firm pays is then determined by two terms; the first term decreases and the second term increases the share of taxes as political capital spending is increasing. Suppose the following simple setup. A tax collector is in charge of a firm's filing and has discretion over ϕ_i. The tax collector takes bribes b for setting a lower ϕ_i as in the previous narrative. Suppose that total taxes depend on many different rules, different documents or that it depends on a long list of entries in revenue filings to the tax administration. Suppose that the tax collector charges a bribe for reducing the tax in each document, each data entry or each part of the tax. In this case, the share of taxes paid by the firm can be expressed as a linear rule in bribes: $\phi_i = 1 - \text{const.} * b$. Now suppose that the firm needs to "produce" or "conceal" b so that $b = \widetilde{\text{const.}} * \varepsilon_i * m_R^{\theta_\varepsilon}$ where θ_ε is now the elasticity of this production or concealment technology and ε_i the productivity.

For the second term, suppose the tax collector faces oversight from managers or risk of being checked up on. The tax collector conceals or calculates lower rates for each entry and managers

Figure A.4: Baseline model: Rent-seeking and subsidy variation over TFPQ



Notes: Results for simulated sample of connected firms based on baseline model estimates. Panel A (left): Rent-seeking share (rent-seeking as share of revenue) over TFPQ (log). Panel B (right): Subsidy rate over TFPQ (log).

may sporadically check up on any entry. As the number of entries becomes large, the probability of being detected equals the number of checks. Suppose for simplicity that for each check that leads to corrections, the tax collector does not face any punishment and only the tax demands are changed. The tax collector offers to reduce taxes, but does not insure the risk of corrections. Then the second term captures the number of distorted tax entries that become corrected and one can rewrite this term as const. $* b^{\tilde{\theta}}$, where $\tilde{\theta}$ can be thought of as a span-of-control parameter that captures how close tax collectors are being monitored. For a high $\tilde{\theta}$, this control is high, which leaves little room for tax collectors to change tax rates for connected firms. Importantly, c captures the level of auditing.

A.6 Further validation results

This part of the Appendix reports further validation results that are cited in the main text. Figure A.4 plots model-implied distributions of rent-seeking and subsidies for a large random sample of connected firms sampled from the baseline model. Both graphs show that there is a hump-shaped, non-monotonic relationship between TFPQ and rent-seeking as well as subsidies. While variation in rent-seeking and subsidies is driven by a combination of underlying productivity variation (that drives TFPQ) and by variation in connections, there is visibly more variation across TFPQ than within TFPQ.

Next, Table A.2 reports regression results of differential revenue shares of various components of reported intermediate inputs across connected and non-connected firms. Column 1 reports the baseline gap in total intermediates as reported as a main untargeted moment in the main text. Column 2 reports “other expenditures” which are a subcategory of intermediate inputs, showing that non-connected firms report lower revenue shares. Note that differential other expenditure shares only account for roughly 8% of the overall gap in intermediate input shares. The large remainder is still driven by the remaining components related to fuels and materials. Columns 3-9 report subcomponents of "other expenditures", showing that connected firms spend larger shares on management fees to third parties (column 5), royalty fees (column 8) and other components of other expenditures (column 9). I view these differential spending patterns as consistent with higher rent-seeking spending by connected firms.

An important additional empirical fact is that I can also look at R&D spending as one direct measure related to the physical productivity of firms. A key implication of the model is that connected and non-connected firms have the same underlying distribution of physical productivity. Column 6 shows that – consistent with this pattern – connected firms do not spend more on R&D since the point estimate is small and not statistically significantly different from zero. Of course, only about the top 10% of firms report any spending on R&D, limiting the power of this test.

At last, I consider variation in political connections ε, comparing firms that are connected by "blood" to Suharto (i.e. family ties) and "normally connected" firms. Column 1 in Table A.3 shows that both non-connected and normally connected firms are smaller than blood-connected firms, altough the latter difference is not significantly different. A larger average size of blood connected firms is in line with the comparative statics of the model, assuming that blood connected firms have a higher ε. Of course, expected size differences depend on whether one assumes that sampling is conditional on productivity or unconditional. Columns 2-3 zoom in on expected differential rent-seeking across blood connected and normally connected firms. The model predicts that conditional on observed TFPQ, more connected firms have larger rent-seeking shares. To test this, columns 2-3 look at differential intermediate shares after controlling for TFPQ and residualizing on the standard set of fixed effects used throughout the paper. In contrast to the model predictions, normal connected firms – if anything – have a larger differential intermediate share. When restricting only to connected firms (column 2) these differences are, however, not significant. In column 3, I estimate differences on the entire sample in which case differences become significant. It is important to note that column 2 is the more accurate test of the model, given that the relationship between TFPQ and intermediates is heterogeneous across connected and non-connected firms. Ideally, one would like to strictly compare "within TFPQ", but unfortunately this leaves no variation to identify within-TFPQ differences in the intermediate shares.

Table A.2: Subcomponents of intermediate inputs: Connected vs. Non-connected firms

Dep. Var.:	Intermed.	Other exp	Advert.	HR	Mngmt fee	R&D	Repr	Royalty	Other
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables									
Non-connected?	-0.0566***	-0.0033*	-0.0003	-1.08×10^{-5}	-0.0004***	-0.0001	-0.0004	-0.0003**	-0.0019***
	(0.0181)	(0.0017)	(0.0002)	(3.42×10^{-5})	(0.0002)	(8.57×10^{-5})	(0.0003)	(0.0002)	(0.0006)
Fixed-effects									
Industry 4-digit	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
state-owned major	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
state-owned partly	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
est year bin	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	18,558	18,558	18,558	18,558	18,558	18,558	18,558	18,558	18,558
R^2	0.17230	0.07414	0.09345	0.02328	0.02405	0.02449	0.04136	0.04872	0.04382
Within R^2	0.00093	0.00025	0.00020	1.61×10^{-6}	0.00073	0.00037	0.00018	0.00093	0.00079

Clustered (industry 4-digit) standard-errors in parentheses. All dependent variables are in terms of revenue shares.
Columns 3-9 report subcomponents of "other expenditures" which are part of reported total intermediates.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.3: Regression evidence on variation in connections type: Blood vs. normally connected

Dependent Variables:	log TFPQ	Intermediate share	
Sample:	(Full)	(Only C)	(Full)
Variables			
Non-connected?	-0.4181***		0.0984***
	(0.0437)		(0.0332)
Normal connected?	-0.0405	0.0348	0.0604*
	(0.0375)	(0.0374)	(0.0324)
log TFPQ		0.0786	0.2988***
		(0.0950)	(0.0159)
Fixed-effects			
Industry 4-digit	Yes	Yes	Yes
Province	Yes	Yes	Yes
State-owned major?	Yes	Yes	Yes
State-owned partly?	Yes	Yes	Yes
Est. year bin	Yes	Yes	Yes
Fit statistics			
Observations	18,558	241	18,558
R^2	0.36387	0.52059	0.31348
Within R^2	0.02297	0.01308	0.17133

Clustered (Industry 4-digit) standard-errors in parentheses
Outside category: Blood connected firms (N = 89)
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

B Further quantitative results

This section of the Appendix provides details on the quantitative exercises. In the first part, I provide details on the counterfactual exercises and the algorithm(s) to solve for the counterfactual steady state equilibrium and the transition path towards the new steady state equilibrium. The second part provides additional results that are referenced in the main results section.

B.1 Counterfactual and computational details

B.1.1 Modeling entry

I start by expanding on how I model entry and specifically entry costs, which matters for counterfactuals. As described in the main text, I denote entry costs f_E in terms of the output good. Technically, since firm profits go to absentee owners and not to households, it doesn't matter for output nor for consumption effects whether entry costs are truly in the output good or instead a utility cost on entrants. It does however matter for reporting profits.

Quantitatively, I found that whether entry costs are in goods or labor matters. I started out with denoting entry costs in terms of labor following Klenow and Li (2024). This had the unwanted effects that more entrants basically became "bads", more firms in the economy implied output losses, which seems unrealistic. A key driver of this was the combination of having relatively high estimated entry costs and letting these entry costs drive up wages more due to the labor indexation.

In the current version that gives realistic results on entry and exit, I treat entry costs as an actual cost that affects firm profits. Additionally, I make one slightly ad-hoc assumption: in counterfactuals, I let the entry costs f_E change in accordance with the wage, so that total entry costs for potential entrants are $w \cdot f_E$ (still denoted in the output good). This is saying that innovations in the entry cost technology comoves 1:1 with the wage. The implication is that in counterfactuals in which the wage decreases slightly, it also becomes slightly cheaper to enter. Given that the baseline wage is equal to 1 and counterfactuals only drive small variations in the aggregate wage, this seems innocuous. In practice, I found that this difference makes the computation much more well-behaved, as it stabilizes the free entry condition. However, it is important to note that this is completely model consistent and still ensures that all markets clear.

B.1.2 Main counterfactuals and algorithm

This subsection gives more details on the main counterfactuals I run and gives details on the algorithm for solving for counterfactual equilibria. I focus here on steady state counterfactuals and discuss the transition results and the algorithm for them further below.

The baseline counterfactual abolishes political connections, which means that previously connected firms do not have access to the political connections technology anymore. I solve for the counterfactual steady state by first solving the firm problem and then solve for results on the household side. On the firm side, I find the wage and aggregate output Y that clear markets, including the free entry condition that determines counterfactual entry, exit and the mass of firms. Any other primitives stay unchanged. On the household side, I solve for household consumption taking into account changes in government transfers due to changes in tax revenue and the absence of subsidies to connected firms. As I discuss further below, the household problem requires to take a stand on the initial level of household savings, as is common for counterfactuals in open economy models.

Algorithm for firm problem I start with the algorithm for the firm problem. Given the primitives of the model economy, the algorithm to solve for the steady state equilibrium is as follows.

Step 1: Guess value for Y_g.

Step 2: Guess value for w_g.

Step 3: Solve value function (via Value Function Iteration) given guesses: (w_g, Y_g). Compute the entry value $EV(w_g, Y_g) \equiv \mathbb{E}_{\varepsilon,z} V(z, \varepsilon; w_g, Y_g)$. Compute:

$$\text{Diff}_w \equiv \frac{EV(w_g, Y_g) - w_g f^E}{w_g f^E}$$

If $|\text{Diff}_w| < \text{crit}_w$ move to **Step 4**, otherwise return to **Step 2** using the updated wage guess: $w_{g'} = w_g * (1 + \text{Diff}_w \cdot \alpha_w)$ where $\alpha_g \in (0, 1]$ is an update parameter to ensure convergence and crit_w is the critical value chosen by the researcher (I use $\text{crit}_w = 1e - 6$ throughout).

Step 4: Denote the wage that ensures the free entry condition holds by w_g^*. Then solve for the stationary distribution $\mathcal{F}_{z,\varepsilon}(w_g^*, Y_g)$ implied by $V(\varepsilon, z; w_g^*, Y_g)$.

Step 5: Find the mass of firms $N(w_g^*, Y_g)$ by solving for the mass that is needed to clear the labor market given total labor supply L.

Step 6: Compute aggregate output $Y(w_g^*, Y_g)$ implied by the new stationary distribution $\mathcal{F}_{z,\varepsilon}(w_g^*, Y_g)$ with mass $N(w_g^*, Y_g)$. Compute:

$$\text{Diff}_Y \equiv \frac{Y(w_g^*, Y_g) - Y_g}{Y_g}$$

If $|\text{Diff}_Y| < \text{crit}_Y$ move to **Step 7**, otherwise return to **Step 1** using the updated output guess: $Y_{g'} = Y_g * (1 + \text{Diff}_Y \cdot \alpha_Y)$ where $\alpha_Y \in (0, 1]$ is an update parameter to ensure convergence and crit_Y is the critical value chosen by the researcher (I use $\text{crit}_Y = 1e - 6$ throughout).

Step 7: Return w_g^*, Y_g.

Solving the household side To compute household income in the new steady state, I make use of the fact that in an open economy, households will want to completely smooth consumption along the transition. As I proof formally below (Section B.1.3), if new household income is given by transfers and labor income according to: $Y' = T' + w'\bar{L}$, then household consumption in the new equilibrium (and along the transition) is given by: $C' = rA_0 + Y'$, a standard permanent income result. Thus, to compute household consumption in the new equilibrium, I need to take a stand on initial asset holdings A_0. I make a conservative choice here by simply assuming that initial assets A_0 are equal to total capital demand in the baseline distorted equilibrium (implying that Indonesia was running a balanced international asset position in 1997). This is a conservative choice because in the data, Indonesia tended to run a negative international asset position at that time. A negative position would imply a (slightly) lower A_0, which would then imply larger consumption gains in any counterfactuals in which income rises.

B.1.3 Proof for household consumption along transition in open economy

For completeness, I am adding a proof below for the fact that in an open economy model, household consumption along the transition and in the new steady state only depends on asset holdings at the original steady state and final permanent income. That is, new consumption C^* is given by: $C^* = rA_0 + \bar{Y}$ where $\bar{Y}$ is steady-state household income (which here comes from government transfers and household labor income only, but could also include profits).

For the proof, I use the Linear Recurrence Relations results.

$$A_{t+1} = (1+r)A_t + \underbrace{Y(t) - C}_{\Gamma(t)}$$

$$A_{t+1} = (1+r)A_t + \Gamma(t)$$

The characteristic polynomial is: $L(\alpha) = \alpha - (1+r), \quad L(\alpha) = 0 \rightarrow \alpha = (1+r)$

$$\frac{\partial L}{\partial \alpha} = 1 \quad \text{so:}$$

$$A(t) = \lambda(1+r)^t + (1+r)^t \sum_{p=0}^{t-1} \frac{\Gamma(p)}{(1+r)^{p+1}} \quad \lambda \in \mathbb{R}$$

As $\Gamma(t) = Y(t) - C$ it follows :

$$A(t) = \lambda(1+r)^t - (1+r)^t \sum_{p=0}^{t-1} \frac{C}{(1+r)^{p+1}} + (1+r)^t \sum_{p=0}^{t-1} \frac{Y(p)}{(1+r)^{p+1}}$$

$$A(t) = \lambda(1+r)^t - C\left[\frac{(1+r)^t - 1}{r}\right] + (1+r)^t \sum_{p=0}^{t-1} \frac{Y(p)}{(1+r)^{p+1}}$$

As $t \to \infty$, $\quad Y(t) \to \bar{Y}$ so, around infinity, we have :

$$\sum_{p=0}^{\infty} \frac{Y(p)}{(1+r)^{p+1}} = \sum_{p=0}^{\infty} \frac{\bar{Y}}{(1+r)^{p+1}} = \bar{Y} \sum_{p=0}^{\infty} \frac{1}{(1+r)^{p+1}} = \bar{Y}\left(\frac{1-(1+r)^{-t}}{r}\right)$$

$$(1+r)^{-t} A(t) = \lambda - C\left[\frac{1-(1+r)^{-t}}{r}\right] + \bar{Y}\left(\frac{1-(1+r)^{-t}}{r}\right)$$

$$\lim_{t\to\infty} (1+r)^{-t} A(t) = \lambda - \frac{C}{r} + \frac{\bar{Y}}{r} = 0$$

$$\lambda = \frac{C - \bar{Y}}{r}$$

A(t) becomes : $\quad A(t) = \frac{C-\bar{Y}}{r}(1+r)^t - C\left(\frac{(1+r)^{-t}-1}{r}\right) + (1+r)^{-t} \sum_{p=0}^{t-1} \frac{Y(p)}{(1+r)^{p+1}}$

$$A(0) = A_0 \Rightarrow \frac{C-\bar{Y}}{r} = A_0 \Rightarrow \boxed{C = A_0 r + \bar{Y}}$$

We finally have:

$$\boxed{A(t) = A_0(1+r)^t - \left(rA_0 + \bar{Y}\right)\left(\frac{(1+r)^{-t}-1}{r}\right) + (1+r)^{-t} \sum_{p=0}^{t-1} \frac{Y(p)}{(1+r)^{p+1}}}$$

B.1.4 Algorithm Transition (Firm side)

Start from an initial known distribution $\mathcal{F}_{z,\varepsilon}^{\text{init}}$ with mass N^{init} and given a final steady state characterized by prices $(w_g^{\text{Final}}, Y_g^{\text{Final}})$, distribution $\mathcal{F}_{z,\varepsilon}(w_g^{\text{Final}}, Y_g^{\text{Final}})$ and mass N^{Final}. Then the algorithm for solving the economy's transition path is given by:

Step 1: Guess the path $\{Y_{g,t}\}_0^T$ and T is a large number that ensures convergence (I pick T = 150, allowing the economy 150 years to converge.)

Step 2: Guess the path for $\{w_{g,t}\}_0^T$.

Step 3: Solve the time-varying value function given guesses for the paths: $\{w_{g,t}, Y_{g,t}\}_0^T$. Specifically, first solve the final value function at T using VFI (assuming the economy is at steady state in T). Then, solve the value function backwards enforcing the guesses. Compute the time-varying entry value: $\forall t \in [0,T]: \ EV(w_{g,t}, Y_{g,t}) \equiv \mathbb{E}_{\varepsilon,z} V(z, \varepsilon; w_{g,t}, Y_{g,t}, t)$. Compute the vector:

$$\overrightarrow{\text{Diff}_{w,t}} \equiv \frac{\overrightarrow{EV(w_{g,t}, Y_{g,t})} - \overrightarrow{w_{g,t}} f^E}{\overrightarrow{w_{g,t}} f^E}$$

If $\max_t |\overrightarrow{\text{Diff}_{w,t}}| < \text{crit}_w$ move to **Step 4**, otherwise return to **Step 2** using the updated wage path guess: $\overrightarrow{w_{g',t}} = \overrightarrow{w_{g,t}} * (1 + \overrightarrow{\text{Diff}_{w,t}} \cdot \alpha_w)$ where $\alpha_g \in (0,1]$ is an update parameter to ensure convergence and crit_w is the critical value chosen by the researcher (I use $\text{crit}_w = 1e-6$ throughout).

Step 4: Denote the wage path that ensures the free entry condition holds by $\overrightarrow{w^*_{g,t}}$. Solve for the path of the firm distribution and the mass of firms along the transition by iterating forward from the initial distribution. While firm exit is pinned down by the time path of $V(z, \varepsilon; w_{g,t}, Y_{g,t}, t)$, firm entry is pinned down by the labor market clearing condition, ensuring that the labor market clears in every period along the transition.

Step 5: Compute the implied path of aggregate output $\overrightarrow{Y(w^*_{g,t}, Y_{g,t})}$. Compute:

$$\overrightarrow{\text{Diff}_{Y,t}} \equiv \frac{\overrightarrow{Y(w^*_{g,t}, Y_{g,t})} - \overrightarrow{Y_{g,t}}}{\overrightarrow{Y_{g,t}}}$$

If $\max_t |\overrightarrow{\text{Diff}_{Y,t}}| < \text{crit}_Y$ move to **Step 6**, otherwise return to **Step 1** using the updated output guess: $\overrightarrow{Y_{g',t}} = \overrightarrow{Y_{g,t}} * (1 + \overrightarrow{\text{Diff}_{Y,t}} \cdot \alpha_Y)$ where $\alpha_Y \in (0,1]$ is an update parameter to ensure convergence and crit_Y is the critical value chosen by the researcher (I use $\text{crit}_Y = 1e-6$ throughout).

Step 6: Stop. Return $\{w^*_{g,t}, Y_{g,t}\}$ and the implied paths of the distribution and mass of firms.

As a final check for the convergence, check that $Y_{g,T} = Y_g^{\text{Final}}$ and $w_{g,T} = w_g^{\text{Final}}$ (as well as for the distribution and mass) to ensure that the path has converged to the true final steady state equilibrium.

B.1.5 Transition (Household side)

For the transition on the household side, I can simply make use of the permanent income result that determines household consumption along the transition. The supply side then determines household income along the transition, which means that household asset changes along the transition can be backed out using the household budget constraint.

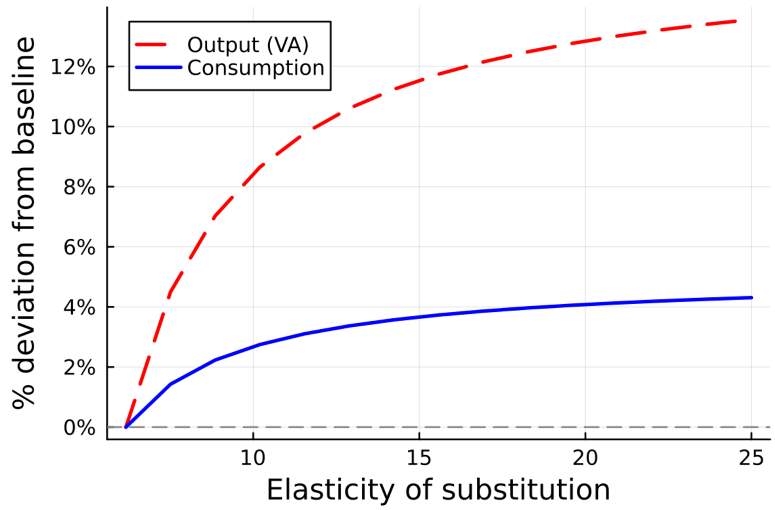
Figure B.1: Baseline costs of political connections along the transition

Notes: Year zero denotes the initial (distorted) steady state. Year 1 is the first year of the transition towards the new steady state. Each series is shown in percentage deviations from its own baseline distorted value.

B.1.6 Transition results

In the following, I report transition results for the baseline costs of political connections. Figure B.1 plots transitions of the key variables. Overall, transitions are extremely fast. The only factor that slows down transitions is firm exit; given that firms face dispersed costs that determine exit, exit only occurs slowly over time. Entry – due to the free entry condition – immediately follows any changes in exit. At the same time, the change in the economic environment induces an immediate larger entry shock. The wage and output are remarkably stable from the very beginning of the transition, an artifact of free entry. Overall, the mass of firms increases by roughly 3.3% in the long-run; the initial entry drives a large part of this in the first years of the transition, while exit rates also increase, undoing some of the entry gains.

Figure B.2: Aggregate costs of Political Connections for different elasticities of substitution



Notes: For each value of the elasticity of substitution, the plot shows results from a counterfactual economy without political connections and where any additional tax revenue is redistributed lump-sum to households (exactly as for the baseline results). The plot reports steady-state consumption and output (value-added) results. Aggregate costs are reported in percentage deviations from the baseline distorted economy. The left-most point gives the baseline estimates reported in the paper. Lower values of the elasticity of substitution are not shown, because they would imply increasing returns to scale at the firm level and introduce unwanted aggregation properties.

B.2 Additional results on costs of connections

B.2.1 Aggregate costs when varying the elasticity of substitution

This subsection of the appendix shows the aggregate costs of political connections as a function of the choice of the elasticity of substitution σ. The benefit of the estimation approach in this paper is that the baseline economy is observationally equivalent for different values of σ, ensuring that varying σ is still consistent with the observed baseline distorted equilibrium. Specifically, this means that the value of $\tilde{\eta}$ is fixed in the data (given by the total revenue-based returns pinned down by non-connected firms), and different values of σ mean that the primitive η will change in response according to: $\frac{\sigma-1}{\sigma}\eta = \tilde{\eta}$. At the risk of being repetitive, this implies that whenever I change σ it is as if I were reestimating all parameters in the model that are consistent with this new value of σ.

Figure B.2 reports results. Costs of political connections are monotonically increasing in the elasticity of substitution. The intuition is straightforward: as the elasticity of substitution increases, aggregate output can substitute more easily across varieties, being less dependent on individual varieties from connected firms. This leads to more reallocation towards better (more productive firms) in the counterfactual without political connections and higher costs of misallocation. This is related to why Hsieh and Klenow (2009) find higher costs for higher values of σ. However, note that the exercise is different because Hsieh and Klenow (2009) do not vary η when changing σ. However, the aggregate costs of political connections do not vary strongly with σ; consumption effects would only be roughly 4% different for the limit case of homogeneous goods. Output effects – due to the misallocation forces discussed previously – are more sensitive but still stay within a 10% bound for any reasonable estimate of σ.

Why don't I compute the aggregate costs for even lower values of σ? The reason is that lower values of σ than the baseline estimate (the left-most point in Figure B.2) would imply increasing returns to scale at the firm level ($\eta > 1$). One might think that this does not matter and that the only value that matters is the net revenue-based return for firms (as given by $\tilde{\eta}$). This is incorrect. In fact, $\eta > 1$ implies aggregation properties that are highly unwanted. To see this, note that in the absence of firm-level subsidies, aggregate output is proportional to a function of firm-level productivity:

$$Y \propto \left(\int_0^N z_i^{\frac{\sigma-1}{\sigma} \frac{1}{1-\tilde{\eta}}} di \right)^{\frac{\sigma(1-\tilde{\eta})}{(\sigma-1)-\sigma\tilde{\eta}}}$$

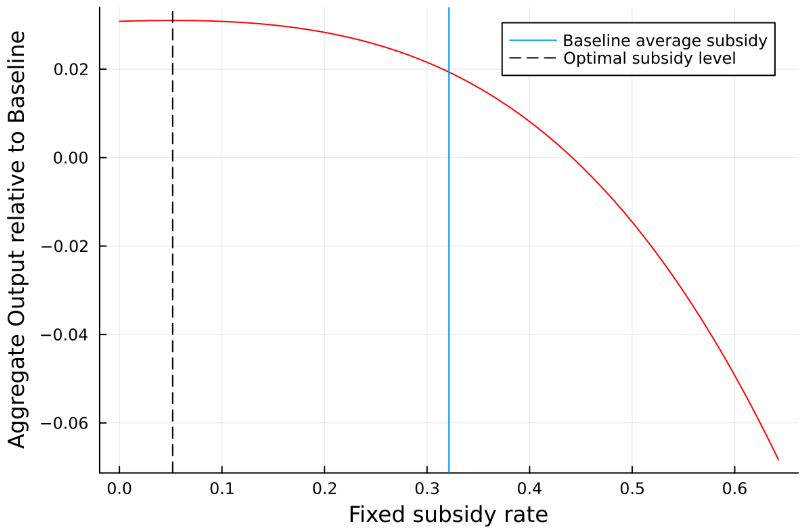
Given empirical values for $\tilde{\eta}$, it turns out that for values of σ that imply $\eta > 1$, the outer exponent turns negative, implying that in the aggregate, more firms and higher firm-level productivity decreases equilibrium output. I conjecture that this is related to a winner-take-all effect that basically implies a hate-for-variety effect that seems economically implausible. To be clear, I can still solve the equilibrium of the economy for lower σ, but finding these equilibria goes against economic intuition (e.g. if labor demand is too high, I need to further decrease rather than increase wages).

B.2.2 The optimal level of a fixed subsidy rate to connected firms

As discussed in Section 4.1, I consider an exercise in which I compute a series of counterfactual (steady state) equilibria in which I enforce a constant output subsidy rate across connected firms. This exercise is meant to quantify whether the level of subsidies paid to connected firms is far from the (constrained) optimum level. Note that there is an optimal level here since subsidies to connected firms undo frictions in the baseline economy that are driven by the value-added tax (in a static sense) and by the corporate income tax (to the extent that this tax also distorts entry and exit). In practice, I consider a grid of fixed subsidy rates that ranges from zero to twice the baseline average rate, which is around 32%.

Figure B.3 reports results. To be able to compare output results, I express all output results as percentage deviations from the baseline (distorted) value added output. The vertical blue line draws in the average subsidy level of the baseline economy and its output effect corresponds to Row 3 in Table 5. As discussed in the main text, output gains would be maximized for a smaller average subsidy rate around 5% (given by the dotted vertical line), but output gains are relatively flat

Figure B.3: Output effects of different levels of subsidy rates



Notes: Each point on the red curve reports value added output (net of intermediates and rent-seeking) for a counterfactual economy (in steady state) with that level of a fixed subsidy rate enforced across all connected firms. Output is reported as percentage deviations from the baseline (distorted) output in which firms receive differential subsidy rates based on their endogenous rent-seeking activities. The blue vertical line denotes the average subsidy rate in the baseline economy and the equilibrium at this point coincides with the results in Table 5, Row 3 in the main text. The vertical black dotted line denotes the subsidy level that maximizes value added output (which is larger than zero because the baseline economy features distortive taxes).

between 0-20%.

B.2.3 Aggregate costs with "wrong" DRS technology

This subsection describes how I derive aggregate costs when incorrectly enforcing the DRS technology. I start by discussing parameter estimation. Table B.1 gives an overview of all estimated parameters, except the ones that stay unchanged with respect to the baseline model. All estimation steps follow closely the estimation steps for the baseline model, with the only difference that the underlying *Political Connections Technology* differs. Parameter estimation and model fit for the *Political Connections Technology* is already discussed in the Estimation section. Given the different *Political Connections Technology*, I also find slightly different values for the joint distribution of connections and productivity, though the correlation of connections ε and productivity z is still almost perfectly negative. Estimation of the parameters of the productivity process and the preference shocks that determine exit follow the same indirect inference approach as for the baseline model estimation. As for the baseline estimation, estimated parameters perfectly fit the targeted moments, giving identical results as Table 3 (up to the 3rd digit). Estimated parameters are also very close to the baseline estimates, given that the targeted moments are the same. The main difference is that average model-implied profits are slightly lower for the DRS technology, which leads to a slightly

Table B.1: Overview of estimated parameters (DRS model)

Object	Description	Type	Identification idea	Value
Within-period Estimation:				
Sub-Step: Political Connections Technology				
F_C	Fixed cost of connection	F	min{TFPQ^C}	0
π_C	Probability of connection	F	Share connected firms	0.013
θ_ε	DRS elasticity	F	TFPQ-QR variation	0.155
$\{\alpha^*_{\varepsilon\|z^*}, \beta^*_{\varepsilon\|z^*}, \sigma^2_{\varepsilon\|z^*}\}$	ε distribution conditional on z	F^*	TFPQ-QR variation	$\{0.21, -0.05, 1.17\text{e}{-4}\}$
ρ	Correlation of ε and z	F	TFPQ-QR variation	-0.979
Across-period Estimation:				
Productivity process:				
$\{\rho_z, \mu_{\zeta^*}, \sigma^2_{\zeta^*}\}$	Persistence, Mean & Var of z	F^*	TFPQ dynamics NC	{0.968,0.084,0.013}
Entry/Exit process:				
$\{\mu^X, \sigma^X\}$	Scale & Var of fixed costs	F	Exit proba over TFPQ	$\{-6.35e7, 3.05e7\}$
f^E	Entry cost	F	Free entry condition	$0.86e6$
For counterfactuals:				
L	Aggregate Labor Supply	F	SS value given $\{N, w\} = 1$	2.02e6
σ	Elasticity of substitution	F	Implied by $\tilde{\eta}$ & CRS	6.16

Details: Types are: F(undamental) and E(quilibrium object). The former stay fixed in counterfactuals, the latter change endogenously. F^* denotes fundamentals that are still functions of the elasticity of substitution and general equilibrium objects, which change endogenously in counterfactuals. The baseline economy is observationally equivalent for different values of the elasticity of substitution, but not counterfactually equivalent.

lower implied entry cost and lower preference shocks to rationalize the same exit patterns.

B.2.4 Details on the benefits of public oversight

This subsection provides a few more details on the exercise to quantify the benefits of public oversight. As discussed in the main text, I consider counterfactuals in which the government varies the extent of public oversight as governed by c in the *Political Connections Technology*. For this, I consider counterfactuals in which any net government revenue (after paying for subsidies and auditing) are redistributed lump sum back to households.

To derive a rough estimate of the cost P_c, I try to come up with a conservative estimate of the total government expenditure on auditing $P_c \cdot c$ in the baseline distorted economy, which is the Indonesian economy in 1996/7, shortly before the Asian Financial Crisis. For this I draw on the Indonesian government budget in 1996/7, and in particular the functional classification of development expenditures reported in IMF (1996) and reproduced in Figure C.1. Ideally, the reported budget would have an entry called "Share of government expenditure paid to all kinds of auditing activities on politically connected firms". This is obviously not the case. I thus decided to construct this measure as a conservative residual, simply using the total government expenditure

Figure C.1: Overview of Indonesian government budget 1990-1997 (from IMF 1996)

Table 26. Indonesia: Functional Classification of Development Expenditure and Net Lending, 1990/91-1996/97 1/

	1990/91	1991/92	1992/93	1993/94	1994/95	Budget —1995/96—	Est. —1995/96—	Budget 1996/97
	(In billions of rupiah)							
General public services	250	321	401	448	657	803	802	992
Government apparatus	215	269	327	368	551	664	676	819
Law and order	35	52	74	80	106	139	126	173
Education	2,607	2,847	3,733	3,786	3,569	4,070	3,590	4,776
Education, national culture, and development of youth	2,052	2,417	3,147	3,264	3,067	3,359	2,976	3,971
Science and technology, research and statistics	555	430	586	522	502	711	614	806
Health, family planning, and welfare	723	891	957	1,146	1,333	1,352	1,152	1,693
Housing and water supply	677	801	1,054	861	929	1,102	1,168	1,326
Other community and social services	621	766	966	918	1,137	1,380	1,185	1,562
Manpower and transmigration	579	719	888	836	1,006	1,197	1,043	1,308
Religion	42	47	78	82	131	183	142	254
Economic services	8,500	9,986	11,925	12,549	14,310	14,886	14,865	16,482
Agriculture and irrigation 2/	2,043	2,412	3,065	2,712	2,356	3,003	2,466	3,475
Industry and mining	714	722	861	575	540	592	533	612
Electric power	1,707	2,286	3,042	3,230	3,806	3,800	4,619	3,997
Transportation and tourism	3,743	3,910	4,537	5,192	6,392	6,904	6,742	7,815
Information and communications	94	77	82	121	160	153	128	183
Trade and cooperatives	199	579	338	719	1,056	434	377	402
Regional, business and environment	2,812	3,328	3,719	4,541	5,616	5,731	5,501	6,003
Regional development	1,938	2,479	2,920	3,632	4,805	5,114	4,994	5,388
Investment through banking system	334	410	409	364	354	100	130	0
Natural resources	540	439	390	545	457	517	377	616
Total (adjusted official data)	16,191	18,939	22,756	24,249	27,551	29,323	28,264	32,834
Residual 3/	-3,969	1,061	2,849	862	-278	0	-4,056	0
Total (staff estimate) 4/	12,222	20,000	25,605	25,111	27,273	29,945	24,208	32,834

Notes: The figure is taken from IMF (1996) staff report, page 85.

share on the item "Law and Order", which captures the entire judicial system. I believe this to be a conservative estimate, because only a small part of the judicial system would be related to investigating corruption by connected firms, while there are few government auditing activities that happen outside "Law and Order". As an even more conservative estimate, I also report results when multiplying the costs by a factor of 10, which roughly coincides with the total budget for "General public services", the overarching category of "Law and Order" which includes the much larger budget item "Government apparatus".

There is a legitimate concern that my model does not capture all government revenues. Since I enforce the share of government expenditure spent on auditing, I use my model-implied total government revenue to scale up the total costs of auditing, which may lead to an underestimate. I believe that this is unlikely to systematically bias the estimates. The main reason is that I do already restrict the government budget to developmental expenditures in the data, which excludes almost 60% of the total government budget (see IMF 1996, 83). Thus, I accurately capture the extent of government revenues if the taxes in my model economy roughly capture 40% of the observed government revenue in 1996/7. This seems to be a good approximation. VAT revenue accounts for roughly 30% of the 1996 government budget and I estimate the government revenue from firm profit taxes to be in the range of 12% of the total budget.[29] There are also reasons why my model may overestimate the extent of government revenue. The two main reasons are that (1) I enforce de jure tax rates and do not account for systematic tax evasion (connected firms in my setup still pay taxes, but then get subsidized from the tax revenue), and (2) I only focus on formal manufacturing firms while the full Indonesian economy has large fractions of the firm population that pay very little taxes given their size and informality.

C Further details on extensions

C.1 Details on wedge extension

This section provides details on the model extension with firm-specific wedges. I start by describing optimal firm choices and defining the equilibrium of this economy. I then move to the identification of wedges and model estimation.

C.1.1 Optimal firm choices

The model economy with additional input wedges is as follows. Individual firms are characterized by their idiosyncratic productivity z_i, connections ε_i, capital input wedge τ_i^K and labor input wedge τ_i^L. They take as given prices and taxes/wedges and solve the following profit-maximizing problem:

$$\pi^*(z_i, \varepsilon_i, \tau_i^K, \tau_i^L) \equiv \max_{k,l,m,m_R} \left\{(1-\tau^V)\Big[(1+\tau(m_R,\varepsilon_i))py(z_i,k,l,m) - m - m_R\Big] - (1+\tau_i^L)wl - (1+\tau_i^K)Rk\right\}$$

$$\text{subject to:} \qquad p = P \cdot Y^{\frac{1}{\sigma}} y(z_i,k,l,m)^{-\frac{1}{\sigma}} \quad \text{(CES demand)}$$

where I have directly used the same restriction of $F_C = 0$ as for the baseline results, have enforced $P = 1$ and have written firm profits before profit taxes.

[29] Specifically, the budget in IMF (1996) does not split profit tax revenue from firms vs individuals in 1996, but enforcing ratios from earlier years has firm revenue roughly at 40% of the total revenue from taxes on income and profits. Scaling these 40% with the total share of taxes on income and profits in total revenue, I get to roughly 12%.

To derive firms' optimal choices, we start by firms' optimal input choices given optimally chosen τ_i^*:

$$\begin{aligned}
k^* &= (1-\tau^V)(1+\tau_i^*)P \cdot Y^{\frac{1}{\sigma}}((\sigma-1)/\sigma)y_i^{\frac{\sigma-1}{\sigma}}\left(\frac{\alpha}{(1+\tau_i^K)R}\right) \\
l^* &= (1-\tau^V)(1+\tau_i^*)P \cdot Y^{\frac{1}{\sigma}}((\sigma-1)/\sigma)y_i^{\frac{\sigma-1}{\sigma}}\left(\frac{\beta}{(1+\tau_i^L)w}\right) \\
m^* &= \qquad\qquad (1+\tau_i^*)P \cdot Y^{\frac{1}{\sigma}}((\sigma-1)/\sigma)y_i^{\frac{\sigma-1}{\sigma}}\left(\frac{\gamma}{P}\right)
\end{aligned}$$

In comparison to the baseline model, one can now clearly see that firms' labor and capital decisions are additionally distorted by firm-specific input wedges. From this, we can construct optimal output y_i^*:

$$y_i^* = z_i\,(k^*)^\alpha\,(l^*)^\beta\,(m^*)^\gamma = \left(z_i(1+\tau_i^*)^\eta\,(\bar{x})^\eta\,(x_i^*)^{\frac{\sigma}{\sigma-1}}\right)^{\frac{1}{1-\tilde{\eta}}}$$

where: $\eta \equiv \alpha+\beta+\gamma$, $\bar{x} \equiv PY^{\frac{1}{\sigma}}$, and $x_i^* \equiv \left(\frac{(1-\tau^V)\tilde{\alpha}}{(1+\tau_i^K)R}\right)^{\tilde{\alpha}}\left(\frac{(1-\tau^V)\tilde{\beta}}{(1+\tau_i^L)w}\right)^{\tilde{\beta}}\left(\frac{\tilde{\gamma}}{P}\right)^{\tilde{\gamma}}$, and where revenue elasticities are given by a tilde (e.g. $\tilde{\alpha} \equiv \frac{\sigma-1}{\sigma}\alpha$). The key difference with respect to the baseline model is that x_i^* is now firm-specific as it depends on both wedges. Plugging this into the CES demand function gives the implied optimal variety-specific price:

$$p_i^* = \bar{x}\left(z_i(1+\tau_i^*)^\eta\,(\bar{x})^\eta\,(x_i^*)^{\frac{\sigma}{\sigma-1}}\right)^{\frac{-1}{\sigma(1-\tilde{\eta})}}$$

And combining the two gives optimal revenues similar to Proposition 3.1:

$$(1+\tau_i^*)p_i^*y_i^* = (1+\tau_i^*)\bar{x}\left(z_i(1+\tau_i^*)^\eta\,(\bar{x})^\eta\,(x_i^*)^{\frac{\sigma}{\sigma-1}}\right)^{\frac{\sigma-1}{\sigma(1-\tilde{\eta})}} = \tilde{z}_i(1+\tau_i^*)^{\frac{1}{1-\tilde{\eta}}}$$

with: $\tilde{z}_i \equiv [z_i^* x_i^*]^{\frac{1}{1-\tilde{\eta}}}$ and $z_i^* = z_i^{\frac{\sigma-1}{\sigma}}\bar{x}$.

Next, we can solve for optimal implied (gross) profits using the previously derived optimal revenues and input choices:

$$\pi^*(z_i,\varepsilon_i) \equiv (1-\tau^V)\left[\underbrace{(1-\tilde{\alpha}-\tilde{\beta}-\tilde{\gamma})}_{\equiv(1-\tilde{\eta})}\tilde{z}_i(1+\tau_i^*)^{\frac{1}{1-\tilde{\eta}}} - Pm_R^*\right]$$

Finally, we can solve for the first-order condition for optimal rent-seeking activities:

$$\frac{\partial\pi^{\text{net}}}{\partial m_R^*} = 0: \quad P = (1-\tilde{\eta})\tilde{z}_i(1-\tilde{\eta})^{-1}(1+\tau_i^*)^{\frac{\tilde{\eta}}{1-\tilde{\eta}}}\frac{\partial\tau_i(m_R^*,\varepsilon_i)}{\partial m_R^*} = \frac{\partial\tau_i(m_R^*,\varepsilon_i)}{\partial m_R^*}\tilde{z}_i(1+\tau_i^*)^{\frac{\tilde{\eta}}{1-\tilde{\eta}}}$$

C.1.2 General equilibrium

I focus on a static economy without entry and exit, in line with Hsieh and Klenow (2009). In this economy, there is an exogenous distribution of firms $\mathcal{F}_{z,\varepsilon,\tau^K,\tau^L}$ over $(z_i, \varepsilon_i, \tau_i^K, \tau_i^L)$, where $\mathcal{I}$ denotes the exogenous set of active firms in the economy. The *competitive equilibrium* of the economy is defined by an international interest rate R, prices $\{w, P, \{p_i\}_{i\in\mathcal{I}}\}$, allocations $\{C, A, \Pi, T, Y, \{y_i, k_i, l_i, m_i, m_{Ri}\}_{i\in\mathcal{I}}\}$ and aggregate labor supply L such that:

- firms make optimal input and pricing decisions $\{p, y, k, l, m, m_R\}$ given $(z, \varepsilon, \tau^K, \tau^L)$ and $\{P, R, w, Y\}$
- the labor market clears: $L = \int l(z, \varepsilon, \tau^K, \tau^L) d\mathcal{F}_{z,\varepsilon,\tau^K,\tau^L}$
- the government collects taxes, subsidizes connected firms and rebates the rest back to households:

$$\int \Big(\underbrace{\tau^V \left[(1-\tilde{\gamma})\text{Rev}(z,\varepsilon,\tau^K,\tau^L) - Pm_R(z,\varepsilon)\right]}_{\text{VAT revenue}} + \underbrace{\tau^C \pi^*(z,\varepsilon,\tau^K,\tau^L)}_{\text{CIT revenue}} - \underbrace{(\tau * p * y)(z,\varepsilon,\tau^K,\tau^L)}_{\text{Govt Subsidies}} \Big) d\mathcal{F}_{z,\varepsilon,\tau^K,\tau^L} = T$$

C.1.3 Implied patterns of wedges and TFPQ

Wedges τ_i^K and τ_i^L are directly identified from variation in capital and labor cost shares according to:

$$\tau_i^K = \tilde{\alpha}\frac{(1-\tau^V)\text{Rev}_i^*}{Rk_i} - 1 = \tilde{\alpha}(1-\tau^V)\,(\text{Capital share}_i)^{-1} - 1$$
$$\tau_i^L = \tilde{\beta}\frac{(1-\tau^V)\text{Rev}_i^*}{wl_i} - 1 = \tilde{\beta}(1-\tau^V)\,(\text{Labor share}_i)^{-1} - 1$$

where Rev_i is observed firm revenue (net of subsidies) and input costs are given respectively by the firm's capital bill and wage bill. As in Hsieh and Klenow (2009), key for identification is that the revenue elasticities $\tilde{\alpha}$ and $\tilde{\beta}$ are known. Following standard practice and the interest in variation (rather than the level) of wedges across firms, I assume that the median wedge among non-connected firms is zero such that the baseline estimates of $\tilde{\alpha}$ and $\tilde{\beta}$ remain valid for the case with wedges. In contrast to the baseline model in which I implicitly treated variation in input cost shares as measurement error in inputs, the extension with wedges assumes that inputs are reported without measurement error and differences are explained by wedges instead.

Two key data cleaning steps ensure consistency of the results and robustness to outliers. Specifically, I first residualize observed capital and labor input cost shares by the same set of fixed effects as

Table C.1: Wedge extension: Descriptives

Moment	Connected	Non-connected
Median labor share	0.146	0.169
Median capital share	0.099	0.123
Median labor wedge	0.044	-0.098
Median capital wedge	0.160	-0.067
Interquartile range labor wedge	[-0.147,0.538]	[-0.397,0.298]
Interquartile range capital wedge	[-0.38,1.49]	[-0.56,0.74]
Variance labor wedge	0.306	0.333
Variance capital wedge	2.11	1.60

Details:

used in the baseline estimation for TFPQ. This ensures that measured wedges are only identified from variation within highly disaggregated industries, in line with how the misallocation literature has thought about wedges. Second, I winsorize residualized labor and capital cost shares to ensure results are not driven by outliers. I do so generously at the 10th and 90th percentile respectively, also because prior residualization can cause unrealistic shares at the tails – e.g. shares below zero that cannot be rationalized with any economically meaningful wedges.

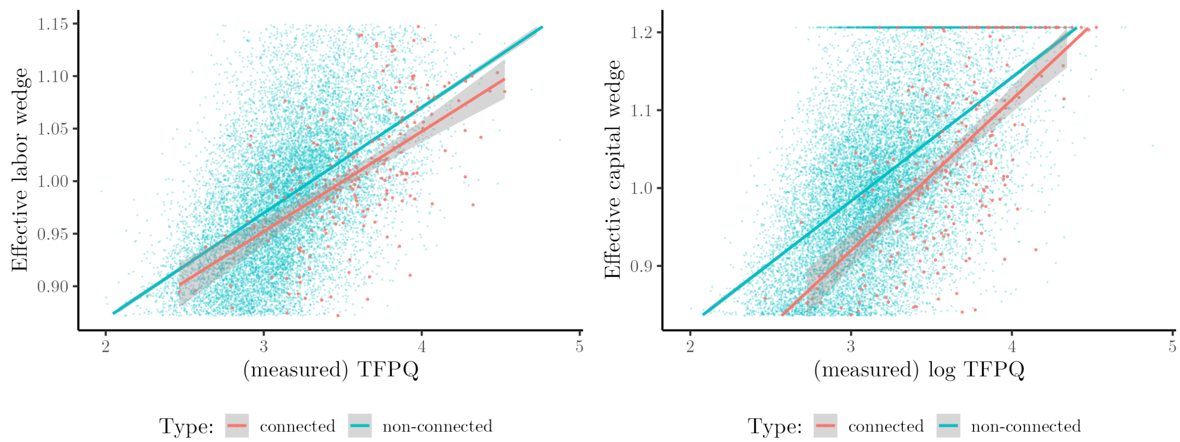
Table C.1 provides an overview of differences in wedges and factor shares across connected and non-connected firms, which are partly cited in the main paper. While the main paper directly plots a summary measure of capital and labor wedges against firm-level TFPQ, Figure C.2 also plots TFPQ against labor and against capital wedges separately. Results indicate that both wedges qualitatively move similarly with TFPQ.

C.1.4 Model estimation with wedges

To quantify how wedges affect the aggregate costs of political connections, I reestimate the *Political Connections Technology* allowing for firm-specific wedges. For this, I have to make an assumption on the dependence between productivity z_i, wedges $\{\tau_i^K, \tau_i^L\}$ and connections ε_i. I assume that productivity z_i is correlated with wedges through a summary measure of wedges:

$$\tau_i^T \equiv (1+\tau_i^K)^{\tilde{\alpha}}(1+\tau_i^L)^{\tilde{\beta}}$$

Figure C.2: Distribution of TFPQ vs. labor and capital wedges



(A) Correlation: labor wedges and TFPQ (B) Correlation: capital wedges and TFPQ

Notes: Panel (A) plots firm TFPQ against the effective labor wedge defined as: $(1+\tau_i^L)^{\tilde{\beta}}$, where τ_L are firm-level labor wedges. Panel (B) plots firm TFPQ against the effective capital wedge defined correspondingly as: $(1+\tau_i^K)^{\tilde{\alpha}}$

Specifically, I assume that total wedges τ_i^T and productivity are jointly log-normally distributed:

$$(log(z), log(\tau^T)) \sim \mathcal{N}(\mu_z, \sigma_z^2, \mu_{\tau,j}, \sigma_{\tau,j}^2, \rho_j) \quad \text{with:} \quad j \in \{C, NC\}$$

with connection-specific CDF $F_{z,\tau}^j$. The connection-specific mean and standard deviation of wedges are given by $(\mu_\tau^j, \sigma_\tau^j)$, and the connection-specific correlation between productivity and wedges is captured by ρ_j. Similar to the dependence of connections ε and productivity, it is most intuitive to rewrite the dependence of wedges and productivity as the distribution of wedges conditional on productivity:

$$f_{\tau|z}^j \sim \mathcal{N}\Big(\mu_\tau^j + \rho_j(\sigma_\tau^j/\sigma_z)\big[log(z) - \mu_z\big], (1-\rho_j^2)(\sigma_\tau^j)^2\Big) \tag{23}$$

$$f_{\tau|z^*}^j \sim \mathcal{N}\Big(\mu_\tau^j + \rho_j(\sigma_\tau^j/\sigma_{z^*})\big[log(z^*) - \mu_{z^*}\big], (1-\rho_j^2)(\sigma_\tau^j)^2\Big) \tag{24}$$

where the second equation instead writes the dependence based on z^*, which I use for the model estimation as in the baseline model estimation. The key statistical assumption is that connections are independent from wedges conditional on productivity: $\varepsilon|z \perp\!\!\!\perp \tau^T$. For the within-period estimation, I do not have to take a stance on the relative distribution of τ^K and τ^L conditional on τ^T, but I subsequently allow factor-specific wedges $\{\tau_i^K, \tau_i^L\}$ to be differently distributed for connected and non-connected firms. While I can in principle allow for connection-specific distributions of $\{\tau_i^K, \tau_i^L\}$ that depend flexibly on the total wedge τ_i^T, empirically I do not find a systematic correlation between the total wedge and the relative share of capital to labor wedges. Conditional on having drawn τ_i^T, I thus assume that relative shares of labor and capital wedges are IID within connections-status

Table C.2: Parameter overview wedge extension

Object	Description	Type	Identification idea	Value
Within-period Estimation:				
Sub-Step: Wedges and Productivity				
$\{\mu_{z^*}, \sigma^2_{z^*}\}$	Mean & Variance $log(z^*)$	F^*	TFPQ Variation NC	$\{2.951, 0.135\}$
$\{\mu_{\tau,NC}, \mu_{\tau,C}\}$	Mean wedges NC vs C	F	Observed wedges	$\{-0.023, 0.042\}$
$\{\sigma^2_{\tau,NC}, \sigma^2_{\tau,C}\}$	Variance wedges NC vs C	F	Observed wedges	$\{0.023, 0.023\}$
ρ_{NC}	Correlation wedges & z^* NC	F	Corr wedges & TFPQ NC	0.824
Sub-Step: Political Connections Technology				
F_C	Fixed cost of connection	F	$\min\{\text{TFPQ}^C\}$	0
π_C	Probability of connection	F	Share connected firms	0.013
$\{\theta_\varepsilon, c, \theta_c\}$	DRS, cost level & elasticity	F	TFPQ-QR variation	$\{0.20, 1\text{e}{-8}, 1.04\}$
$\{\alpha^*_{\varepsilon\|z^*}, \beta^*_{\varepsilon\|z^*}, \sigma^2_{\varepsilon\|z^*}\}$	ε distribution conditional on z	F^*	TFPQ-QR variation	$\{0.07, -0.013, 5.35\text{e}{-7}\}$
ρ	Correlation of ε and z	F	TFPQ-QR variation	-0.998
ρ_C	Correlation wedges & z^* C	F	Corr wedges & TFPQ C	0.76
For counterfactuals:				
L	Aggregate Labor Supply	F	SS value given $\{N, w\} = 1$	1.90e6
σ	Elasticity of substitution	F	Implied by $\tilde{\eta}$ & CRS	6.71

Details: Types are: F(undamental) and E(quilibrium object). The former stay fixed in counterfactuals, the latter change endogenously. F^* denotes fundamentals that are still functions of the elasticity of substitution and general equilibrium objects, which change endogenously in counterfactuals. The baseline economy is observationally equivalent for different values of the elasticity of substitution, but not counterfactually equivalent.

and directly draw from their respective empirical distributions.

How does parameter estimation change in this new economy? In contrast to the baseline economy, the economy with wedges features a set of new model parameters that need to be estimated on top of reestimating the remaining parameters. Fortunately, apart from one single parameter – ρ_C – the additional parameters can be directly estimated using observed variation in wedges and productivity. Specifically, $\{\mu^j_\tau, \sigma^j_\tau\}$ can be directly estimated using the respective mean and variance of the observed marginal distributions $F_{\tau|j}$. Likewise, ρ_{NC} is directly identified from the slope coefficient of the regression of log total wedges on log productivity for non-connected firms. Parameter estimates are reported in Table C.2.

In the next step, I jointly estimate the seven parameters: $\widetilde{\Omega}^{\text{within}} = \{\alpha^*_{\varepsilon|z}, \beta^*_{\varepsilon|z}, \sigma^2_{\varepsilon|z}, \theta_\varepsilon, c, \theta_c, \rho_C\}$. The only difference to the baseline estimation is that estimation requires to additionally draw a wedge τ^T conditional on z_i and include the corresponding ρ_C in the estimation loop. I estimate $\widetilde{\Omega}^{\text{within}}$ by minimizing the sum of two types of errors: (1) the error on the TFPQ quantile ratio as for the baseline estimation, and (2) the regression error when regressing the (log) total wedge on (log) TFPQ for connected firms. Formally:

$$\min_{\widetilde{\Omega}^{\text{within}}} \frac{\sum_p \left(QR^E(p) - QR^M(p;\widetilde{\Omega}^{\text{within}})\right)^2}{\sum_p \left(QR^E(p) - \overline{QR^E}\right)^2} + \frac{\left(\beta_\tau^E - \beta_\tau^M(\widetilde{\Omega}^{\text{within}})\right)^2}{\left(\beta_\tau^E\right)^2} \tag{25}$$

$$\text{where:} \quad log(\tau_i^T) = \beta_0 + \beta_\tau log(TFPQ_i) + \eta_i \quad \text{with:} \quad i \in C \tag{26}$$

Parameter estimates for the connections technology are broadly similar to the baseline estimates, which is unsurprising given the similar shape of the quantile ratio. Additionally, I find a lower correlation of wedges with productivity for connected firms. Together with the higher unconditional mean and similar variance of wedges, this leads connected firms to face higher wedges (or lower factor shares that translate into higher profit shares).

As in the baseline model estimation, the last step before taking the estimated model to study the aggregate costs of political connections is to pin down the aggregate labor supply L that is consistent with labor market clearing and the normalizations $\{N, w\} = 1$. The corresponding value of the aggregate labor supply is slightly lower than for the baseline model estimation because aggregate labor supply in the static economy does not include the labor costs of entry.

C.2 Details on production network extension

This section provides details on the model extension where firms are producing in different industries and industries are linked through a production network following Bigio and La'o (2020). I start by formally defining the environment, describing optimal firm choices and defining the equilibrium of this new economy. I then describe details on how I take this setup to the data and estimate the extended model allowing for heterogeneity in *Political Connections Technologies* across industries. I end with details on computing the aggregate costs of political connections in counterfactual scenarios in which political connections are shut down.

C.2.1 Setup: Production network economy

The model setup combines the production network setup in Bigio and La'o (2020) with the previous model of firm heterogeneity and endogenous rent-seeking. In contrast to the homogeneous firm setup in Bigio and La'o (2020), firms in my setup are heterogeneous along two dimensions (productivity and connections), revenue taxes are firm-specific, rather than sector-specific, and these taxes are endogenously determined by firms investing in rent-seeking, rather than exogenously set by the government.

The economy features J different production sectors (or interchangeably: industries), indexed by $j \in \mathbb{J} = \{1, ..., J\}$. Each sector consists of a fixed mass of monopolistically competitive firms, indexed by $i \in [0, N_j]$. In each sector, there is a perfectly competitive producer who aggregates all sector-specific varieties into a uniform sector-specific aggregate good according to:

$$Y_j = \left[\int_0^{N_j} y_{i,j}^{\frac{\sigma_j - 1}{\sigma_j}} \, di \right]^{\frac{\sigma_j}{\sigma_j - 1}}$$

where the only difference to the benchmark model is that the elasticity of substitution is now allowed to be sector-specific. The sector-specific good can be used as an intermediate input used in other sectors or as a final input Y_j^F in producing an aggregate good according to:

$$Y = \prod_{j=1}^{J} (Y_j^F)^{\nu_j} \quad \text{with:} \quad \sum_{j=1}^{J} \nu_j = 1$$

where $\nu_j \in [0, 1]$ denote sector-specific output elasticities to produce the aggregate good Y. This aggregate good is used either as a consumption good by households or as capital. Isomorphically, one can specify the same aggregator on the demand side (e.g. as a consumption aggregator as part of the household utility function) in which case ν_j denote demand elasticities. In any case, the model extension leaves the household side of the baseline model unchanged, given that households consume C units of Y.

Within a sector j, firm i's revenue is given by:

$$\text{Rev}_{i,j} = (1+\tau_{i,j})p_{i,j}y_{i,j} \quad \text{with} \quad y_{i,j} = z_{i,j}k_{i,j}^{\alpha_j}l_{i,j}^{\beta_j}m_{i,j}^{\gamma_j} \quad \text{and} \quad \alpha_j + \beta_j + \gamma_j = 1$$

which only differs from the benchmark model in that output elasticities are now sector-specific and that $m_{i,j}$ are not simply total intermediates, but a composite of a firm's intermediate inputs defined as:

$$m_{i,j} = \prod_{k=1}^{J} m_{i,j,k}^{g_{j,k}} \quad \text{with:} \quad \sum_{k=1}^{J} g_{j,k} = 1$$

where $g_{j,k} \in [0,1]$ denotes the share of good k in the intermediate composite of sector j. Firms are heterogeneous in productivity z_i and connections ε. As in the baseline model, they invest in rent-seeking m_R (assumed to be also paid in terms of the final consumption good) to obtain revenue subsidies from the government. The only distinction is that I now allow the rent-seeking technology $\tau(m_R, \varepsilon, j)$ to vary by sector j, capturing the idea that it is easier to obtain government favors in some sectors than in others. The next subsection formalizes the firm problem and characterizes optimal choices.

C.2.2 Optimal firm choices

Firms, characterized by their idiosyncratic productivity z_i, connections ε_i and sector j, take as given (sectoral) prices and aggregate taxes, solving the following profit-maximizing problem:

$$\pi^*(z_i, \varepsilon_i, j) \equiv \max_{k,l,m,m_R} (1-\tau^C)\Big\{(1-\tau^V)\Big[(1+\tau(m_R,\varepsilon_i))py(z_i,k,l,m,j) - P_j^m m - P m_R\Big] - wl - Rk\Big\}$$

$$\begin{aligned} \text{subject to:} \qquad & p = P_j \cdot Y_j^{\frac{1}{\sigma_j}} y(z_i,k,l,m,j)^{-\frac{1}{\sigma_j}} \quad \text{(within-sector CES demand)} \\ & \forall k: \quad P_k \cdot m_{i,j,k} = P_j^m \cdot g_{j,k} \cdot m \qquad \text{(Interm. demand equation)} \\ & P_j^m = \left(\prod_{k=1}^{J}\left(\frac{g_{j,k}}{P_k}\right)^{g_{j,k}}\right)^{-1} \qquad \text{(Interm. price index)} \end{aligned}$$

where I have directly used the same restriction of $F_C = 0$ as for the baseline results, P denotes the price of the aggregate good, P_j^m denotes the price index of the intermediate bundle used in sector j (as defined by the intermediate price index and demand equations) and P_j denotes the price of sectoral good j. Throughout, the aggregate good is chosen as numeraire such that $P = 1$. Note that given prices and optimal firm-level m, the intermediate demand equation implies optimal choices for $m_{i,j,k}$ for all k.

To derive firms' optimal choices conditional on sectoral and aggregate prices, we start by firms' optimal input choices given optimally chosen τ_i^*:

$$
\begin{aligned}
k^* &= (1-\tau^V)(1+\tau_i^*)P_j \cdot Y_j^{\frac{1}{\sigma_j}}((\sigma_j-1)/\sigma_j)y_i^{\frac{\sigma_j-1}{\sigma_j}}\left(\frac{\alpha_j}{R}\right)\\
l^* &= (1-\tau^V)(1+\tau_i^*)P_j \cdot Y_j^{\frac{1}{\sigma_j}}((\sigma_j-1)/\sigma_j)y_i^{\frac{\sigma_j-1}{\sigma_j}}\left(\frac{\beta_j}{w}\right)\\
m^* &= \qquad\qquad (1+\tau_i^*)P_j \cdot Y_j^{\frac{1}{\sigma_j}}((\sigma_j-1)/\sigma_j)y_i^{\frac{\sigma_j-1}{\sigma_j}}\left(\frac{\gamma_j}{P_j^m}\right)
\end{aligned}
$$

In comparison to the baseline model, the only difference is that demand is sector-specific and there are more prices. From this, we can construct optimal output $y_{i,j}^*$:

$$
y_{i,j}^* = z_i\,(k^*)^{\alpha_j}\,(l^*)^{\beta_j}\,(m^*)^{\gamma_j} = \left(z_i(1+\tau_i^*)\,(\bar{x}_j)\left(x_j^*\right)^{\frac{\sigma_j}{\sigma_j-1}}\right)^{\sigma_j}
$$

where I have used: $\alpha+\beta+\gamma=1$, $\bar{x}_j \equiv P_j Y_j^{\frac{1}{\sigma_j}}$, and $x_j^* \equiv \left(\frac{(1-\tau^V)\tilde{\alpha}_j}{R}\right)^{\tilde{\alpha}_j}\left(\frac{(1-\tau^V)\tilde{\beta}_j}{w}\right)^{\tilde{\beta}_j}\left(\frac{\tilde{\gamma}}{P_j^m}\right)^{\tilde{\gamma}_j}$, and where revenue elasticities are given by a tilde (e.g. $\tilde{\alpha}_j \equiv \frac{\sigma_j-1}{\sigma_j}\alpha_j$). The key difference with respect to the baseline model is that more terms are now sector-specific. Plugging this into the CES demand function gives the implied optimal variety-specific price:

$$
p_{i,j}^* = \bar{x}_j\left(z_i(1+\tau_i^*)\,(\bar{x}_j)\left(x_j^*\right)^{\frac{\sigma_j}{\sigma_j-1}}\right)^{\frac{-1}{\sigma_j(1-\tilde{\eta}_j)}}
$$

And combining the two gives optimal revenues similar to Proposition 3.1:

$$
(1+\tau_i^*)p_{i,j}^*y_{i,j}^* = (1+\tau_i^*)\bar{x}_j\left(z_i(1+\tau_i^*)\bar{x}_j\left(x_j^*\right)^{\frac{\sigma_j}{\sigma_j-1}}\right)^{\frac{\sigma_j-1}{\sigma_j(1-\tilde{\eta}_j)}} = \tilde{z}_{i,j}(1+\tau_i^*)^{\sigma_j}
$$

with: $\tilde{z}_{i,j} \equiv \left[z_{i,j}^* x_j^*\right]^{\sigma_j}$ and $z_{i,j}^* = z_i^{\frac{\sigma_j-1}{\sigma_j}}\bar{x}_j$.

Next, we can solve for optimal implied (gross) profits using the previously derived optimal revenues and input choices:

$$
\pi^*(z_i,\varepsilon_i,j) \equiv (1-\tau^V)\left[\underbrace{(1-\tilde{\alpha}_j-\tilde{\beta}_j-\tilde{\gamma}_j)}_{\equiv(1-\tilde{\eta}_j)}\tilde{z}_{i,j}(1+\tau_i^*)^{\frac{1}{1-\tilde{\eta}_j}} - Pm_R^*\right]
$$

Finally, we can solve for the first-order condition for optimal rent-seeking activities:

$$\frac{\partial \pi^{\text{net}}}{\partial m_R^*} = 0: \quad P = (1-\tilde{\eta}_j)\tilde{z}_{i,j}(1-\tilde{\eta}_j)^{-1}(1+\tau_i^*)^{\frac{\tilde{\eta}_j}{1-\tilde{\eta}_j}}\frac{\partial \tau_i(m_R^*, \varepsilon_i)}{\partial m_R^*} = \frac{\partial \tau_i(m_R^*, \varepsilon_i)}{\partial m_R^*}\tilde{z}_{i,j}(1+\tau_i^*)^{\sigma_j - 1}$$

C.2.3 General equilibrium

As in the previous model extension, I focus on a static economy without entry and exit as in Bigio and La'o (2020). In this economy, there is an exogenous distribution of firms $\mathcal{F}_{z,\varepsilon,j}$ over (z_i, ε_i, j), where $\mathcal{I}_j$ denotes the exogenous set of active firms in sector j. The *competitive equilibrium* of the economy is defined by an international interest rate R, prices $\{w, \{P_j, \{p_{i,j}\}_{i\in\mathcal{I}_j}, P_j^m\}_{j=1}^J\}$, allocations $\{C, A, \Pi, T, Y, \{\{y_{i,j}, k_{i,j}, l_{i,j}, m_{i,j}, m_{Ri,j}\}_{i\in\mathcal{I}_j}, Y_j\}_{j=1}^J\}$ and aggregate labor supply L such that:

- firms make optimal input and pricing decisions $\{p, y, k, l, m, m_R\}$ given (z, ε) and $\{P_j, R, w, Y_j\}$
- the labor market clears: $L = \sum_{j=1}^J \int l(z, \varepsilon, j) d\mathcal{F}_{z,\varepsilon,j}$
- the goods market clears in each sector: $\forall k: \quad Y_k = Y_k^F + \sum_{j=1}^J m_{k,j}$
- the government collects taxes, subsidizes connected firms and rebates the rest back to households:

$$\sum_{j=1}^J \int \Big(\underbrace{\tau^V\left[(1-\tilde{\gamma}_j)\text{Rev}(z,\varepsilon,j) - Pm_R(z,\varepsilon,j)\right]}_{\text{VAT revenue}} + \underbrace{\tau^C\pi^*(z,\varepsilon,j)}_{\text{CIT revenue}} - \underbrace{(\tau * p * y)(z,\varepsilon,j)}_{\text{Govt Subsidies}}\Big) d\mathcal{F}_{z,\varepsilon,j} = T$$

C.2.4 Data and Estimation

The estimation approach closely follows the baseline model. The key difference is that there are now many more sector-specific parameters, such as sector-specific output elasticities, the elasticities that determine the production network and sector-specific *Political Connections Technologies*. The key to tractability is that I can apply the baseline model estimation "sector by sector", by either directly backing out or estimating the model parameters conditioning on equilibrium prices and allocations. In the following, I discuss estimation and related data for each set of model parameters.

Table C.3: Industry Extension: Overview & parameter estimates

Industry	Sales share	Domar	Firms	Share C	$\tilde{\alpha}_j$	$\tilde{\beta}_j$	$\tilde{\gamma}_j$	Scale $\tilde{\eta}_j$	σ_j	$\alpha^{j*}_{\varepsilon\|z}$	$\beta^{j*}_{\varepsilon\|z}$	$\sigma^{j}_{\varepsilon\|z}$	ρ^j	θ^j_ε	c^j	θ^j_c	ν_j
Textiles	0.12	0.35	3,955	0.004	0.16	0.26	0.48	0.91	10.9	4.61e-2	-1.58e-2	4.45e-4	-1.000	0.29	1.19e-8	1.44	0.22
Wood	0.13	0.33	3,581	0.008	0.11	0.18	0.53	0.82	5.59	0.103	-1.91e-2	8.33e-4	-0.999	0.20	9.36e-8	0.89	0.02
Minerals	0.04	0.08	1,765	0.012	0.18	0.35	0.41	0.95	18.2	1.98e-2	-9.55e-3	8.87e-4	-0.998	0.27	7.22e-9	1.10	0.01
Food	0.27	0.67	4,653	0.013	0.09	0.10	0.65	0.85	6.56	4.59e-2	-8.85e-3	7.71e-4	-0.996	0.22	5.15e-9	1.00	0.51
Machinery	0.24	0.63	2,196	0.024	0.15	0.17	0.51	0.84	6.09	6.90e-2	-1.35e-2	7.61e-4	-0.998	0.21	1.01e-8	1.11	0.19
Chemicals	0.19	0.57	2,022	0.028	0.10	0.10	0.63	0.82	5.63	5.57e-2	-1.18e-2	6.86e-4	-0.998	0.23	1.02e-8	1.00	0.06

Details: Sales share gives the industry's share in total (value added) sales. Domar gives the Domar weight (gross sales over total value added). Share C gives share of connected firms. Sector names are abbreviated. Food includes 'Food, Beverages and Tobacco', Machinery includes 'Metals and Machinery', Minerals refers to 'Non-metalic Minerals', and Wood includes 'Wood and Paper'. Excluding 'Other manufacturing' industries, as they only include 2 connected firms and cannot be reasonably aggregated with any of the other industries. Shares may not sum to one due to rounding.

Definition of sector As shown in Table C.3, I use a relatively coarse definition of a sector, looking at 6 different manufacturing industries: 'Textiles', 'Wood & Paper', 'Non-metallic minerals', 'Food, Beverages & Tobacco', 'Metals & Machinery' and 'Chemicals'. This choice is made due to data availability, which is constrained by the combination of three data inputs. First, I need to restrict attention to manufacturing industries given that the firm-level data is Indonesia's manufacturing census. This exludes many industries in which political connections may also play an important role, such as mining, transportation, communications and finance. Second, I need to find the right level of aggregation that is in line with the input-output table data available. Specifically, I take Indonesia's input-output table for 1997 from the World Input-Output table database from Timmer et al. (2015). While this database covers 35 sectors, restricting to manufacturing industries leaves only 15 industries. In practice, this does not additionally restrict the choice of sectors. At last, I require to observe a sufficient number of connected firms in each industry to be able to estimate industry-specific *Political Connections Technologies*, where I take 10 connected firms as a minimal threshold. This constraint together with having to restrict to manufacturing industries reduces industry-variation to six major manufacturing industries: 'Textiles', 'Wood & Paper', 'Non-metallic minerals', 'Food, Beverages & Tobacco', 'Metals & Machinery' and 'Chemicals'. I drop firms with the ISIC 2-digit category 'Other manufacturing' since this industry only includes two connected and 384 non-connected firms and has no clear match to merge it together with one of the other industries.

Table C.3 provides industry-level information on a number of variables of interest. The first column reports the industry's share in total manufacturing output (value-added). The largest two industries are 'Metals and Machinery' and 'Food, Beverages and Tobacco', while 'Non-metallic minerals' production is by far the smallest industry. Importantly, the share of connected firms varies strongly across industries. More upstream industries such as 'Chemicals' have a share of connected firms that is more than five times as large as for downstream industries such as 'Textiles'.

Within-sector output elasticities and elasticity of substitution Within each sector, I use firm-level data to pin down output elasticities and the sector-specific elasticity of substitution among within-sector varieties: $\{\alpha_j, \beta_j, \gamma_j, \sigma_j\}$. Specifically, the model's first-order conditions give the following restriction on within-sector revenue elasticities:

$$\tilde{\alpha}_j = \frac{Rk^*}{(1-\tau^V)Rev^*_{i,j}} \quad \text{and} \quad \tilde{\beta}_j = \frac{wl^*}{(1-\tau^V)Rev^*_{i,j}} \quad \text{and} \quad \tilde{\gamma}_j = \frac{P^m_j m^*}{Rev^*_{i,j}} \tag{27}$$

where revenue elasticities map to output elasticities as follows: $\tilde{\alpha}_j \equiv \frac{\sigma_j - 1}{\sigma_j}\alpha_j$ (correspondingly for labor and materials). As for the baseline estimation, I estimate revenue elasticities using within-sector median input cost shares of non-connected firms. I construct these using observed revenue, the official value-added tax rate τ^V and the reported wage bill, total intermediate spendings and the capital stock multiplied by the model-implied rental rate R. Estimated elasticities, reported in Table C.3 show that there is considerable variation in input shares across industries. For example, production of food products and chemicals is particularly intermediate input intensive, textiles and non-metallic minerals (which captures mostly small-scale pottery and glass manufacturing) are particularly labor intensive, and machinery is particularly capital intensive.

Next, to disentangle σ_j from output elasticities, I assume constant returns to scale within each sector, such that $\eta_j \equiv \alpha_j + \beta_j + \gamma_j = 1$, and back out the implied elasticity of substitution using the observed (median) profit share. Analogous to the baseline estimation, the constant returns to scale assumption has no effect on the observed equilibrium (i.e. different combinations of η_j & σ_j are observationally equivalent), but matters for counterfactuals. Variation in the elasticity of substitution σ_j is then the main driver of differences in profit shares across industries (apart from political connections at the firm-level). As reported in Table C.3, estimated elasticities of substitution broadly align with economic intuition. For example, the most substitutable varieties are within non-metallic minerals (think pottery varieties) and textiles, while among the least substitutable varieties are Chemicals and Machinery.

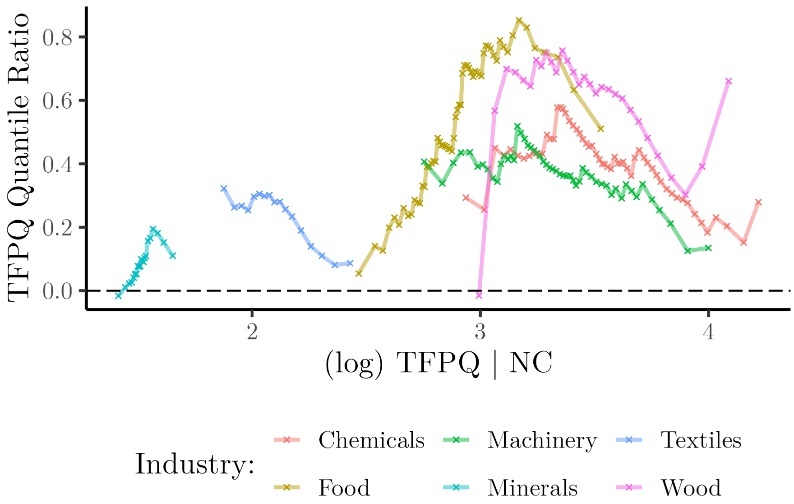
Within-sector TFPQ variation & Political Connections Technologies Using the previous sector-level estimates of revenue elasticities, I construct firm-level TFPQ defined as:

$$\text{TFPQ}_{i,j} \equiv \frac{\text{Rev}_{i,j}}{k_{i,j}^{\tilde{\alpha}_j} l_{i,j}^{\tilde{\beta}_j} (P_j^m m_{i,j})^{\tilde{\gamma}_j}} = (1+\tau_i^*)\tilde{z}_{i,j}^* \qquad \text{where:} \quad \tilde{z}_{i,j}^* \equiv z_{i,j}^* (P_j^m)^{-\tilde{\gamma}_j}$$

where I again use reported firm-level revenue and model-implied values for capital, labor and intermediate inputs drawing on the revenue elasticity estimates to ensure that inputs are not contaminated by rent-seeking activities. The only small difference is that the sector-specific input price P_j^m can now not be normalized and thus has to be carried around. Similar to the baseline estimation, I residualize the resulting TFPQ measure by a stringent set of fixed effects to ensure that measured differences in TFPQ across connected and non-connected firms within sectors are not driven by confounding factors that I do not model. Correspondingly to the baseline estimation, I now residualize *within* industry j by province, state ownership, establishment year bin and 4-digit industry fixed effects. This ensures that while TFPQ cannot be strictly compared across industries (given the different production functions), TFPQ is comparable within industries.

Next, I use the (residualized) TFPQ measure to estimate *Political Connections Technologies* at the

Figure C.3: Relative TFPQ distributions within industries



Notes: The X axis plots TFPQ (log) for non-connected firms (NC). Sector names are abbreviated. Food includes 'Food, Beverages and Tobacco', Machinery includes 'Metals and Machinery', Minerals refers to 'Non-metalic Minerals', and Wood includes 'Wood and Paper'.

sectoral level, drawing on relative TFPQ distributions across connected and non-connected firms. Figure C.3 plots these relative distributions, showing TFPQ quantile ratios by industry over the TFPQ distribution of non-connected firms. One can clearly see similar hump-shaped patterns within each of the six major sectors as found for the baseline estimation that pooled across sectors. At the same time, there is important sectoral variation in terms of (1) the level of TFPQ (stemming from differences in production functions as well as a different selection of firms), and (2) the patterns of the hump-shaped quantile ratios. For example, "Chemicals", "Wood & Paper" and "Metals & Machinery" exhibit broadly similar hump-shaped patterns as the baseline estimates, while "Food" and "Non-metallic minerals" industries exhibit much longer upward sloping ratios.

Given the hump-shaped patterns, I assume the same previous functional form for the *Political Connections Technology*:

$$\forall j \in \mathbb{J}: \quad \tau(\varepsilon_i, m_R, j) = \varepsilon_i^j m_R^{\theta_\varepsilon^j} - c^j m_R^{\theta_c^j} \qquad \text{with:} \quad 0 < \theta_\varepsilon^j < 1 \geq \theta_c^j$$

but allow all parameters to vary at the sector-level (including the parameters that govern the joint distribution of productivity and connections, as shown below). Note that even without differences in the underlying *Political Connections Technology*, resulting subsidy distributions would endogenously vary across sectors due to (1) sector-specific productivity distributions, (2) sectoral differences in the revenue-based returns to scale and hence profit rates, and (3) sectoral differences in demand (as captured by P_j and Y_j) that depend on the entire production network. At the same time, there are good reasons for why one would expect *Political Connections Technologies* to vary across sectors. For example, sectoral differences in project size, government regulation or the complexity of operations may all contribute to how easy it is to conceal illicit relations with the government. Whether underlying rent-seeking technologies meaningfully differ across sectors is in the end an empirical question.

As for the baseline estimation, I estimate conditioning on $\tilde{z}^*_{i,j}$ and focus on the sector-specific conditional distribution $f^j_{\varepsilon|\tilde{z}^*}$, which is given by:

$$f^j_{\varepsilon|\tilde{z}^*} \sim \mathcal{N}\Big(\alpha^{j*}_{\varepsilon|z} + \beta^{j*}_{\varepsilon|z} log(\tilde{z}^*), \sigma^j_{\varepsilon|z}\Big) \quad \text{with: } \alpha^{j*}_{\varepsilon|z} \equiv \mu_\varepsilon - \beta^{j*}_{\varepsilon|z}\mu_{\tilde{z}^*} \;\;\&\;\; \beta^{j*}_{\varepsilon|z} \equiv \rho_j \frac{\sigma_\varepsilon}{\sigma_{\tilde{z}^*}} \;\;\&\;\; \sigma^{j*}_{\varepsilon|z} \equiv \sqrt{(1-\rho_j^2)\sigma^2_\varepsilon}$$

This implies conditioning on equilibrium sector-specific prices and demand and fixing them throughout the estimation, as identification rests solely on within-sector variation across connected and non-connected firms. Analogous to the baseline estimation, within-sector estimation requires to find the following 6 sector-specific parameters:

$$\Omega^{\text{within}}_j = \Big\{\alpha^{j*}_{\varepsilon|z}, \beta^{j*}_{\varepsilon|z}, \sigma^j_{\varepsilon|z}, \theta^j_\varepsilon, c^j, \theta^j_c\Big\} \tag{28}$$

where I have already enforced the assumption that fixed costs F_C are zero and that the probability of becoming connected π^j_C can be directly estimated from the observed share of connected firms in each sector.[30] I estimate Ω^{within}_j separately for each sector by minimizing the distance between the empirical TFPQ quantile ratio (E) and its model counterpart (M) according to:

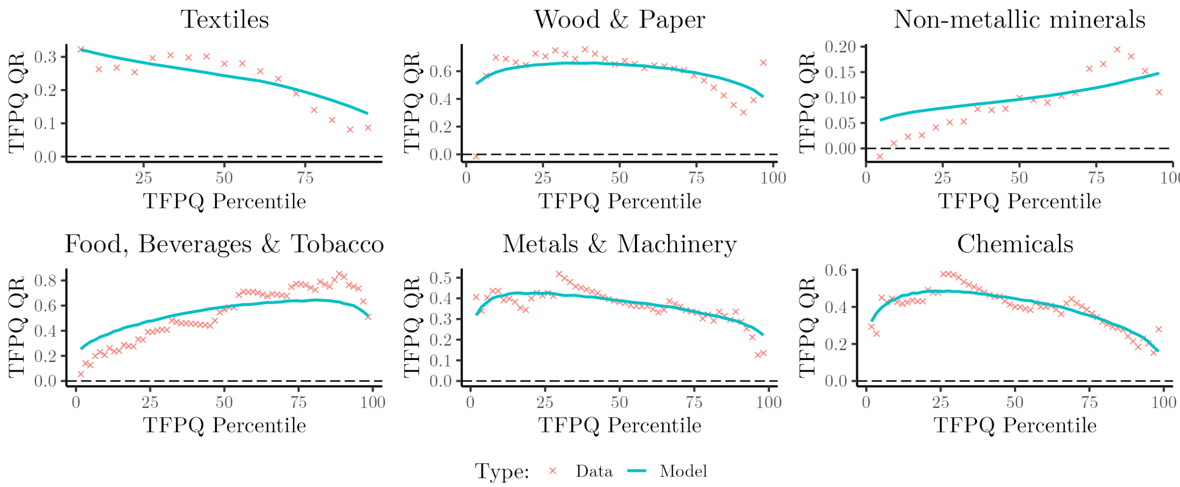
$$\min_{\Omega^{\text{within}}_j} \frac{\sum_p \big(QR^E_j(p) - QR^M_j(p; \Omega^{\text{within}}_j)\big)^2}{\sum_p \big(QR^E_j(p) - \overline{QR^E_j}\big)^2} \tag{29}$$

This objective function is equivalent to maximizing the model's R^2 with respect to the empirical within-sector TFPQ quantile ratio. Technically, I estimate the six parameters using the entire relative TFPQ distribution of connected firms within a sector, which gives as many moments as there are connected firms within a sector. For the sector with the fewest number of connected firms (Textiles) this still gives 17 moments, while it gives 61 moments for the sector with the most connected firms (Food/Beverages/Tobacco).

Estimated parameters are reported in Table C.3 and the model's fit for each industry is shown in Figure C.4. Overall, the model can explain observed TFPQ quantile ratios well. Despite more noisy

[30] $F_C \approx 0$ is still the empirically relevant assumption given that the TFPQ of the lowest TFPQ connected firm is similar to the TFPQ of the lowest TFPQ among non-connected firms, ruling out larger fixed costs. This is even more true in the case where connections and productivity are negatively correlated, which is what I estimate and what is in line with observed hump-shaped TFPQ quantile ratios.

Figure C.4: Model fit: TFPQ Quantile Ratio distributions by industry



Notes: Figure plots for each of the six industries, the observed TFPQ quantile ratio over the TFPQ percentile distribution. Each dot is a connected firm. Lines denote the best model fit.

empirical quantile ratios at the industry level due to the smaller sample size, the model still achieves an average R^2 of more than 65%, with very close fits for a number of sectors such as "Metals & Machinery", "Chemicals" and "Wood & Paper". The only sector that the model struggles with is "non-metallic minerals" due to a combination of high scale (and thus high returns to subsidies) and low observed relative TFPQ ratios. Despite sectoral differences in the hump-shape TFPQ quantile ratio profile, parameter estimates across industries are broadly similar. In particular, all industries exhibit strong decreasing returns to scale in rent-seeking ($\theta_\varepsilon^j < 0.3$), much more strongly increasing costs ($\theta_c^j >> \theta_\varepsilon^j$), and an almost perfect negative correlation between connections and productivity ($\rho^j \approx 1.0$). Importantly, implied levels and distributions of subsidies do differ across industries. For example, I find the largest average subsidy rates in the food and wood/paper industries (with average rates around 60%) and the lowest in the non-metallic minerals industry (around 9.5%). However, since the number of firms, scale of operations and profit rates differ across industries, higher average subsidy rates do not necessarily translate into higher aggregate sectoral subsidies.

Elasticities of production network & final good aggregation The last estimation step seeks to recover the production network elasticities g_{jk} and the final good expenditure weights ν_j, for which I draw on Indonesia's input-output table for 1997, taken from the World Input-Output table database (Timmer et al. 2015). Specifically, I draw on the following two equations to back out both sets of elasticities:

$$\forall j,k \in \mathbb{J}x\mathbb{J}: \quad g_{j,k} = \frac{\int_0^{N_j} P_k m_{i,j,k} di}{\sum_k^J \int_0^{N_j} P_k m_{i,j,k} di} = \frac{P_k m_{j,k}}{P_j^m m_j} \quad \text{and} \quad \forall j \in \mathbb{J}: \quad \nu_j = \frac{P_j Y_j^F}{\sum_j P_j Y_j^F} \tag{30}$$

using their respective empirical analogues: reported expenditures by sector j on goods produced by sector k[31] and reported final use of sector j's production. The latter takes the sum of final use by households and for capital, in line with my model. To construct the empirical analogues, I aggregate reported sectors at the sectoral level of my model. For example, I aggregate "Textiles and Textile Products" and "Leather & Footwear" to the overarching sector "Textiles", in line with my firm-level data. An important caveat is that I have to drop the non-manufacturing sectors that do not enter my model, such as agriculture, transportation and other services. To the extent that intermediate input demand in sectors that are included in my model economy comes from sectors that are outside my model, the formulas above implicitly reallocate input demand using fixed relative shares across sectors as weights. This is more consequential in some sectors than others. For example, for "Textiles", 75% of the actual intermediate demand is for sectoral goods that my model covers, only leaving out 25% (which splits up roughly equally between agriculture and different services). However, for "Food, Beverages and Tobacco" the sectors in my model only cover 22.5% of the total actual intermediate demand respectively (in the data, more than 50% of the input demand comes from agricultural goods). While it is not clear how this biases the results, it does overstate the linkages among sectors in my model by proportionally increasing their expenditure weights.[32]

Following this approach, I back out a matrix of intermediate input expenditure weights $g_{j,k}$. A key feature of this matrix is that diagonal entries make up the lion's share of total weights, indicating that sectors mostly use varieties from its own sector as intermediate inputs. For example, the share of own intermediates is around 89% for "Textiles" and 84% for "Chemicals". Second, there are clear differences in how much sectors supply to other sectors. For example, "Chemicals" are more upstream in that they are used as an important intermediate input for most sectors, while "Textiles" are used only little as intermediate goods by other sectors. Finally, the last column in Table C.3 reports estimated final expenditure weights ν_j. Not surprisingly, the aggregate final good mostly consists of food (50.5%), textiles (22.2%) and machinery (18.5%), the latter includes both many household appliances, motorcycles and bicycles. Capital only makes up 7% of total final usage, but is almost entirely machinery.

[31] Note that observed input expenditures may in principle be contaminated by rent-seeking spending by connected firms. Given that (1) rent-seeking spending is only a small fraction of total intermediate spending among connected firms and (2) only about 1% of firms are connected, this issue is not a concern in practice. An alternative would be to assume that rent-seeking uses the same intermediate bundle as sector-specific intermediates, which would ensure that the input-output coefficients are not (differentially) contaminated by rent-seeking.

[32] To reiterate, I fix relative demand for inputs (and the final good) and reallocate all the demand for goods that are not in my model in proportion to the relative shares of the industries that are in my model. An alternative to this approach would be to only call "intermediates" the total spending on sectors that I have and add the remainder of all the non-included sectors to capital or – in a similar spirit – add the non-included sectors to intermediates using the final aggregate good. It is not obvious whether this would give systematically different results.

C.2.5 Solving the model

Finding the equilibrium of the model economy is different for the baseline distorted equilibrium and for counterfactuals. For the baseline equilibrium, I can normalize relative prices and find the corresponding quantities that are in line with market clearing in the estimated model. The baseline equilibrium also allows me to move from any reduced-form estimated parameters to model primitives. Solving for the model equilibrium for model counterfactuals is different, as I need to explicitly solve for prices and quantities that clear markets given model primitives that stay fixed. I discuss each in turn.

Solving for the observed equilibrium The algorithm for solving the observed equilibrium is as follows:

Step 1: For each sector: Solve the firm problem enforcing observed distributions of $\tilde{z}^*_{i,j}$ and corresponding (estimated) distributions of connections using $f^j_{\varepsilon|\tilde{z}^*}$. (This step is a function of all the estimated parameters)

Step 2: Aggregate firm-level production and revenue decisions to obtain:

$$\{P_j Y_j\}_j \quad \text{using:} \quad \int_0^{N_j} p_{i,j} y_{i,j} di = P_j Y_j \quad \text{(Sectoral expenditure)}$$

$$\bar{L} = \sum_j \int_0^{N_j} l_{i,j}\, di \quad \text{(Aggr Labor Supply)}$$

$$Y^F = \sum_j P_j Y_j - \sum_j \sum_k \int_0^{N_k} g_{k,j} \tilde{\gamma}_k \text{Rev}_{i,k}\, di \quad \text{(Aggr Final Use)}$$

Step 3: Normalize sector-level prices $\{P_j\}_j = \bar{P}$ such that $\bar{P}$ fulfills the equilibrium condition:

$$1 = \prod_{j=1}^{J} \left(\frac{\nu_j}{\bar{P}}\right)^{\nu_j} \quad \text{(Aggregate Price Index)}$$

Then find the quantities and remaining prices that clear the market:

$$Y_j = \frac{P_j Y_j}{P_j} \qquad \text{(Sectoral Quantities)}$$

$$P^m_j = \left(\prod_{k=1}^{J} \left(\frac{g_{j,k}}{\bar{P}}\right)^{g_{j,k}}\right)^{-1} \qquad \text{(Interm. price index)}$$

Solving for counterfactual equilibria In the general version of the model with endogenous firm-level subsidies, firm-level decisions (and subsidies) depend non-linearly on relative prices and quantities in a way that precludes closed-form solutions. This means that in contrast to Bigio and La'o (2020), solving for general counterfactuals in which subsidies change requires to find a fixed point in the wage, relative sectoral prices *and* relative sectoral quantities: $\{w, \{P_j, Y_j\}_j\}$. This requires a fixed point over $2 * J + 1$ objects, in contrast to just two objects ($\{w, Y\}$) in the baseline model without the network extension. Economically, this is because endogenous firm-level distortions drive a wedge between firm-level revenue and sectoral output. That being said, particular cases of counterfactuals may be simpler to solve. For example, the main counterfactual in which political connections are shut down gets rid of firm-level subsidies and thus simplifies to the standard setup in Bigio and La'o (2020) with firm-level heterogeneity, but closed-form firm-level decisions. I start with the general algorithm and then describe the algorithm for the economy without political connections.

The general algorithm to find the equilibrium of the static economy is as follows:

Step 1: Guess values for $\{w, \{P_j, Y_j\}_j\}$.

Step 2: Given relative prices $\{P_j\}_j$, construct $\{P_j^m\}_j$ using the intermediate price index and knowledge of elasticities $\{g_{j,k}\}_{j,k}$

Step 3: Within each sector, solve the firm's problem over the fixed sector-specific distribution of $z_{i,j}^*$ (taken from non-connected firms in each sector). Aggregate up across firms within sectors and across sectors to construct model-implied $\{Y_j^F, Y_j, m_j\}_j$.

Step 4: Check convergence by comparing model-implied quantities (M) and guesses (G):

$$\forall j \in \mathbb{J}: \quad \text{Diff}_{Y_j} \equiv \left\{ \frac{Y_j^M - Y_j^G}{Y_j^G} \right\}_j \qquad \text{and} \qquad \text{Diff}_w \equiv \left\{ \frac{L(\{w, \{P_j, Y_j\}_j\}) - \bar{L}}{\bar{L}} \right\}_j$$

Stop if $\max\{|\text{Diff}_w|, \max_j\{|\text{Diff}_{Y_j}|\}_j\} <$ crit, otherwise return to **Step 2** with updated guesses according to:

$$\begin{aligned} \forall j \in \mathbb{J}: \quad Y_j^{G'} &= Y_j^G * (1 + \text{Diff}_{Y_j} \cdot \alpha_Y) \\ \forall j \in \mathbb{J}: \quad P_j^{G'} &= P_j^G * (1 + \text{Diff}_{Y_j} \cdot \alpha_Y) \\ w^{G'} &= w^G * (1 + \text{Diff}_w \cdot \alpha_w) \end{aligned}$$

where crit is a small number (I use crit $= 0.001$), and $\{\alpha_Y, \alpha_w\} \in (0, 1]$ are updating parameters (I choose $\{\alpha_Y, \alpha_w\} = \{0.5, 0.5\}$). (Is it a problem if updating is the same for prices and quantities? Maybe update them differently? If so, how?)

Instead, the algorithm for the economy without political connections simplifies because the firm problem is given in closed-form. I still use an algorithm that iterates over guesses of prices and quantities, although one can also directly compute the equilibrium using the Leontief inverse (which is more direct but computationally harder as the number of sectors grows):

Step 1: Guess values for $\{P_j, Y_j\}_j$.

Step 2: Find corresponding guesses for the wage, final output and prices of sectoral input bundles $\{w, Y^F, \{P_j^m\}_j\}$ using:

$$w^* = \frac{(1-\tau^V)}{\bar{L}} \sum_j \tilde{\beta}_j P_j Y_j \qquad \text{(Wage equation)}$$

$$Y^F = \sum_j P_j Y_j - \sum_j \sum_k g_{k,j} \tilde{\gamma}_k x_k^*(w, P_k^m)^{\sigma_k} P_k^{\sigma_k} Y_k \int_0^{N_k} z_{i,k}^{\sigma_k - 1}\, di \quad \text{(Aggr Final Use)}$$

$$\forall j \in \mathbb{J}: \quad P_j^m = \left(\prod_{k=1}^{J} \left(\frac{g_{j,k}}{P_k} \right)^{g_{j,k}} \right)^{-1} \qquad \text{(Interm price index)}$$

$$P = \left(\prod_{k=1}^{J} \left(\frac{\nu_k}{P_k} \right)^{\nu_k} \right) \qquad \text{(Aggr price index)}$$

with the latter price index subsequently set as numeraire.

Step 3: Given guesses for $\{\{P_j, Y_j, P_j^m\}_j, w, Y^F\}$, verify the guesses using:

$$\forall j \in \mathbb{J}: \quad P_j = \left[x_j^*(w, P_j^m)^{\sigma_j} \int_0^{N_j} z_{i,j}^{\sigma_j - 1} di \right]^{\frac{1}{1-\sigma_j}} \qquad \text{(Sectoral supply)}$$

$$\forall j \in \mathbb{J}: \quad P_j Y_j = \nu_j Y^F + \sum_k g_{k,j} \tilde{\gamma}_k x_k^*(w, P_k^m)^{\sigma_k} P_k^{\sigma_k} Y_k \int_0^{N_k} z_{i,k}^{\sigma_k - 1}\, di \quad \text{(Sectoral demand)}$$

If guess is incorrect, update guesses (e.g. using a standard solver for non-linear equation systems).

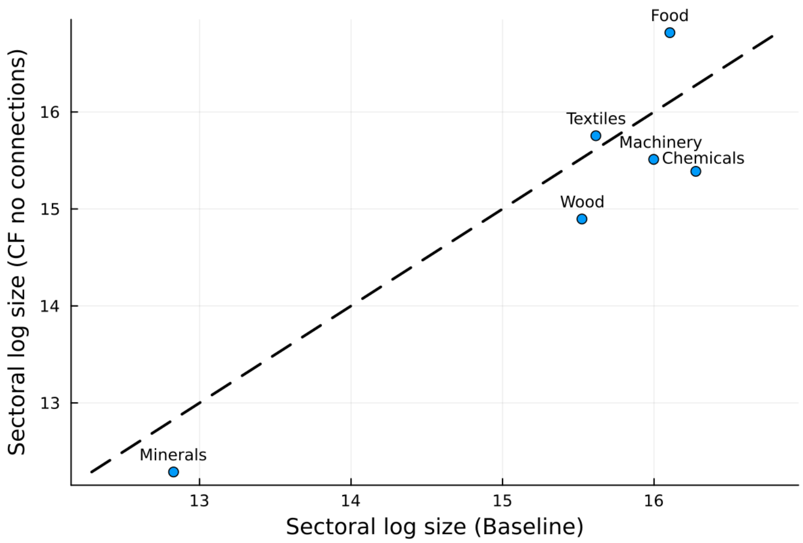
C.2.6 Details on counterfactuals

The main counterfactual is analogous to the main baseline result: I consider a counterfactual economy in which political connections are shut down and any additional tax revenue is redistributed lump-sum to households. The algorithm for this counterfactual is explained above. The second counterfactual that I run is slightly more complicated. Here, I first solve the initial distorted economy under the alternative assumption that the elasticity matrix ð with entries $g_{j,k}$ is an identity matrix, which means that firms within a sector only use this sectors' sectoral good as their intermediate inputs. In this case, $P_j^m = P_j \quad \forall j$. This means I also solve for the alternative primitives that rationalize the economy under this assumption on ð. In the second step, I then consider the baseline counterfactual with respect to this economy as the starting point. That is, I abolish political connections and redistribute any additional tax revenue lump-sum back to households.

C.2.7 Additional result(s)

At last, I report an additional result that is not discussed in the paper. Specifically, Figure @(fig:plot-network-sectoral-size-distortions) visualizes sectoral size distortions by political connections by plotting (log) sectoral size ($P_j Y_j$) in the baseline distorted economy against the (log) sectoral size in the counterfactual economy without political connections. One can clearly see that more upstream sectors tend to be differentially subsidized, leading them to be larger in the distorted economy than they would otherwise be. The more downstream sectors 'Food' and 'Textiles' are the only sectors that would be larger in the counterfactual economy, with 'Food' seeing the largest size distortions.

Figure C.5: Sectoral size distortions by political connections



Notes: The figure shows (log) sectoral size ($P_j Y_j$) in the distorted baseline economy versus the counterfactual economy without political connections and where any additional tax revenue is redistributed lump-sum to households. The dashed black line denotes the 45 degree line, so that all points above the line gives industries that are larger in the counterfactual world without connections.