INDUSTRIAL POLICIES IN PRODUCTION NETWORKS*

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Abstract

Many developing countries adopt industrial policies favoring selected sectors. Is there an economic logic to this type of intervention? I analyze industrial policy when economic sectors form a production network via input-output linkages. Market imperfections generate distortionary effects that compound through backward demand linkages, causing upstream sectors to become the sink for imperfections and have the greatest size distortions. My key finding is that the distortion in sectoral size is a sufficient statistic for the social value of promoting that sector; thus, there is an incentive for a well-meaning government to subsidize upstream sectors. Furthermore, sectoral interventions’ aggregate effects can be simply summarized, to first order, by the cross-sector covariance between my sufficient statistic and subsidy spending. My sufficient statistic predicts sectoral policies in South Korea in the 1970s and modern-day China, suggesting that sectoral interventions might have generated positive aggregate effects in these economies.

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Many developing countries adopt industrial policies to selectively promote economic sectors: Japan from the 1950s to the 1970s, South Korea and Taiwan from the 1960s to the 1980s, and modern-day China. One of the oldest problems in economics is understanding how industrial policies can facilitate economic development (Hirschman (1958)).

In this paper, I provide the first formal analysis of the economic rationale behind industrial policies in the presence of cross-sector linkages and market imperfections. My key finding is that the effects of market imperfections accumulate through what I call backward demand linkages, causing certain sectors to become the sinks for market imperfections and thereby creating an incentive for well-meaning governments to subsidize those sectors. Within the networks literature, the sectors in which imperfections accumulate are typically designated as “upstream,” meaning they supply to many other sectors and use few inputs from other sectors. In the data, the sectors considered upstream correspond with the same sectors policymakers seem to view as important targets for intervention in historical South Korea and modern-day China, and my analysis suggests that industrial policies in these economies may have generated positive aggregate effects.

To develop my results, I embed a generic formulation of market imperfections into a canonical model of production networks. Market imperfections represent inefficient, non-policy features of the market allocation, such as financial and contracting frictions. These features generate deadweight losses with input use, raising effective input prices and production costs. The distortionary effects lead to misallocation of resources across sectors, thereby creating room for welfare-improving policy interventions.

Consider the problem faced by a government with limited fiscal capacity, one that cannot directly remove all imperfections but can only selectively intervene and subsidize sectoral production. Which sector should be promoted first? This is not easy to answer, either conceptually or empirically. First, distortionary effects of imperfections compound through input-output linkages; consequently, subsidizing the most-distorted sectors might not improve efficiency, and policy prescriptions need to incorporate network effects. Second, because input-output structures are not necessarily invariant to interventions, policy prescriptions could be sensitive to structural assumptions on aggregate production technologies. Finally, policy prescriptions might depend on the severity of market imperfections, which is difficult to measure.

My analysis tackles these difficulties. My first result shows that, starting from a decentralized, no-intervention economy, policies can be guided by a simple measure I call “distortion centrality.” This measure integrates all distortionary effects of market imperfections in the production network and is

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1Public documents from interventionist governments often explicitly state that “network linkages” are a criterion for choosing sectors to promote; see Li and Yu (1982), Kuo (1983), Yang (1993) for Taiwan; Kim (1997) for Korea; State Development Planning Commission of China (1995) for China.
a nonparametric sufficient statistic for the marginal social value of policy subsidies in each sector. A well-meaning government should prioritize funds toward sectors with high distortion centrality.

Formally, distortion centrality is the ratio between sectoral influence and the Domar weight. Influence is a local notion of importance and optimal sectoral size; it captures the aggregate effect of marginally expanding sectoral resources. The Domar weight, on the other hand, captures equilibrium sectoral size and is thus the cost of proportionally promoting a sector. Subsidizing influential sectors brings great benefits, and subsidizing large sectors is costly; hence, the ratio—distortion centrality—captures the marginal social value of policy expenditure. Distortion centrality is a nonparametric sufficient statistic—additional features of production technologies are irrelevant—because, starting from the no-intervention economy, policy-induced network changes have only second-order effects on the aggregate economy.

Sectors with the highest distortion centrality are not necessarily the most distorted ones, nor are they the largest or most influential. Instead, they tend to be upstream sectors that supply inputs, directly or indirectly, to many distorted downstream sectors. This is because the distortionary effects of imperfections accumulate through backward demand linkages. Imperfections cause less-than-optimal input use, thereby depressing the resources used by the input suppliers, which in turn purchase less from their own input suppliers. The effects keep transmitting upstream through intermediate demand, and, as a result, the most upstream sector becomes the sink for all market imperfections and thus has the highest distortion centrality. The distinctions between distortion centrality and other notions of importance are substantive, as promoting large, influential, or very distorted sectors can indeed amplify—rather than attenuate—market imperfections and therefore lead to aggregate losses.

In an efficient economy, distortion centrality is identically one, and there is no role for intervention. With market imperfections, as I show, distortion centrality averages to one across sectors; thus, uniformly promoting all sectors generates no aggregate gains. Effective interventions must disproportionately allocate policy funds to sectors with high distortion centrality. My second result shows that, to first-order, the aggregate general equilibrium effect of selective interventions can be succinctly captured by the covariance between each sector’s distortion centrality and government spending on sectoral subsidies. This simple formula enables nonparametric evaluation of sectoral interventions’ aggregate effects using cross-sector variation in policy spending.

In a general production network, distortion centrality depends on market imperfections, which are challenging to estimate. Indeed, a leading criticism of industrial policies is that governments have difficulty identifying market imperfections (Pack and Saggi (2006)). Yet, precisely because imperfections accumulate through backward linkages, I show that if the network follows a “hierarchical” structure—one in which sectors follow a pecking order so that upstream sectors supply a disproportionate fraction of output to other relatively upstream sectors—then distortion centrality is insensitive
to underlying imperfections. In hierarchical networks, distortion centrality tends to align with the “upstreamness” measure proposed by Antras et al. (2012).

I apply my theoretical results and empirically examine the input-output structures of South Korea during the 1970s and modern-day China, as these are two of the most salient economies with interventionist governments that actively implement industrial policies. I first show that, in these economies, productive sectors closely follow a hierarchical structure, and my theory suggests that distortion centrality should be insensitive to underlying market imperfections. To empirically verify this, I estimate market imperfections using a variety of strategies based on distinct assumptions, pushing available data in as many directions as possible. To complement the estimation strategies, I also randomly simulate imperfections from a wide range of distributions. My results show that distortion centrality is almost perfectly correlated across all specifications, and correlates strongly with the measure of Antras et al. (2012), thereby validating that distortion centrality is largely driven by variations in these economies’ hierarchical network structure and is insensitive to underlying imperfections.

I then evaluate sectoral interventions in these economies. I show that the heavy and chemical manufacturing sectors promoted by South Korea in the 1970s are upstream and have significantly higher distortion centrality than non-targeted sectors. In modern-day China, non-state-owned firms in sectors with higher distortion centrality have significantly better access to loans, receive more favorable interest rates, and pay lower taxes; these sectors also tend to have more state-owned enterprises, to which the government directly extends credit and subsidies. These patterns survive even after controlling for a host of other potential, non-network motives for state intervention. My sufficient statistics reveal that, to first-order, differential sectoral interest rates, tax incentives, and funds given to state-owned firms have all generated positive aggregate effects in China. Using estimates based on firm-level data, these policies together improve aggregate efficiency by 6.7%. I also perform various policy counterfactuals.

To be clear, my findings by no means suggest that these governments’ economic policies were optimal, as my main results capture only the first-order effects of interventions. Further, my analysis does not address the decision process behind these policies, as the model abstracts away from various political economy factors that affect policy choices in these economies (Krueger (1990), Rodrik (2008), Lane (2017)). Nevertheless, the predominant view is that industrial policies tend to generate resource misallocations and harm developing economies (e.g., see Krueger (1990), Lal (2000), Williamson (1990, 2000), and the survey by Rodrik (2006)). Yet, my findings challenge this view by showing there may be an economic rationale behind certain aspects of the Korean and Chinese industrial strategy, and these policies might have generated positive network effects.

The literature on industrial policies reaches back to Rosenstein-Rodan (1943) and Hirschman (1958). More recently, Song et al. (2011) study resource reallocation between state-owned enter-
prises and private firms during China’s recent economic transition. Itskhoki and Moll (2018) study optimal Ramsey policies in a multi-sector growth model with financial frictions. Also related is Aghion et al. (2015), who show Chinese industrial policy increases productivity growth by fostering competition. These papers do not consider input-output linkages, which are the focus of my study. In contemporaneous work, Lane (2017) empirically studies South Korea’s industrial policies during the 1970s through the lens of a production network and finds that sectors downstream of promoted ones experienced positive spillovers. Rather than focusing on cross-sector spillovers, I theoretically and empirically analyze the general equilibrium effects of interventions on the aggregate economy. The first-order nature of my policy analysis relates to an older body of literature, including Hatta (1977), Ahmad and Stern (1984), Deaton (1987), Ahmad and Stern (1991) and Dixit (1985), regarding marginal policy reforms in the different context of commodity taxation. More broadly, my paper contributes to a large literature on the aggregate implications of micro imperfections, including the seminal work by Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and other important studies such as Banerjee and Duflo (2005), Banerjee and Moll (2010), Buera et al. (2011), Midrigan and Xu (2014), Buera et al. (2015), Rotemberg (2017), Cheremukhin et al. (2017b), and Cheremukhin et al. (2017a), among many others.

Methodologically, my paper builds on the production networks literature. Papers on efficient networks include Hulten (1978), Acemoglu et al. (2012, 2016, 2017), and Baqaee and Farhi (2018a); on inefficient networks, see Bartelme and Gorodnichenko (2015), Altinoglu (2017), Baqaee (2017), Boehm (2017), Caliendo et al. (2017), Grassi (2017), and Boehm and Oberfield (2018), among others. Particularly related to my theoretical results are papers that study properties of inefficient networks with generic “wedges,” including Jones (2011, 2013), and Bigio and La’O (2017), who study Cobb-Douglas networks, and, more recently, Baqaee and Farhi (2018b), who study nonparametric and CES networks. Unlike these papers, I separate “wedges” into market imperfections and policy subsidies, and I study the impact of subsidies taking pre-existing imperfections as given. My theoretical contribution starts with the novel discovery that, by modeling payments associated with imperfections as quasi-rents, the ratio between influence and Domar weights—what I call “distortion centrality”—is an 
\textit{ex-ante, nonparametric} sufficient statistic that \textit{predicts} the aggregate impact of introducing subsidies to the decentralized economy. This sufficient statistic provides an empirically-feasible way to evaluate, ex-ante, the aggregate impact of sectoral interventions in production networks. By contrast, the nonparametric results in Baqaee and Farhi (2018b) are \textit{ex-post} in nature, requiring allocations to be measured from both the pre- and post-shock economies. Those results are therefore useful for ex-post accounting but cannot be used for policy evaluation and prescription.

1 Model

There is a composite production factor $L$ in fixed supply and a numeraire consumption good that is endogenously produced. There are $N$ intermediate goods; each is used as a production input for both the consumption good and other intermediate goods. The aggregator for the consumption good is

$$Y^G = \mathcal{F}(Y_1, \cdots, Y_N),$$

where $Y_i$ is the intermediate good $i$ used for consumption. Intermediate good $i$ is produced by

$$Q_i = z_i F_i \left( L_i, \{M_{ij}\}_{j=1}^N \right),$$

where $L_i$ is the factor used by sector $i$, $z_i$ is the Hicks-neutral sectoral productivity, and $M_{ij}$ is the amount of intermediate good $j$ used by sector $i$. I assume production functions $\{F_i\}$ and $\mathcal{F}$ are continuously differentiable, increasing and concave in arguments, and exhibit constant returns to scale.

**Market Imperfections and Policy Interventions**

I introduce market imperfections into the economy, and I study how policy interventions can affect aggregate efficiency, taking imperfections as given.

Market imperfections represent inefficient and non-policy features that affect the market allocation, including transaction costs, financial frictions, and contracting frictions; they can also arise from production externalities and monopoly markups. Such imperfections are modeled as reduced-form “wedges” $\chi$ and have two properties. First, market imperfections raise input prices: for every dollar of good $j$ that producer $i$ buys, he must make an additional payment that is $\chi_{ij} \geq 0$ fraction of the transaction value. Second, these payments represent “quasi-rents,” meaning they are competed away and can thus be seen as deadweight losses that leave the economy in terms of the consumption good.

Importantly, market imperfections do not represent government interventions, which are separately modeled as production subsidies represented by $\tau$. My goal is to analyze how policy interventions $\tau$ affect aggregate efficiency, taking market imperfections $\chi$ as given.

In what follows, I use financial frictions as a running narrative for market imperfections, motivated by financial frictions’ well-documented importance in developing countries (Banerjee and Munshi (2004), Banerjee and Duflo (2005), Banerjee and Moll (2010), Buera et al. (2011)). A more-elaborated microfoundation is provided in Appendix A.2, where I also show imperfection wedges $\chi$ with the aforementioned two features can be microfounded by various other imperfections, including monopoly markups (with profits dissipated by entry), contracting frictions, and externalities.
**Producer Problem**  Suppose market imperfections arise because seller $j$ requires each buyer $i$ to pay a fraction $\delta_{ij}$ of transaction value up front. Buyers can achieve this by borrowing working capital, which carries an interest rate $\lambda$. Effectively, for every dollar producer $i$ spends on input $j$, he must pay $\chi_{ij} \equiv \lambda \delta_{ij}$ dollars to a lender. These interest payments raise producer $i$’s production costs. On the other hand, producer $i$ also receives government subsidies $\tau_{ij}$ and $\tau_{iL}$ proportional to input expenditures. Producers otherwise behave competitively, and equilibrium prices solve the following cost-minimization problem:

$$ P_i \equiv \min_{\ell_i, \{m_{ij}\}_{j=1}^N} \left( \sum_{j=1}^N (1 - \tau_{ij} + \chi_{ij}) P_j m_{ij} + (1 - \tau_{iL}) W \ell_i \right) \text{ s.t. } z_i F_i \left( \ell_i, \{m_{ij}\}_{j=1}^N \right) \geq 1, \quad (3) $$

where $P_i$ is the market price of good $i$ and $W$ is the factor price.

**Imperfections Generate Deadweight Losses**  Lenders receive interest payments in proportion to loan size but incur the disutility cost of financial monitoring in order to ensure loan repayment. Interest rates are competitive, and lenders’ interest income exactly compensates disutility costs; hence, after spending income on consumption, lenders earn zero net utility. The interest payments can thus be seen as deadweight losses that leave the economy via the consumption good. Payments made by producer $i$ are $\sum_{j=1}^N \chi_{ij} P_j M_{ij}$, and the total deadweight losses in the economy are

$$ \Pi \equiv \sum_{i=1}^N \sum_{j=1}^N \chi_{ij} P_i M_{ij}. \quad (4) $$

For accounting purposes, I assume these payments are always incurred by intermediate buyers and that using factor inputs does not generate deadweight losses, so that factor endowment $L$ accurately represents the total resources in the economy. Misallocation over factor inputs can always be modeled by either relabeling or adding fictitious producers to the economy.

**Price Normalization**  To focus on imperfections and interventions in the intermediate goods network, I assume the consumption good is produced without any wedges. Price normalization implies

$$ 1 \equiv \min_{\{y_j\}_{j=1}^N} \sum_{j=1}^N P_j y_j \text{ s.t. } \mathcal{F} (y_1, \cdots, y_N) = 1. \quad (5) $$

**Government Interventions**  Policy interventions are modeled as sector-input-specific production subsidies $\{\tau_{ij}, \tau_{iL}\}_{i,j=1}^N$ paid by the government. Let $S_i$ denote the total policy expenditure in sector $i$:

$$ S_i \equiv \sum_{j=1}^N \tau_{ij} P_j M_{ij} + \tau_{iL} W L_i. \quad (6) $$
Besides policy interventions, the government also has real expenditure $G$, which represents public consumption. To balance its budget, the government charges lump-sum taxes $T$ from the consumer:

$$G + \sum_{i=1}^{N} S_i = T. \quad \text{(Government Budget Constraint)} \quad (7)$$

**Consumer**  The representative consumer spends post-tax factor income on consumption $C$:

$$C = WL - T. \quad \text{(Consumer Budget Constraint)} \quad (8)$$

**Aggregation**  The expenditure accounting identity follows:

$$Y^G - \Pi \equiv Y = C + G. \quad \text{(expenditure accounting identity)} \quad (9)$$

The identity states that $Y^G$, the gross output of the consumption good, is equal to the sum of private, public, and lenders’ consumption ($C$, $G$, and $\Pi$). Since lenders earn zero utility and their consumption $\Pi$ is seen as deadweight loss, I refer to the sum of private and public consumption $Y = C + G$ as “aggregate consumption” or, simply, “output”. $Y$ is the aggregate variable of interest in my analysis.

The income accounting identity is obtained by substituting budget constraints (7) and (8) into (9):

$$Y = WL - \sum_{i=1}^{N} S_i. \quad \text{(income accounting identity)} \quad (10)$$

The identity states that the output $Y$ is equal to total factor income net of policy expenditures.

**Definition 1.** Given productivities $z_i$, market imperfections $\chi_{ij} \geq 0$, subsidies $\{\tau_{ij}, \tau_i\}$, and public consumption $G$, an equilibrium is the collection of prices $\{P_i, W\}$, allocations $\{Q_i, L_i, M_{ij}, Y_i, Y^G, Y, C\}$, lump-sum taxes $T$, and quasi-rents $\Pi$, such that: 1) producers choose allocations to solve cost-minimization problems (3) and (5), setting prices to production costs; 2) government and consumer budget constraints (7) and (8) are satisfied; 3) the income accounting identity (10) holds; and 4) markets for the factor and intermediate goods clear: $L = \sum_{i=1}^{N} L_i$ and $Q_j = Y_j + \sum_{i}^{N} M_{ij}$ for all $j$.

**Model Summary**

This is a canonical model of a constant-returns-to-scale, nonparametric production network augmented by two types of wedges: market imperfections $\chi$ and subsidies $\tau$. The goal of my theory is to derive a set of empirically measurable objects to capture how changes in subsidies $\tau$ affect output $Y$, holding imperfections $\chi$ constant. In the model, both wedges affect prices but differ in that subsidies redistribute—and neither destroy nor generate—resources, whereas imperfections destroy resources.
through deadweight losses $\Pi$ in the form of the consumption good.\footnote{\textsuperscript{3}} Note the size of deadweight losses depends on the value of intermediate transactions and relative prices. This is a source of pecuniary externalities and allocative inefficiency (Greenwald and Stiglitz (1986)). In Appendix A.2, I provide additional microfoundations for market imperfections, including monopoly markups (with profits dissipated by entry), contracting frictions, and externalities.

\textbf{Notations for the Rest of the Paper}

Throughout the paper, I refer to the economy with neither imperfections nor subsidies ($\chi = \tau = 0$) as “efficient.” In this economy, the First-Welfare Theorem holds, and sectoral allocations $\{L_i, M_{ij}, Q_i\}$, as well as output $Y$, clearly coincide with those chosen by a social planner.

I refer to the economy with market imperfections but without any government interventions ($\tau = 0$) as “decentralized.” The decentralized economy serves as an important benchmark: my main theoretical results will characterize the first-order impact of introducing subsidies to this benchmark.

I now introduce notations to capture several objects that describe local features of an equilibrium. These objects are “reduced-form,” meaning they are defined with respect to equilibrium allocations and are not necessarily policy invariant.

Let $\Sigma \equiv [\sigma_{ij}]$ be the $N \times N$ matrix of equilibrium intermediate production elasticities:

$$
\sigma_{ij} = \frac{\partial \ln F_i \left( L_i, \{M_{ij}\}_{j=1}^N \right)}{\partial \ln M_{ij}}.
$$

Let $\Omega \equiv [\omega_{ij}] \equiv \left[ \frac{P_i M_{ij}}{P_j Q_j} \right]$ be the $N \times N$ matrix of equilibrium intermediate expenditure shares. I similarly define $\sigma_L \equiv [\sigma_{iL}]$ and $\omega_L \equiv [\omega_{iL}]$ as the elasticity and expenditure share vector of the factor input. Expenditure shares relate to elasticities by market imperfections and subsidies: $(1 + \chi_i - \tau_{ij}) \omega_{ij} = \sigma_{ij}$ for intermediate input $j$ and $(1 - \tau_{iL}) \omega_{iL} = \sigma_{iL}$ for the factor.

Let $\beta$ be the $N \times 1$ expenditure share for producing the consumption good, $\beta_j \equiv \frac{P_j Y_j}{\sum_i P_i Y_i}$.

Let $\mu$ be $N \times 1$ vector of sectoral influence $\mu' \equiv \beta' (I - \Sigma)^{-1}$. Influence is an elasticity-based centrality measure of sectoral importance. The Leontief inverse in the expression (i.e. $(I - \Sigma)^{-1} \equiv I + \Sigma + \Sigma^2 + \cdots$) captures the infinite rounds of network effects, i.e., how productivity shocks to one sector affect prices in another, taking all higher-order effects into account (Acemoglu et al. (2012)).

Let $g_i \equiv \frac{P_i Q_i}{W L}$ be sector $i$’s Domar weight, which is an expenditure-based centrality measure of

\textsuperscript{3}The treatment of wedges varies in the literature. Caliendo et al. (2017) also use factor income as the aggregate variable and discard $\Pi$ as deadweight losses. By contrast, Jones (2013), Bigio and La’O (2017), and more recently, Baqaee and Farhi (2018b), rebate $\Pi$ back to the consumer; the “aggregate output” in these papers corresponds to the “gross output” ($Y^G \equiv Y + \Pi$) in my model. The role of this deadweight-loss assumption will be discussed in Section 2.4.4.
equilibrium sectoral size. The Domar weight captures the value of production resources in each sector relative to total factor income. The measure can also be expressed in vector form as

$$\gamma^\prime = \beta^\prime (I-\Omega)^{-1} \omega.$$ 

In efficient economies, $\gamma^\prime$’s are used as sectoral weights for growth accounting (Domar (1961)).

The ratio between influence $\mu$ and Domar weight $\gamma$ is the key object of this paper.

**Definition 2.** The distortion centrality $\xi_i$ of sector $i$ is defined as $\xi_i \equiv \mu_i / \gamma_i$.

In efficient economies, $\mu = \gamma$ but differ in distorted economies; influence can thus be seen as a local measure of potential sectoral size under optimal production. $\xi_i$ is therefore the local ratio between a sector’s potential and actual size. The name “distortion centrality” reflects the fact that this measure integrates all distortionary effects through input-output linkages and summarizes the aggregate degree of misallocation in each sector.

Distortion centrality is not policy invariant and depends on both market imperfections and policy subsidies. It is identically equal to one across all sectors in an efficient economy. In the decentralized economy, distortion centrality differs from one because of market imperfections.

The rest of my paper revolves around distortion centrality $\xi$. Section 2 shows its economic significance: policymakers should first subsidize sectors with higher $\xi$, and the cross-sector covariance between $\xi$ and policy spending on subsidies reveals the aggregate effect of interventions. Section 3 analyzes how $\xi$ depends on network structures and shows why $\xi$ tends to be higher in upstream sectors. In Section 4, I measure distortion centrality, show it predicts sectoral interventions in South Korea and China, and quantify the aggregate impact of interventions in these economies. All proofs are in Appendix B.

### 2 Theory: Distortion Centrality and Sectoral Interventions

This section provides several results that highlight distortion centrality’s importance for policy design. Proposition 1 shows that, starting from the decentralized economy, sectors with high distortion centrality should be promoted first, because the measure is a sufficient statistic for the marginal social value of policy expenditure and captures the “bang for the buck” of subsidies. Proposition 2 presents a simple formula for policy evaluations and counterfactuals, indicating that, to first order, the aggregate impact of sectoral interventions can be nonparametrically assessed by the covariance between subsidy spending and distortion centrality across sectors. Proposition 3 shows that under Cobb-Douglas, distortion centrality is a sufficient statistic for constrained-optimal subsidies to the factor input. Through an example in Section 2.2, I demonstrate that distortion centrality differs substantively from other notions of sectoral importance. I discuss various interpretation and robustness issues in Section 2.4.

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4The expression follows from market clearing (see Appendix B). The denominator equals one in an efficient economy.
To begin, note that the income accounting identity (equation 10; reproduced below) maps aggregate consumption $Y$ into total factor income net of policy expenditures:

$$ Y = WL - \sum_{i=1}^{N} S_i. $$

The identity enables one to analyze the policy impact on $Y$ by first analyzing the policy impact on prices. This transformation is useful because, even with full knowledge of market imperfections, one generically cannot predict the policy response of allocations using empirical objects measured from the pre-intervention economy; how allocations respond is governed by production technologies’ structural features, which are not directly observable. This highlights a key conceptual difficulty in industrial policy design: policy prescriptions are generically sensitive to ex-ante parametric assumptions on production technologies.

By contrast, the policy response of prices can always be summarized by reduced-form objects measured from the equilibrium before the policy change. This is because producers engage in cost-minimization, and, according to the envelope theorem, policy-induced changes in production elasticities have only second-order effects on prices even in the presence of imperfections and subsidies. I exploit this fact and separately analyze the effects of subsidies on factor income and policy expenditures, and I then apply the income accounting identity to obtain net effects on output $Y$.

First, note subsidies’ effect on factor income is similar to that of input-augmenting productivity shocks; hence, the following lemma is useful for finding $dW/L/d\tau_{ij}$.

**Lemma 1.**

$$ \frac{d\ln WL}{d\ln z_i} = \mu_i. $$

Influence is a sufficient statistic for how factor income responds to TFP shocks. This is because production elasticities capture how changes in one price affect another, and $\mu'$ summarizes TFP’s general equilibrium effects on the factor price $W$ through the Leontief-inverse of the elasticity matrix, $(I - \Sigma)^{-1}$ (recall $L$ is exogenous, thus $d\ln W = d\ln WL$).

As a technical note, Lemma 1 relates to Hulten’s (1978) theorem, which only holds in efficient economies and states that Domar weight summarizes how output responds to TFP shocks ($d\ln Y/d\ln z_i = \gamma_i$). By contrast, Lemma 1 shows the dual of Hulten’s theorem holds even in inefficient economies: influence always summarizes how the factor price $W$ responds to TFP shocks. The Lemma also reveals that Hulten’s theorem fails in inefficient economies for two distinct reasons: 1) influence differs from Domar weights, and 2) output is decoupled from factor income. In a generic inefficient economy, neither influence nor Domar weight is a sufficient statistic for how output responds to TFP.\(^5\)

\(^5\)Jones (2013) and Bigio and La’O (2017) analyze Cobb-Douglas networks, rebating quasi-rents $\Pi$ to the consumer. Aggregate output in these papers is equivalent to gross output in mine ($Y^G = Y + \Pi$). These papers show $\frac{d\ln Y^G}{d\ln z_i} = \mu_i \neq \gamma_i$. 

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The next Lemma establishes sufficient statistics that predict subsidies’ impact on $Y$ in the decentralized economy.

**Lemma 2.** In the decentralized economy, the effect of subsidies on output $Y$ is

$$
\frac{d \ln Y}{d \tau_{ij}} \bigg|_{\tau=0} = \omega_{ij} (\mu_i - \gamma_i) \text{ for } j = 1, \ldots, N, L.
$$

(11)

By the income accounting identity, the aggregate impact of subsidies on $Y$ is the net effect on both factor income and policy expenditures. On the one hand, subsidies raise factor income $WL$ in ways similar to input-augmenting productivity shocks, and the effect scales with the influence $\mu_i$ of the targeted sector $i$. On the other hand, subsidies cost the government resources, and, starting from the decentralized economy, subsidies’ first-order impact on the government budget ($\sum_{i=1}^N S_i$) is proportional to total resources in the targeted sector, captured by Domar weight $\gamma_i$. The aggregate impact of subsidies is therefore proportional to the distance between the targeted sector’s influence and its Domar weight. The effect in (11) is scaled by intermediate expenditure share, $\omega_{ij}$, because the subsidy $\tau_{ij}$ only targets a single input $j$ in the sector.

The sufficient statistics in Lemma 2 are nonparametric in the sense that, in order to predict the left-hand-side, one does not need to specify structural properties of production technologies on the right-hand-side: intermediate expenditure shares ($\omega_{ij}$), influence ($\mu_i$), and Domar weights ($\gamma_i$) are all reduced-form objects in the local equilibrium and are, in principle, observable. The formula holds in the decentralized economy. As noted above, nonparametric characterizations of allocations are generically not possible away from this benchmark.\(^6\) To understand why the decentralized economy is special, consider the impact of subsidies on the government budget, i.e. the second term in (10):

$$
\frac{d}{d \tau_{ij}} \left( \sum_{i=1}^N S_i \right) = P_j M_{ij} \quad \text{direct impact from targeted input}
$$

\[+ \sum_{k,n=1}^N \tau_{kn} \frac{d (P_n M_{kn})}{d \tau_{ij}} + \sum_{k=1}^N \tau_{kL} \frac{dWL_k}{d \tau_{ij}} \quad \text{indirect effects due to endogenous changes in network structure}
\]

Subsidy $\tau_{ij}$ expands the use of targeted input $M_{ij}$ and directly raises policy expenditure in proportion to the equilibrium value of the input ($P_j M_{ij}$). The intervention also induces reallocations, which causes producers in other sectors to adjust inputs, and generates endogenous changes in production elasticities and the network structure. Such reallocations interact with existing subsidies and have but their equality sign relies crucially on the Cobb-Douglas assumption. Generically, $\frac{d \ln Y^G}{d \ln z_i} \neq \frac{d \ln Y}{d \ln z_i} \neq \frac{d \ln WL}{d \ln z_i} = \mu_i \neq \gamma_i$.

\(^6\)Baqaee and Farhi (2018b) provide ex-ante but parametric formulas for how $Y^G$ responds to shocks under CES assumptions. To apply these formulas, one needs to know elasticities of substitutions and productivities in every sector of the economy as well as the CES weights and distortions on every intermediate input in every sector. The paper also provides nonparametric but ex-post accounting formulas, requiring both ex-ante level and ex-post changes in elasticities and expenditure shares to be observed. By contrast, my results are nonparametric and ex-ante, enabling one to perform policy evaluation and counterfactuals on $Y$ only using reduced-form objects from the pre-intervention economy.
indirect but first-order effects on total policy expenditures (the second term). These indirect effects are the source of difficulty in industrial policy design: short of making difficult-to-verify, parametric assumptions about production technologies, policy interventions’ aggregate impact cannot be ex-ante predicted. In the decentralized economy, however, existing subsidies are zero, and the indirect effects are second-order—hence Lemma 2.

My main propositions, which I now introduce, leverage this special property of the decentralized economy and highlight the economic implications of Lemma 2.

2.1 Social Value of Policy Expenditures and Counterfactuals

My first proposition directly interprets influence and the Domar weight as the marginal social benefit and social cost of policy subsidies, respectively, thereby highlighting the role of their ratio, i.e. distortion centrality, as a first-order sufficient statistic that guides interventions.

Aggregate consumption \( Y \) is the sum of private and public consumption, \( C \) and \( G \), which satisfy the consumer and government budget constraints, respectively:

\[
C = WL - T, \quad \text{consumer budget constraint}
\]

\[
G + \sum_{i=1}^{N} S_i = T, \quad \text{government budget constraint}
\]

Now consider the trade-off between private and public consumption as subsidies, holding constant the lump-sum tax \( T \). In this case, subsidies raise factor income, thereby raising private consumption \( \frac{dC}{d\tau_{ij}} = \frac{dWL}{d\tau_{ij}} \). To finance the subsidy, the government cuts back public consumption in order to balance its budget \( \frac{dG}{d\tau_{ij}} = -\frac{d\sum_{i=1}^{N} S_i}{d\tau_{ij}} \). The following result shows that distortion centrality captures the marginal rate of transformation between private and public consumption through policy subsidies.

**Proposition 1.** In the decentralized economy, the social value of policy expenditure on \( \tau_{ij} \) is

\[
SV_{ij} \equiv -\frac{dC/d\tau_{ij}}{dG/d\tau_{ij}} \bigg|_{\tau=0, T_{\text{constant}}} = \xi_i \quad \text{for } j = 1, \ldots, N, L.
\]

The social value of policy expenditure captures the gains in private consumption per unit reduction of public consumption (“bang for the buck”) that is spent on subsidy \( \tau_{ij} \). This measure is informative for policy design because it is a general equilibrium spending multiplier. Proposition 1 shows that \( SV_{ij} \) is sector-specific, i.e., distortion centrality \( \xi_i \) is a sufficient statistic for the social value of policy expenditure on subsidies to any input in the sector. A benevolent government that trades off private and public consumption should therefore prioritize subsidies to sectors with high distortion centrality.

Intuitively, while influence captures the marginal benefit of subsidies accrued to the consumer
through higher factor income, the marginal costs of subsidies—the impact on a government’s budget and thus the reduction in public consumption—is captured by the Domar weight. Their ratio, i.e. distortion centrality, captures the social value of policy spending by integrating all distortionary effects of market imperfections in the network and summarizing the aggregate degree of misallocation in each sector. Note that this result holds only in the decentralized economy (as does Lemma 2), in which the indirect effects of policy-induced network changes on government budget are only second-order.

According to the government budget constraint, subsidies can also be financed by raising lump-sum taxes while holding public consumption \( G \) constant. In this case, Proposition 1 can be recast.

**Corollary 1.**

\[
\frac{dY}{dT} \bigg|_{\tau=0, G \text{ constant}} = \xi_i - 1.
\]

\((\xi_i - 1)\) captures the net effect on output for every unit of policy spending on subsidies. Industrial policy raises output if and only if the promoted sector has distortion centrality above one.

In an efficient economy, distortion centrality is always one, and interventions generate one-to-one transfers between public and private consumption, leaving no first-order aggregate effects. Under market imperfections, distortion centrality differs from one, and policy interventions do have first-order effects starting from the decentralized economy. Nevertheless, interventions can improve aggregate efficiency only through effective targeting. As I show next, uniformly promoting all sectors is guaranteed to be ineffective, and poor sectoral targeting could in fact lead to aggregate losses.

Consider multiple and simultaneously adopted subsidies \( \{\tau_{ij}, \tau_{iL}\}_{i,j=1}^N \), and let \( s_i \equiv S_i/WL_i \) denote policy spending per value-added in each sector.

**Proposition 2.** (a) In the decentralized economy, distortion centrality averages to one \((\mathbb{E} [\xi] = 1)\).

(b) The proportional output gains from policy interventions, as a first-order approximation around the decentralized economy, is the covariance between distortion centrality and sectoral policy spending per value-added: \(^7\)

\[
\Delta \ln Y \approx \text{Cov}(\xi, s_i).
\]

The expectation and covariance are taken across sectors using relative sectoral value added as the distribution, e.g. \( \mathbb{E} [\xi] \equiv \sum_i (\xi_i \cdot L_i/L) \).

Part (a) of the result shows that distortion centrality averages to one in the decentralized economy; hence, promoting sectors uniformly—with \( s_i \) equalized across sectors—does not have aggregate effects. This is because subsidies affect allocations only through redistributing resources; uniform intervention does not redistribute resources and is equivalent to a lump-sum transfer from the government to the consumer, generating zero net effect.

\(^7\)Formally, \( \Delta \ln Y \equiv (Y|_{\{\tau_{ij}, \tau_{iL}\}} - Y|_{\tau=0}) / (Y|_{\tau=0}) \).
Even though distortion centrality always averages to one, its range and cross-sector variance depend on the magnitude of underlying imperfections. Intuitively, when imperfections are small in the economy, allocations are close to the first-best, and distortion centrality is close to one in all sectors. Conversely, severe imperfections lead to significant cross-sector dispersion in distortion centrality.

Part (b) of Proposition 2 provides a succinct covariance formula that nonparametrically summarizes the first-order, general equilibrium impact of sectoral interventions. For a policy program to be effective in aggregate, subsidy expenditures must be positively selected toward sectors with high distortion centrality, and sectors with low distortion centrality should be taxed. To apply the formula, distortion centrality and policy spending $s_i$ can be evaluated using prices and allocations from either the pre- or post-intervention economy, as the differences therein have only second-order impact on the covariance term.

Proposition 2 enables econometricians and policymakers to conduct nonparametric policy evaluations and perform counterfactuals to compare alternative interventions. The result is useful, because it is usually difficult for empirical before-after studies that compare across sectors (the difference in differences approach) to shed light on interventions’ aggregate effect. That promoted industries use more resources and pay lower prices or interest rates is evidence of interventions at work—i.e. that funds are not entirely siphoned off into bureaucrats’ pockets—and does not indicate policy failure; conversely, expanded production in promoted sectors is not evidence of policy success. To evaluate policies, it is important to ask the counterfactual, “What would have happened in aggregate, absent these interventions?” The answer inevitably hinges on general equilibrium reallocative effects, about which before-after studies are silent.

In Section 4, I apply Proposition 2 to evaluate industrial policies in South Korea and China.

### 2.2 Distortion Centrality ≠ Other Notions of Importance: An Example

Standard intuitions might suggest that, to improve efficiency, subsidies should be given to the most distorted sectors. However, this intuition is incomplete because it ignores input-output linkages, along which market imperfections’ distortionary effects accumulate. Alternatively, one might also believe, based on Lemma 1 and Hulten (1978), that governments should first subsidize influential or large sectors. My results show that these intuitions are also incomplete. Although influence captures the effect of subsidies on factor income, it misses the fiscal costs. Unlike productivity shocks, which do not cost resources, subsidies affect allocations by redistributing resources. Therefore, it is crucially important to include the cost of subsidies into policy calculations. Targeting sectors by influence only considers benefits while targeting by size only considers costs, and neither intuition is complete.

The distinctions between distortion centrality and these other notions of “importance” are substantive, as promoting large, influential, or very distorted sectors can indeed amplify—rather than atten-
uate—misallocations and lead to aggregate losses. I now turn to a simple example to illustrate how
distortion centrality relates to these other measures. Later in Section 4, I also empirically demonstrate
that distortion centrality differs substantially from these other measures in real-world networks.

Example Setup: A Vertical Production Network with Three Intermediate Sectors

Upstream good 1 is produced linearly from the factor input; midstream good 2 is produced from the
factor and good 1; downstream good 3 is produced from the factor and good 2. The downstream good
directly transforms into the consumption good. Producers $i = 2, 3$ face imperfections $\chi_i > 0$ when
purchasing intermediate good $(i - 1)$. The network is demonstrated below, omitting the final sector.

![Diagram of production network](Figure)

$$
\text{Production Functions}
\begin{align*}
Q_1 &= z_1 L_1 \\
Q_2 &= z_2 L_2^{1-\sigma_2} M_2^{\sigma_2} \\
Y^G &= z_3 L_3^{1-\sigma_3} M_3^{\sigma_3}
\end{align*}
$$

In the decentralized economy, sectoral influence, Domar weights, and distortion centrality follow

\begin{align*}
\text{(Influence)} & \quad (\mu_1, \mu_2, \mu_3) \propto \begin{pmatrix} \sigma_2 \sigma_3, & \sigma_3, & 1 \end{pmatrix}, \\
\text{(Domar weights)} & \quad (\gamma_1, \gamma_2, \gamma_3) \propto \begin{pmatrix} \sigma_2/(1+\chi_2), & \sigma_3/(1+\chi_3), & 1 \end{pmatrix}, \\
\text{(Distortion centrality)} & \quad (\xi_1, \xi_2, \xi_3) \propto \begin{pmatrix} (1+\chi_2)(1+\chi_3), & (1+\chi_3), & 1 \end{pmatrix}
\end{align*}

For notational simplicity, these objects are expressed in proportional terms. The term $\sigma_i < 1$ is the
production elasticity of intermediate input in sector $i$. Derivations are in Appendix A.7.

**Downstream Is Large And Influential, But Upstream Has High Distortion Centrality**

I wish to highlight two observations. First, influence and Domar weights are highest in downstream
sector 3 and lowest in upstream sector 1. Influence is a measure of sectoral importance and the Domar
weight is a measure of size; the two coincide absent market imperfections. Downstream is influential
because its productivity raises the value not only for factor inputs in the downstream sector but also
for those in midstream and upstream sectors through production linkages. Likewise, the downstream
sector is large because it provides additional value-added over midstream (and, indirectly, upstream)
production. Conversely, upstream sector 1 has low influence and is small because its productivity only
benefits its own factor input and because its output constitutes only a fractional value of midstream
and downstream production.
Second, observe that the sectoral rankings by distortion centrality are unambiguously the inverse of the rankings by influence or by size: upstream sector 1 has the highest distortion centrality and downstream has the lowest ($\xi_1 > \xi_2 > \xi_3$), irrespective of the magnitude of imperfections in midstream and downstream sectors. This is because the distortionary effects of market imperfections accumulate into distortion centrality through *backward demand linkages*. Market imperfections in downstream sector 3 depress intermediate demand and lower midstream sector’s size relative to its influence; midstream imperfections further depress demand for upstream goods, generating compounding effects and leaving upstream with the highest distortion centrality. In other words, it is not the imperfections within a sector itself that contribute to its distortion centrality, but instead, imperfections in sectors to which it supplies, directly and indirectly. The further upstream a sector is and the more layers of distorted linkages its output must travel through before reaching the final consumer, the higher the sector’s distortion centrality.

**Promoting Upstream Mitigates Misallocations**

Because upstream sector 1 has the highest distortion centrality, my results show that subsidizing upstream improves aggregate efficiency and conversely, because distortion centrality averages to one, subsidizing the large, influential, and potentially most-distorted downstream sector 3 leads to aggregate losses. This is because market imperfections generate resource misallocations, causing too few inputs in the upstream sector and too many inputs in the downstream. Promoting downstream production therefore exacerbates the misallocation. To see this more explicitly, consider factor allocations, which can be solved in closed-form in this example because of the Cobb-Douglas assumption:

\[
\begin{align*}
    \left(L_1^*, L_2^*, L_3^*\right) &\propto \left(\sigma_2 \sigma_3, \sigma_3 (1 - \sigma_2), (1 - \sigma_3)\right), \\
    \left(L_1, L_2, L_3\right) &\propto \left(\frac{\sigma_2}{(1 + \chi_2)}, \frac{\sigma_3}{(1 + \chi_3)}, \frac{\sigma_1}{1 + \chi_3} (1 - \sigma_2), (1 - \sigma_3)\right),
\end{align*}
\]

where $L_i^*$’s represent efficient factor allocations and $L_i$’s are those in the inefficient decentralized economy. Relative to efficient allocations, the inefficient economy allocates too few factor inputs upstream and too many downstream. Policy interventions improve efficiency only if they counteract misallocations, redirecting the factor input to the upstream sector.

Here is a roadmap for the remaining theoretical results. In Section 2.3, I characterize non-marginal interventions in Cobb-Douglas networks and further elaborate on the allocative inefficiency of distorted economies. I discuss a few conceptual issues and extensions in Section 2.4. Section 3 analyzes how network structure generally shapes distortion centrality, formalizing the intuition that distortionary effects accumulate through backward demand linkages.
2.3 Cobb-Douglas Case: Optimal Subsidies and Misallocations

Now consider constrained optimal (as opposed to marginal) interventions, which, given constraints \( \mathcal{P} \) over policy instruments, is the solution to \( \{ \arg \max_{\tau \in \mathcal{P}} Y \} \). Away from the decentralized economy, \( dY/d\tau_{ij} \) generically depends on production technologies’ parametric structures because the network changes endogenously in response to policy. I now analyze a knife-edge case: Cobb-Douglas production functions, with policy instruments constrained to be sector-specific subsidies to value-added factor inputs, \( \mathcal{P} = \{ \tau_{il} \}_{i=1}^N \). The solution to this case is particularly simple and provides additional insights into the role of distortion centrality.

**Proposition 3.** Under Cobb-Douglas, the solution \( \{ \tau_{il}^* \}_{i=1}^N \) to the problem \( \{ \arg \max_{\{ \tau_{il} \}_{i=1}^N} Y \} \) satisfies \( \left\{ \frac{1}{1-\tau_{il}^*} = \xi_i \right\}_{i=1}^N \). Moreover, \( \{ \tau_{il}^* \}_{i=1}^N \) is also the solution to maximizing gross output, \( \{ \arg \max_{\{ \tau_{il} \}} Y^G \} \).

Distortion centrality is a sufficient statistic for optimal value-added subsidies under Cobb-Douglas. This result holds under arbitrary outstanding subsidies to intermediate inputs \( \tau_{ij} \notin \{ \tau_{il} \}_{i=1}^N \), the levels of which are implicitly reflected in sectoral Domar weights and hence in distortion centrality.

To understand the result, note that factor allocations in efficient and distorted economies follow

\[
(\text{first-best}) \quad L_i^* = \mu_i \sigma_{il} L, \quad (\text{distorted}) \quad L_i = \frac{\gamma_i}{1-\tau_{il}} \sigma_{il} L. \tag{12}
\]

Optimal subsidies therefore align distorted allocations with efficient ones, setting \( \frac{\gamma_i}{1-\tau_{il}} = \mu_i \). Another interpretation is to consider a fictitious sector that buys the factor and sells to sector \( i \), with \( \mu_i \sigma_{il} \) and \( \gamma_i \sigma_{il} \) representing the influence and the Domar weight, respectively, of this fictitious sector. Proposition 3 states that subsidies to the fictitious sector should be chosen to align the sector’s influence with its Domar weight.

The intuition that non-marginal interventions should align with distortion centrality ignores the indirect budgetary effects caused by endogenous network changes. These indirect effects are shut down in this case because 1) elasticities are constant under Cobb-Douglas and 2) value-added subsidies do not affect expenditure shares on intermediate inputs.

As a technical note, the assumption that imperfections generate quasi-rents, as opposed to real economic rents, is inconsequential in the case analyzed in Proposition 3, as constrained-optimal policies that maximize net and gross output \( (Y \text{ and } Y^G \equiv Y + \Pi) \) coincide. This is because under Cobb-Douglas, the network structure is policy invariant, and \( Y \) always moves proportionally to \( Y^G \) in response to value-added subsidies.
2.4 Discussions and Extensions

In the next section, I analyze how general network structure shapes distortion centrality. Before moving on, I will briefly discuss some conceptual issues within my results. I also address many additional theoretical issues and extensions in Appendix A.

2.4.1 Within-Sector Heterogeneity

In the real world, firms within a narrowly defined industry classification may produce differentiated goods and are subject to distinct market imperfections. Ideally, to apply my theory, one would compute distortion centrality for each “variety”, which is the level of differentiation at which heterogeneity is defined. Nevertheless, I show in Appendix A.1 that \( \xi \) remains sector-specific under the following condition: there exist sectoral aggregators that combine within-sector varieties into sectoral bundles so that cross-sector transactions take place using these bundles. Intuitively, this condition implies that each firm is subject to one common imperfection wedge when buying different varieties produced by a common sector. When this condition holds, government interventions’ first-order aggregate effects depend on the net—not gross—subsidy spending within each sector, as subsidizing one variety while taxing another in the same sector generates exactly zero aggregate effect.

2.4.2 Policy Instruments

Propositions 1 and 2 are formulated using input-specific subsidies, but they also apply more broadly to other practical and real-world policy instruments that affect production input use. For instance, a policy that promotes overall sectoral production is isomorphic to a uniform subsidy to all inputs; likewise, under financial frictions, credit market interventions can also be represented by subsidies to inputs under working capital constraints. To see the latter, suppose the government subsidizes sectoral interest rates to \((\lambda - u_i)\), paying the difference \(u_i\) to the lender out of the government budget. The profit-maximization problem of producer \(i\) becomes

\[
\max_{\Gamma, Q, L, \{M_{ij}\}} \quad P_i Q_i - \left( \sum_{j=1}^{N} P_j M_{ij} + WL_i + (\lambda - u_i) \Gamma_i \right) \quad \text{s.t.} \quad (2) \quad \text{and} \quad \sum_{j=1}^{N} \delta_{ij} P_j M_{ij} \leq \Gamma_i,
\]

Credit subsidy \(u_i\) generates production decisions and policy expenditures that are identical to those induced by the set of simultaneous input subsidies \(\{\tau_{ij} \equiv u_i \delta_{ij}\}\); thus, Propositions 1 and 2 apply.

2.4.3 Subsidies Redistribute Resources But Do Not Counteract Market Imperfections

The social value of policy expenditure \((SV_{ij})\) depends on the distortion centrality of sector \(i\) and not on the targeted input \(j\). This is because imperfection \(\chi_{ij}\) generates deadweight losses \(\chi_{ij} P_j M_{ij}\) instead of \(\chi_{ij} (1 - \tau_{ij}) P_j M_{ij}\): the former scales with transactions’ market value, whereas the latter scales with the subsidized value. I adopt the former specification because it subjects policy instruments to the
same imperfections faced by market-based transactions, thereby isolating only the reallocative effects of policy interventions. This distinction is elaborated upon in Appendix A.5.

2.4.4 Market Imperfections Generate Deadweight Losses

In my model, market imperfections generate quasi-rents that are competed away as deadweight losses. The assumption is used to motivate net output \( Y \equiv Y^G - \Pi \) as the aggregate outcome variable of interest instead of the gross output \( Y^G \). The mathematical statements in Propositions 1 and 2 nonparametrically predict the policy response of \( Y \); by contrast, parametric assumptions are always necessary in order to predict how gross output \( Y^G \) responds to policy shocks. When imperfections generate real economic rents, my propositions are policy relevant insofar as net output \( Y \) is policy relevant. Finally, as Proposition 3 shows, the assumption is inconsequential under Cobb-Douglas for the constrained-optimal subsidies to value-added.

2.4.5 Market Imperfections ≠ Iceberg Costs

Despite the quasi-rent assumption, market imperfections are not isomorphic to iceberg trade costs, under which a fraction of inputs are lost during transactions. An iceberg economy is constrained efficient—allocations coincide with the planner’s solution—whereas a decentralized economy with market imperfections is not. Inefficiency arises because, under market imperfections, quasi-rents are proportional to the transaction value and depend on relative prices; hence, pecuniary externalities do not “net out” (Greenwald and Stiglitz (1986)). In other words, under market imperfections (and unlike under iceberg costs), input demand is distorted for given input prices; hence, by affecting prices, subsidies can have first-order aggregate effects. I elaborate on this issue in Appendix A.4, where I demonstrate: 1) allocations in my economy do not coincide with allocations under the first-best economy, and by redistributing resources, policy interventions can raise output \( Y \); 2) factor allocations under an iceberg economy coincide with those under the first-best; and 3) distortion centrality is always equal to one in an iceberg economy, so policy interventions have no first-order effects.

3 Theory: Distortion Centrality and Network Structure

How does distortion centrality relate to network structure? The vertical-network example in Section 2.2 shows that market imperfections accumulate through backward demand linkages, and consequently, sectors with high distortion centrality are upstream and directly or indirectly supply to many other sectors. I generalize this intuition in Proposition 4, which provides a closed-form formula for distortion centrality in arbitrary networks. I then analyze a class of hierarchical networks, in which sectors follow a pecking order, and relatively upstream sectors supply a disproportionate fraction of their output to other relatively upstream sectors. Proposition 5 shows that in hierarchical networks,

\[ \text{Contracting frictions in Boehm and Oberfield (2018) feature pecuniary externalities of the same nature.} \]
the ranking of distortion centrality is insensitive to underlying imperfections. This last result is useful for my empirical analysis later.

To proceed, let \( \theta_{ij} \equiv M_{ij} Q_j \) be the fraction of good \( j \) sold to sector \( i \). This object captures the importance of sector \( i \) as a buyer of good \( j \). Likewise, let \( \theta^F_j = \frac{Y_j}{Q_j} \) capture the importance of consumer demand for intermediate good \( j \). The market clearing condition for good \( j \) implies that \( \theta^F_j + \sum_{i=1}^N \theta_{ij} = 1 \). Note that \( \theta_{ij} \) is different from intermediate expenditure share \( \omega_{ij} \): the latter captures the importance of sector \( j \) as a supplier to \( i \), and the two objects relate by \( \theta_{ij} = \frac{\gamma_i}{\gamma_j} \cdot \omega_{ij} \).

I refer to \( \Theta \equiv [\theta_{ij}] \) as the input-output (IO) demand matrix. Even though the IO expenditure share matrix \( \Omega \equiv [\omega_{ij}] \) is a more common representation of input-output relationships in the literature, the demand matrix \( \Theta \) is the relevant representation for computing distortion centrality.

**Proposition 4.** In the decentralized economy, the distortion centrality of sector \( j \) can be written as

\[
\xi_j = \theta^F_j \cdot \delta + \sum_{i=1}^N \xi_i \cdot (1 + \chi_{ij}) \cdot \theta_{ij}
\]

for scalar \( \delta = \frac{WL}{Y^G} \). In matrix form,

\[
\xi' = \delta \cdot (\theta^F)' \cdot (I - (\Theta + D \circ \Theta))^{-1}
\]

where \( D \equiv [\chi_{ij}] \) is the matrix of sectoral imperfections and \( \circ \) denotes the Hadamard product.

The formula expresses distortion centrality in terms of network structure and underlying imperfections; it formalizes the intuition that imperfections accumulate through backward demand linkages. A sector has high distortion centrality if it sells a disproportionate share of its output to other sectors with high distortion centrality and large imperfections. To see this, consider sector \( j \) which supplies to sectors indexed by \( i \). Imperfections in input-using sectors \( (1 + \chi_{ij}) \) depress demand for good \( j \) and contribute to sector \( j \)'s distortion centrality \( \xi_j \); the effect is magnified by \( \xi_i \) and weighted by the importance of the demand relationship \( \theta_{ij} \). The distortion centrality of sector \( j \) then travels through \( j \)'s input demand and contributes to the distortion centrality of \( j \)'s suppliers further upstream. The proportionality scalar \( \delta \) ensures distortion centrality averages to one across sectors.

**Distortion Centrality and the “Upstreamness” Measure by Antras et al. (2012)**

The “upstreamness” measure by Antras et al. (2012) (“upstreamness” henceforth) is

\[
U' = I' (I - \Theta)^{-1}.
\]

The formulation in (14) was first proposed by Jones (1976) as a measure of “forward linkages.” It captures the notion that sectors selling a disproportionate share of their output to relatively upstream
sectors should themselves be relatively upstream. Distortion centrality is related to the upstreamness measure but instead captures the idea that high distortion centrality sectors sell a disproportionate share of their output to other sectors with high distortion centrality and large imperfections. In an efficient economy, distortion centrality can be written as \( \xi' = (\theta F)' (I - \Theta)^{-1} \), which always collapses to the identity vector \( \mathbf{1}' \).

**Distortion Centrality Aligns with Upstreamness in Hierarchical Networks**

In an arbitrary production network, distortion centrality may depend strongly on the underlying market imperfections and thus correlate poorly with the upstreamness measure. On the other hand, there is a class of networks—what I call “hierarchical” networks—in which distortion centrality tends to be stable across varying distributions of market imperfections and tends to correlate strongly with the upstreamness measure.

**Definition 3.** (Hierarchical Networks) A production network is hierarchical if its \( N \times N \) input-output demand matrix \( \Theta \) has non-increasing partial column sums:

\[
\sum_{k=1}^{K} \theta_{ki} \geq \sum_{k=1}^{K} \theta_{kj} \quad \text{for all } i < j \text{ and } K \leq N.
\] (15)

**Lemma 3.** Let \( U_i \) denote “upstreamness” as in (14). In a hierarchical network, \( U_i \geq U_j \iff i \leq j \).

Figure 1: An illustrative input-output demand matrix of a hierarchical network

Intuitively, a production network is hierarchical if a sectoral ordering exists, so that higher-ranked sectors supply a disproportionate share of their output to other higher-ranked sectors.\(^9\) Figure 1 vi-

\(^9\)A sufficient (but unnecessary) condition for an IO demand matrix \( \Theta \) to satisfy the hierarchical property is for its
ualizes the IO demand matrix $\Theta$ of a hierarchical network, with entry size drawn in proportion to the strength of the demand linkages $\theta_{ij}$. The condition that partial column sums are non-increasing is evident from sparse entries in the bottom-left and dense entries just below the diagonal.

In vertical networks, upstream sectors always have higher distortion centrality, as seen in Section 2.2. Hierarchical networks are generalizations of vertical networks. In hierarchical networks, upstream sectors tend to have higher distortion centrality because imperfections accumulate through backward linkages. To formalize this, I first provide two sufficient conditions under which distortion centrality aligns perfectly with upstreamness in rank-order. I then turn to an example.

**Proposition 5.** Consider a hierarchical production network with input-output demand matrix $\Theta$.

**Case 1.** (Deterministic imperfections) If $D \circ \Theta$ satisfies the hierarchical property, then

$$\xi_i \geq \xi_j \text{ for all } i < j \text{ in the decentralized economy.}$$

**Case 2.** (Random imperfections) Suppose $\Theta$ is lower-triangular. If cross-sector imperfections $\{\chi_{ij}\}$ are i.i.d. and $E[\chi_{ij}] \geq 0$, then

$$E[\xi_i] \geq E[\xi_j] \text{ for all } i < j \text{ in the decentralized economy,}$$

where the expectation is taken with respect to the distribution of $\chi_{ij}$’s.

Case 1 shows that distortion centrality aligns with upstreamness if $D \circ \Theta$ is hierarchical. This condition is satisfied when, for instance, upstream sectors are more financially constrained and more working capital is required for sourcing upstream goods as inputs ($\chi_{im} > \chi_{jn}$ for all $i \geq j$ and $m \geq n$). This condition is reasonable because, as I show later, upstream sectors in real-world economies tend to be heavy manufacturing sectors, which not only use more intermediate inputs but also produce capital goods such as industrial equipment and machinery, the purchase of which is more likely to be subject to financial and contracting frictions. Case 2 of the proposition takes the equilibrium IO demand relationship $\Theta$ as fixed and imposes stochasticity on market imperfections. The result shows that if cross-sector imperfections are i.i.d. in a lower-triangular hierarchical network, then upstreamness and distortion centrality are aligned in expectation.

Note that these are **sufficient but unnecessary** conditions for distortion centrality and upstreamness to align perfectly across all sectors. Even if these conditions do not hold perfectly, the two measures still tend to align across most sectors. Intuitively, in order to break the alignment between distortion centrality and upstreamness in a hierarchical network, producers in the economy must face few imperfections when purchasing upstream goods (even though they use upstream inputs heavily) and face entries $\theta_{im}$ to exhibit log-supermodular in $(i, m)$, i.e. $\theta_{im}\theta_{jm} \geq \theta_{in}\theta_{jm}$ for $i \leq j$, $m \leq n$. 

22
enormous imperfections when purchasing downstream goods (even though they use few downstream inputs in equilibrium). Moreover, the counterintuitive pattern of imperfections must be sufficiently strong—perhaps implausibly so—in order to counteract the network effects.

Consider the following numerical illustration. Sector 1 is upstream, supplying 90% of its output to sector 2 and 10% to sector 3; sector 2 supplies its entire output to sector 3; good 3 is transformed linearly into the consumption good. Producers face imperfections $x$ when buying good 1 ($\chi_{31} = \chi_{21} = x$) and $y$ when buying good 2 ($\chi_{32} = y$). The economy can be summarized by

$$\Theta = \begin{bmatrix} 0 & 0 & 0 \\ 0.9 & 0 & 0 \\ 0.1 & 1 & 0 \end{bmatrix}, \quad \theta^F = (0, 0, 1), \quad D = \begin{bmatrix} 0 & 0 & 0 \\ x & 0 & 0 \\ x & y & 0 \end{bmatrix};$$

$$\xi' \propto ((1 + y) \times 0.9 + 0.1) \times (1 + x), \quad (1 + y), \quad 1.$$  

In this hierarchical (but non-vertical) network, downstream (sector 3) unambiguously has the lowest distortion centrality, but the relative distortion centrality of sectors 1 and 2 depends on the size of market imperfections $x$ and $y$. To break the monotone ranking ($\xi_1 \geq \xi_2 \geq \xi_3$), a necessary condition is $y > \frac{10x}{1-0.9x}$, i.e. market imperfections over input 2 ($y$) have to be at least 10 times higher than those over input 1 ($x$); furthermore, the condition becomes disproportionally more stringent as $x$, the imperfection wedge of using input 1, increases. When $x = 5\%$, $y$ has to be over 18 times higher than $x$; when $x > 11.2\%$, monotonicity is always maintained regardless of how high $y$ is.

The stability of distortion centrality in hierarchical networks plays an important role in my empirical analysis in the next section.

Finally, it is worth emphasizing that, despite similarities, upstreamness differs from distortion centrality in terms of both scale and interpretation, and only the latter is suitable for policy analysis. Upstreamness is an accounting measure and is constructed wholly from the input-output structure; it always lies above one. By contrast, distortion centrality also depends on market imperfections (the $D$ matrix), as the measure captures the degree to which distortionary effects in the network accumulate to each sector. Distortion centrality always averages to one.

4 Application: Evaluating Industrial Policy Episodes

In this section, I apply my theoretical results to evaluate sectoral interventions adopted by South Korea during the 1970s and by modern-day China. These are two of the most salient economies with active industrial policies: from 1973 to 1979, South Korea had a state-led industrial policy program that selectively promoted heavy and chemical industries; likewise, the interventionist government of
modern-day China implements a variety of sectoral policies.

I discuss how to measure distortion centrality in Section 4.1, and I conduct policy evaluations and counterfactuals in Section 4.2. I conduct extensive robustness tests in Section 4.3 and Appendix D.

4.1 Recovering Distortion Centrality

To measure distortion centrality, I apply the formula in Proposition 4, which expresses ξ as a function of 1) the network structure and 2) underlying imperfections.

I use national IO tables to measure network structures. A potential concern is that real-world production data are endogenous to policy interventions; however, because such endogeneity has second-order aggregate effects in the decentralized economy, it can be ignored when applying my first-order formula for policy evaluation. I first suppress this issue and proceed as if real-world production data are not contaminated by sectoral interventions. Later, in Section 4.3 and Appendix D, I present extensive arguments and evidence on the robustness of my empirical approach.

Another empirical challenge is to recover underlying market imperfections. In principle, these can be estimated from rich production data, for instance, if all transactions and payments can be observed. In practice, credibly identifying all market imperfections in the entire economy, with sufficient degrees of precision and certainty, is a demanding task. Ultimately, no strategy can perfectly recover all imperfections, and this is a key argument against industrial policies (Pack and Saggi (2006); also see references in Rodrik (2008)). Indeed, one should be uncomfortable in applying my theory if policy evaluations turn out to be very sensitive to how imperfections are specified.

In addressing this difficulty, the discussion on hierarchical networks proves to be especially useful, and I proceed in two steps to recover distortion centrality. First, I establish that the IO tables of both South Korea and China are hierarchical: sectors in these economies exhibit a clear pecking order, with unambiguously defined upstream and downstream sectors. Second, I empirically show that distortion centrality is not only rank stable in these economies, as my theory suggests, but also quantitatively stable with respect to underlying imperfections. Specifically, I recover market imperfections using a range of strategies from the literature. These strategies come with various pros and cons, require distinct assumptions, and push against data constraints in different ways. I show that distortion centrality almost perfectly correlates across all specifications and correlates strongly with the upstreamness measure, indicating that it is the network structure—not underlying imperfections—that generates the most variations in distortion centrality. This finding lends credence to using distortion centrality for subsequent policy evaluations.

In what follows, I first treat these as closed economies. I discuss how to incorporate international trade into my analysis toward the end of this subsection.
Production Networks in South Korea and China Are Hierarchical

The starting point for measurement is a national input-output table, entries in which capture the value of cross-sector flow of intermediate goods ($P_jM_{ij}$) exclusive of imperfection and subsidy payments.\textsuperscript{10} I work with IO tables from South Korea in 1970 and China in 2007, disaggregated at 148 and 135 three-digit sectors, respectively. For each country, I construct the input-output demand matrix $\Theta \equiv \frac{M_{ij}}{Q_j}$ and vector $\theta^F \equiv \frac{Y_j}{Q_j}$ from the IO table by dividing appropriate entries by the total output of input-supplying sectors.

To illustrate the hierarchical property, I first need to reorder sectors, as the property is defined using a sectoral ordering that maps into upstreamness, which does not align well with standard industrial classification codes. To this end, I construct a simple benchmark distortion centrality measure, $\xi_{i10\%}$, by assuming imperfections to be 10% across all sectors and all inputs, and I reorder sectors to descend in $\xi_{i10\%}$. By construction, all variations in this benchmark measure originate from the input-output structure. As I show later, this benchmark measure is almost perfectly correlated with distortion centrality based on imperfections estimated from data.

Figure 2: The IO demand matrices of South Korea (left) and China (right) are hierarchical

Figure 2 visualizes the input-output demand matrices $\Theta$ of South Korea and China, with sectors arranged to descend in the benchmark distortion centrality $\xi_{i10\%}$. For ease of visualization, entries are drawn in proportion to the strength of demand linkages $\theta_{ij}$ and are truncated below at 5%, so that only important linkages are shown.

\textsuperscript{10}Entries exclude imperfections and subsidies because, by construction, IO tables respect the market-clearing conditions of intermediate goods: total value of good $j$ supplied to all other industries (inclusive of net exports) should be equal to sector $j$’s total output, as recorded in the table (see United Nations Department of Economic and Social Affairs (1999)).
This figure shows a striking pattern of cross-sector linkage structures in these economies. Once sectors are arranged by $\xi_{10\%}$, both matrices bear remarkable resemblance to the hierarchical network depicted in Figure 1. Intermediate sectors in both economies exhibit a clear pecking order and have highly asymmetric input-output relationships. The downstream sectors purchase heavily from upstream ones but the reverse is not true, as both matrices have dense entries below the diagonal and are sparse above. The lower-triangular entries are, on average, an order of magnitude larger than the upper-triangular ones. More importantly, both matrices are hierarchical: the bottom-left area is sparse but gets denser towards the diagonal, indicating that upstream inputs are used more heavily by relatively upstream producers than by downstream producers. These patterns are entirely obfuscated when sectors are arranged by standard industrial codes (Appendix Figure D.2).

Table 1: Testing the hierarchical property of input-output demand matrices in South Korea and China

<table>
<thead>
<tr>
<th>Relax inequalities by $\epsilon$</th>
<th>South Korea</th>
<th>China</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(\sum_{k=1}^{K} \theta_{ik} \geq \sum_{k=1}^{K} \theta_{jk} - \epsilon)$</td>
<td>84.8%</td>
<td>86.0%</td>
</tr>
<tr>
<td>0.001</td>
<td>87.2%</td>
<td>87.4%</td>
</tr>
<tr>
<td>0.005</td>
<td>89.1%</td>
<td>88.9%</td>
</tr>
</tbody>
</table>

To formally assess the hierarchical property in these networks, I follow Definition 3 and exhaustively compare upstream sectors’ partial-column-sums with those of downstream sectors. These comparisons correspondingly generate over one million inequalities to be tested for each economy, 84.8% of which hold true for South Korea and 86.0% for China, as shown in Table 1. This is strong evidence that the production networks in these economies are hierarchical, as only 50% of the inequalities would have held true if demand linkages were randomly generated. Moreover, among the partial-sum comparisons that fail to hold, inequality violations are minuscule and thus unlikely to have large effects on distortion centrality: close to 90% of partial-sum comparisons hold true in both economies if the test tolerates violations smaller than 0.5% of the supplying sector’s total output.

**Recovering Market Imperfections**

Since these networks are hierarchical, their sectoral distortion centrality rankings tend to align with upstreamness and are insensitive to underlying market imperfections, as the results in Section 3 suggest. To verify this, I specify imperfections using multiple strategies from the literature. The goal at this point is not to argue that any particular estimates exhaustively represent all imperfections.

---

11For South Korea and China, respectively, entries below the diagonal average to 0.81% and 0.83%, whereas entries above the diagonal average to 0.13% and 0.33%.
in these economies; instead, this exercise is meant to push available data in as many directions as possible and show that distortion centrality stays extremely stable across all specifications.

The production networks literature has adopted both simulation (e.g. Jones (2013)) and estimation (e.g. Bigio and La’O (2017), Baqae and Farhi (2018b)) approaches to specify imperfections. I employ a variety of specifications based on both of these approaches. For every specification, I overlay the input-output demand matrix $\Theta$ with simulated or estimated imperfections and compute distortion centrality based on Proposition 4. I show that distortion centrality is stable across all strategies.

For the simulation approach, I draw imperfections $\chi_{ij}$ independently across $ij$ from a wide range of distributions, as listed in Tables 2 and D.9. I later show that non-i.i.d. imperfections are unlikely to overturn my findings.

The estimation approach uses sectoral observables to proxy for imperfections and is therefore more reliant on data. For modern-day China, I estimate imperfections using four alternative strategies (B1, B2, B3, and B4, described below), exploiting sectoral data from national accounts as well as the firm-level Annual Survey of Manufacturers, a comprehensive survey of Chinese manufacturing firms. For South Korea, only two strategies (B3 and B4) can be implemented due to the lack of firm-level data from the historical period. Because my contribution does not lie in these estimation strategies, I briefly describe them here and include further details in Appendix C.2.

Strategies B1 and B2 use firm-level data to estimate production elasticities and recover wedges from expenditure shares. B1 nonparametrically estimates elasticities using the methodology of De Loecker and Warzynski (2012). B2 uses input shares by foreign-owned firms in China to estimate production elasticities, following Gandhi et al. (2017), under the assumption that foreign firms face fewer imperfections than domestic producers. B3 uses the measure of external financial dependence by Rajan and Zingales (1998), interacted with the average interest rate in the respective economies. Because this measure intends to capture financial frictions in the United States, it is likely to be a lower bound for financial frictions in the two developing economies I study. Lastly, B4 assumes imperfections arise from non-competitive conduct (see Appendix A.2 for microfoundation) and uses sectoral profit shares to proxy for imperfection wedges.\footnote{Another potential approach is to use cross-country differences in input-output tables to proxy for imperfections (e.g. Bartelme and Gorodnichenko (2015)). I do not use this approach because doing so requires matching cross-country IO tables, and, because industrial codes differ significantly across countries, the approach unavoidably generates very coarse industrial partitions, eliminating many of the cross-sector variations necessary for my analysis. For instance, the standard WIOD database of cross-country IO tables contains only 33 sectors for China, only 13 of which are manufacturing sectors. Careful hand-matching of country-pair IO tables is not significantly better: the finest common coarsening of 135 Chinese sectors and 389 U.S. sectors contain only 52 sectors, 25 of which belong to manufacturing.}

For specifications that recover firm-level imperfections, I compute sectoral averages according to the within-sector heterogeneity analysis in Appendix A.1, so that every specification results in
one wedge per sector. My baseline analysis assumes all intermediate inputs within each sector are equally distorted by the common sectoral wedge. This generates potential misspecification if market imperfections are input specific; misspecification can also arise for strategies B1 and B2 as they recover generic wedges and might confound subsidies as part of market imperfections. I suppress these issues for now and will return to them later in Section 4.3, where I address policy endogeneity and conduct extensive sensitivity analysis to specification errors in imperfection wedges.

Appendix C.2 provides further details on the various procedures as well as robustness and summary statistics for the imperfection wedges. As Table C.1 shows, almost all of the estimated sectoral wedges are positive across all strategies, thereby lending credence to my modeling assumption that $\chi \geq 0$.

**Distortion Centrality Is Highly Correlated Across Specifications**

For each specification described above, I compute the corresponding distortion centrality measure using Proposition 4. I then examine both Pearson’s correlation ($r$) and Spearman’s rank correlation ($\rho$) between these alternative measures and the benchmark measure $\xi_{10\%}^i$. The results are reported in Table 2. Panel A shows simulated specifications, where the reported numbers are correlations averaged over 10,000 simulations. Panel B shows correlations based on estimation strategies.

Strikingly, for both South Korea and China, sectoral distortion centrality is close to being perfectly correlated across all simulated and estimated specifications and correlates strongly with the upstream-ness measure by Antras et al. (2012) (first row). This finding is notable because the simulation strategies draw imperfections independently, and the estimation strategies rely on distinct assumptions and data moments and yield imperfection estimates of varying magnitudes. Yet the corresponding distortion centrality measures are not only rank stable ($\rho \approx 1$) but also quantitatively stable, and the near-perfect Pearson correlations ($r \approx 1$) indicate that these various measures are almost affine transformations of one another. The stability of distortion centrality suggests that most variations therein come from the hierarchical network structure. In fact, if the networks were randomly generated and non-hierarchical, the correlation between simulated distortion centrality and the benchmark measure would have been precisely zero by construction.

The finding in Table 2 suggests that interventions in these economies should always start with a set of upstream sectors, the selection of which is insensitive to how market imperfections are specified. Note, however, that even though they are highly correlated and all average to one, various distortion centrality measures differ in ranges and scales (as reported in Appendix Table C.2). This is because different specifications produce imperfection estimates of varying magnitudes. Intuitively, if market imperfections are small in the economy, distortion centrality is close to one in all sectors; conversely, severe imperfections lead to significant distortion centrality dispersion across sectors.
Table 2: Distortion centrality is highly correlated across specifications

<table>
<thead>
<tr>
<th>Specifications</th>
<th>Average correlation with benchmark $\xi_{10%}$</th>
<th>South Korea in 1970</th>
<th>China in 2007</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pearson’s $r$</td>
<td>Spearman’s $\rho$</td>
<td>Pearson’s $r$</td>
</tr>
<tr>
<td>Upstreamness by Antras et al. (2012)</td>
<td>0.96</td>
<td>0.96</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Panel A: Simulated $\chi_{ij}$’s

<table>
<thead>
<tr>
<th>Specifications</th>
<th>Pearson’s $r$</th>
<th>Spearman’s $\rho$</th>
<th>Pearson’s $r$</th>
<th>Spearman’s $\rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>A1 constant $\chi_{ij} = 5%$</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>A2 log-$N(0.09,0.1)$</td>
<td>0.94</td>
<td>0.92</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>A3 $N(0.1,0.1)$</td>
<td>0.95</td>
<td>0.93</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>A4 $N(0.2,0.2)$</td>
<td>0.93</td>
<td>0.94</td>
<td>0.95</td>
<td>0.97</td>
</tr>
<tr>
<td>A5 max {$N(0.1,0.1),0$}</td>
<td>0.97</td>
<td>0.96</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>A6 $U[0,0.1]$</td>
<td>0.98</td>
<td>0.97</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>A7 $U[0,0.2]$</td>
<td>0.98</td>
<td>0.97</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>A8 $Exp(0.1)$</td>
<td>0.95</td>
<td>0.94</td>
<td>0.98</td>
<td>0.99</td>
</tr>
<tr>
<td>A9 $Exp(0.15)$</td>
<td>0.94</td>
<td>0.94</td>
<td>0.96</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Panel B: Estimated Imperfections

<table>
<thead>
<tr>
<th>Specifications</th>
<th>Pearson’s $r$</th>
<th>Spearman’s $\rho$</th>
<th>Pearson’s $r$</th>
<th>Spearman’s $\rho$</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1 De Loecker and Warzynski</td>
<td>-</td>
<td>-</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>B2 Foreign firms as controls</td>
<td>-</td>
<td>-</td>
<td>0.97</td>
<td>0.98</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>0.98</td>
<td>0.97</td>
<td>0.98</td>
<td>0.97</td>
</tr>
<tr>
<td>B4 Sectoral profit share</td>
<td>0.91</td>
<td>0.91</td>
<td>0.99</td>
<td>0.98</td>
</tr>
</tbody>
</table>

Choosing Specifications for Inference

The reduced-form analysis below is scale-invariant and is robust to using any specification of distortion centrality; for simplicity, I report results using the benchmark measure $\xi_{10\%}$. For the scale-dependent welfare analysis below, I report a range of specifications and discuss their differences.

Note that even though distortion centrality highly correlates with upstreamness, the two measures are defined over different scales, and only the former measure is appropriate for policy evaluation.

Open-Economy Adjustments

Because both South Korea and China engage in international trade, I adjust my empirical distortion centrality measures as follows. Intuitively, a country sells exports abroad in exchange for imports; thus imports can be seen as “produced” from exports. Under this view, an export-intensive sector might appear downstream in a closed economy but can in fact be very upstream if the country exchanges
exports for imported inputs that are used heavily by other upstream producers.

To this end, I extend my model to open economies by adding a fictitious “trade intermediary” sector, which buys exports (as its production inputs) from other domestic sectors and sells imports (as its output) to other sectors. I assume the fictitious producer features constant returns: when exports double, imports also double. Trade imbalance is treated as an exogenous lump-sum transfer. It is easy to see that my theory applies to this extended economy.

Table 3: Distortion centrality after open-economy adjustments

<table>
<thead>
<tr>
<th>Specification</th>
<th>South Korea</th>
<th>China</th>
<th>South Korea</th>
<th>China</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark</td>
<td>0.95</td>
<td>0.98</td>
<td>63%</td>
<td>78%</td>
</tr>
<tr>
<td>B1</td>
<td>-</td>
<td>0.98</td>
<td>-</td>
<td>77%</td>
</tr>
<tr>
<td>B2</td>
<td>-</td>
<td>0.98</td>
<td>-</td>
<td>79%</td>
</tr>
<tr>
<td>B3</td>
<td>0.95</td>
<td>0.98</td>
<td>64%</td>
<td>80%</td>
</tr>
<tr>
<td>B4</td>
<td>0.97</td>
<td>0.98</td>
<td>56%</td>
<td>73%</td>
</tr>
</tbody>
</table>

Guided by this extension, I map the fictitious “intermediary” sector into IO tables and re-run my estimations. Table 3 reports correlations for the various distortion centrality measures before and after open-economy adjustments, showing that all specifications remain quantitatively stable as a whole. Interestingly, the distortion centrality of the fictitious “trade intermediary” sector sits consistently above median in both economies and approximately compares with the third quartile in modern-day China. This pattern indicates that imported inputs are quite upstream in these economies, and promoting export-intensive sectors—in exchange for more imports—can potentially generate aggregate gains. As a result, even though distortion centrality as a whole remains largely unchanged, open-economy adjustments do raise the relative distortion centrality of various textile-related sectors, the output of which both economies tend to export.

Open economy adjustments are made for all empirical results unless noted.

Distortion Centrality Weakly Correlates with Other Sectoral Measures

Table 4 reports correlations between the benchmark distortion centrality and various other sectoral measures. Results show that promoting large sectors (high Domar weights or value-added) and those that produce consumption goods (high consumer expenditure share $\beta$) will likely exacerbate misallocations and lead to aggregate losses. Across the various sectoral measures, only export intensity and expenditure share on intermediates correlate positively with distortion centrality. I later compute welfare counterfactuals using these alternative measures as policy targets.
Table 4: Distortion centrality does not strongly correlate with other sectoral measures

<table>
<thead>
<tr>
<th>Specification</th>
<th>South Korea</th>
<th>China</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pearson’s r</td>
<td>Spearman’s ρ</td>
</tr>
<tr>
<td>C1 Domar weight γ</td>
<td>-0.20</td>
<td>-0.32</td>
</tr>
<tr>
<td>C2 Consumption share β</td>
<td>-0.42</td>
<td>-0.66</td>
</tr>
<tr>
<td>C3 Export intensity</td>
<td>0.31</td>
<td>0.22</td>
</tr>
<tr>
<td>C4 Sectoral value-added</td>
<td>-0.25</td>
<td>-0.52</td>
</tr>
<tr>
<td>C5 Expenditure share on intermediate inputs</td>
<td>0.45</td>
<td>0.23</td>
</tr>
</tbody>
</table>

Which sectors have high distortion centrality?

In both South Korea and China, manufacturing sectors with high distortion centrality tend to supply intermediate inputs such as metals, machines, chemicals, and transportation equipment. Conversely, light industries that supply more heavily to consumers—sectors that sell food and household products, for example—tend to have low distortion centrality. Tables 5 and 6 list the top ten and the bottom ten manufacturing sectors ranked by the benchmark measure in these economies.

Table 5: South Korean manufacturing sectors with high and low distortion centrality

<table>
<thead>
<tr>
<th>Top 10</th>
<th>ξ10%</th>
<th>Bottom 10</th>
<th>ξ10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pig iron</td>
<td>1.43</td>
<td>Tobacco</td>
<td>0.91</td>
</tr>
<tr>
<td>Crude steel</td>
<td>1.38</td>
<td>Condiments</td>
<td>0.91</td>
</tr>
<tr>
<td>Iron alloy</td>
<td>1.35</td>
<td>Bread and pastry</td>
<td>0.92</td>
</tr>
<tr>
<td>Steel forging</td>
<td>1.26</td>
<td>Cosmetics and toothpaste</td>
<td>0.92</td>
</tr>
<tr>
<td>Explosives</td>
<td>1.26</td>
<td>Slaughter, meat, and dairy products</td>
<td>0.93</td>
</tr>
<tr>
<td>Acyclic intermediates</td>
<td>1.25</td>
<td>Leather goods</td>
<td>0.93</td>
</tr>
<tr>
<td>Construction clay products</td>
<td>1.25</td>
<td>Furniture</td>
<td>0.93</td>
</tr>
<tr>
<td>Carbides</td>
<td>1.25</td>
<td>Soaps</td>
<td>0.95</td>
</tr>
<tr>
<td>Non-ferrous metals</td>
<td>1.24</td>
<td>Other miscellaneous food products</td>
<td>0.95</td>
</tr>
<tr>
<td>Machine tools</td>
<td>1.23</td>
<td>Drugs</td>
<td>0.96</td>
</tr>
</tbody>
</table>

4.2 Industrial Policies in South Korea and in China

In this section, I evaluate sectoral interventions adopted by South Korea during the 1970s and by modern-day China, and I perform policy counterfactuals on these economies.
Table 6: Chinese manufacturing sectors with high and low distortion centrality

<table>
<thead>
<tr>
<th>Top 10</th>
<th>$\xi_{10%}$</th>
<th>Bottom 10</th>
<th>$\xi_{10%}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coke making</td>
<td>1.36</td>
<td>Canned food products</td>
<td>0.62</td>
</tr>
<tr>
<td>Nonferrous metals and alloys</td>
<td>1.35</td>
<td>Dairy products</td>
<td>0.65</td>
</tr>
<tr>
<td>Ironmaking</td>
<td>1.35</td>
<td>Other miscellaneous food products</td>
<td>0.68</td>
</tr>
<tr>
<td>Ferrous alloy</td>
<td>1.33</td>
<td>Condiments</td>
<td>0.69</td>
</tr>
<tr>
<td>Steelmaking</td>
<td>1.33</td>
<td>Drugs</td>
<td>0.77</td>
</tr>
<tr>
<td>Metal cutting machinery</td>
<td>1.32</td>
<td>Meat products</td>
<td>0.77</td>
</tr>
<tr>
<td>Chemical fibers</td>
<td>1.31</td>
<td>Grain mill products</td>
<td>0.78</td>
</tr>
<tr>
<td>Electronic components</td>
<td>1.30</td>
<td>Liquor and alcoholic drinks</td>
<td>0.81</td>
</tr>
<tr>
<td>Specialized industrial equipments</td>
<td>1.30</td>
<td>Vegetable oil products</td>
<td>0.82</td>
</tr>
<tr>
<td>Basic chemicals</td>
<td>1.29</td>
<td>Tobacco</td>
<td>0.83</td>
</tr>
</tbody>
</table>

4.2.1 South Korea in the 1970s

Between 1973 and 1979, South Korea implemented a government-led industrialization program, officially termed the “Heavy-Chemical Industry” (HCI) drive. This program promoted six broad sectors, including those producing metal products, machinery, electronics, petrochemicals, automobiles, and ships. Firms that operated in the promoted sectors received very favorable policy incentives (see, e.g., Lane (2017)), and some of today’s largest South Korean manufacturing conglomerates originated in this era.\textsuperscript{13} Appendix Table D.10 shows the full list of 38 targeted three-digit industries.

HCI Sectors are Upstream and Have High Distortion Centrality

That HCI sectors are upstream can be clearly visualized. In Figure 3, I reproduce South Korea’s IO demand matrix with sectors ranked by the benchmark measure, as in Figure 2, but with one small change: cells are now darkened if the corresponding input-using sectors were promoted by the HCI drive. Note the $i$\textsuperscript{th} row and column in the figure correspond to the same sector.

The input-output data strikingly demonstrate that HCI sectors are upstream. All darkened cells appear at the top-left of the figure, indicating that promoted sectors rank highly according to the benchmark measure $\xi_{10\%}$. The targeted sectors supply strongly to non-targeted sectors (i.e., the area below the darkened cells is dense) and demand few inputs in return (i.e., the top-right area is sparse). In manufacturing, all top-ten high-$\xi$ sectors in Table 5 were promoted by the HCI program, and none of the bottom-ten sectors were targeted.

HCI sectors’ upstreamness translates into high distortion centrality, as shown in Table 7. Because results are quantitatively similar across all specifications, I omit some simulated specifications to

\textsuperscript{13}For instance, POSCO (the world’s fourth-largest steelmaker as of 2015) and Hyundai Heavy Industries (the world’s largest shipbuilder as of 2012) were founded during this time.
avoid redundancy. Results show that every HCI sector has distortion centrality consistently above one across all specifications, indicating that promoting HCI sectors likely leads to aggregate gains. Conversely, promoting non-HCI sectors tends to be ineffective and can generate negative value on net. Take the benchmark measure, for instance: the HCI sectors have $\xi \geq 10\%$ averaging to 1.16, meaning that every dollar of public expenditure on subsidies to these sectors translates into aggregate gains of 16 cents. The last two columns show that, across all specifications, 100% of HCI sectors have distortion centrality above one, as compared to 48% of non-HCI sectors. Note that the total value-added from HCI sectors constituted only a small fraction (5.6%) of the South Korean economy in 1970.

I conduct extensive robustness tests in Section 4.3 and Appendix D.

**Counterfactuals**

In Table 8, I compute counterfactuals under which different sectors were promoted. The rows separately select sectors that rank highly according to Domar weights, sectoral share in the consumption bundle ($\beta$), export intensity, sectoral value-added, and intermediate expenditure shares. For each scenario, I maintain the HCI drive’s number (38) of promoted three-digit sectors. Column (1) reports the average benchmark distortion centrality among selected sectors for the corresponding counterfactual; these numbers reflect the gains in private consumption per dollar of public spending, if public
Table 7: HCI sectors have higher distortion centrality than non-targeted ones

<table>
<thead>
<tr>
<th>Specification</th>
<th>$sd(\xi)$</th>
<th>$\xi_i$ of HCI sectors</th>
<th>Share of sectors with $\xi_i &gt; 1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark</td>
<td>0.09</td>
<td>1.16</td>
<td>100%</td>
</tr>
<tr>
<td>Rajan and Zingales</td>
<td>0.06</td>
<td>1.12</td>
<td>100%</td>
</tr>
<tr>
<td>Sectoral profit share</td>
<td>0.16</td>
<td>1.28</td>
<td>100%</td>
</tr>
<tr>
<td>$N(0.1,0.1)$</td>
<td>0.09</td>
<td>1.17</td>
<td>100%</td>
</tr>
<tr>
<td>$U[0,0.2]$</td>
<td>0.09</td>
<td>1.16</td>
<td>100%</td>
</tr>
<tr>
<td>Exp$[0.1]$</td>
<td>0.10</td>
<td>1.17</td>
<td>100%</td>
</tr>
</tbody>
</table>

For the simulated specifications, the reported distortion centrality averaged across 10,000 simulations draws.

Funds were allocated equally per value-added across sectors selected by these alternative measures.\(^{14}\) Net gains in aggregate consumption are equal to the reported numbers minus one. Columns (2) and (3) repeat the exercise using distortion centrality specifications B3 (Rajan-Zingales wedge) and B4 (profit share). On the right panel, I report how net gains in aggregate consumption under each counterfactual compare to the gains under the HCI drive. Note that even though columns (1)–(3) are not scale-free and depend on the distortion centrality specification, the relative gains reported in columns (4)–(6) are scale-free and quite robust across all distortion centrality measures. For completeness, the counterfactual in row CF6 promotes the top 38 sectors ranked by distortion centrality, and the last counterfactual (row CF7) promotes all sectors of the economy equally. By construction, this last counterfactual results in zero gains on net.

Results show that the HCI drive selected sectors with higher distortion centrality—across various specifications for $\xi$—than those that would have been chosen by various sectoral observable measures. Promoting sectors by Domar weights, consumption share, or sectoral value-added would all result in aggregate losses, as sectors that rank highly according to these measures have distortion centrality below one, on average. Promoting export-intensive sectors (row CF3) and those that rely significantly on intermediate inputs (row CF5) could result in aggregate gains, but these gains would be lower than those produced by the HCI drive. For instance, under the benchmark distortion centrality specification, counterfactuals CF3 and CF5 generate net gains that are 46% and 41%, respectively, relative to gains under the HCI drive. Row CF6 shows that promoting the 38 sectors with the highest distortion centrality only generates moderate additional gains (between 9% and 37%) over those generated under the HCI drive.

### 4.2.2 Modern-Day China

State intervention has a long tradition in China and remains alive and well today, as the government employs a wide range of policy levers and instruments to exert influence over sectoral production.\(^{14}\) Reliable data on sectoral policy spending are unavailable for this historical period; see Lane (2017).
Table 8: Policy counterfactuals for South Korea

<table>
<thead>
<tr>
<th>Specification for $\xi_i$:</th>
<th>Average distortion centrality</th>
<th>Gains relative to HCI drive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)  (2)  (3)</td>
<td>(4)  (5)  (6)</td>
</tr>
<tr>
<td>HCI Drive</td>
<td>benchmark B3 B4</td>
<td>benchmark B3 B4</td>
</tr>
<tr>
<td></td>
<td>1.16  1.12  1.28</td>
<td>100% 100% 100%</td>
</tr>
</tbody>
</table>

Counterfactuals (select sector sorted by...)

| CF1  | Domar weight $\gamma$ | 0.98  0.99  0.96 | -11% -9% -13% |
| CF2  | Consumption share $\beta$ | 0.97  0.94  0.94 | -18% -16% -22% |
| CF3  | Export intensity | 1.07  1.05  1.11 | 46% 44% 40% |
| CF4  | Sectoral value-added | 0.98  0.99  0.98 | -10% -9% -8% |
| CF5  | Interim. exp. share | 1.07  1.04  1.08 | 41% 36% 28% |
| CF6  | Distortion centrality $\xi$ | 1.22  1.15  1.30 | 137% 124% 109% |
| CF7  | Uniform promotion | 1  1  1 | 0% 0% 0% |

First, the credit market is predominantly state-controlled: interest rates are heavily regulated, and banks often receive policy directives on lending priorities across sectors. Second, corporate income tax laws feature a national standard tax rate with a menu of policy incentives that are “predominantly industry-oriented” (Ministry of Finance, P. R. China (2008)) and provide tax breaks to selected sectors. Third, the state directly engages in production through state-owned enterprises (SOEs), which receive not only subsidies from the government but also easy access to credit; Song et al. (2011) explicitly model modern-day Chinese SOEs as financially unconstrained market participants. I refer interested readers to Du et al. (2014) and Aghion et al. (2015) for detailed discussions of modern industrial policies in China, and to Boyreau-Debray and Wei (2005), Dollar and Wei (2007), and Riedel et al. (2007) for China’s credit market policies pertaining to SOEs.

I construct several quantitative measures of sectoral interventions in China based on private firms’ interest payments, debt obligations, corporate income taxes, and subsidies received from the government. I also measure SOEs’ sectoral presence. Information on corporate taxes comes from the administrative enterprise income tax records for the year 2008, which contain detailed firm-level records of tax payments and tax incentives. The data are collected by the State Administration of Taxation, which is China’s counterpart to the IRS and is responsible for tax collection, auditing, and supervision of various tax incentive programs. All other variables are extracted from the 2007 edition of the Chinese Annual Survey of Manufacturing, a well-studied, comprehensive survey that contains balance sheets and production data for manufacturing firms. Appendix C.1 provides details on these datasets and variable construction.

15“Private firms” refers to non-SOE throughout the paper.
16That these two datasets are misaligned by one year should not lead to systemic biases because I exploit cross-sector variations.
I exploit cross-sector variations in policy interventions and examine how they covary with distortion centrality. Intervention measures are constructed for 79 three-digit manufacturing sectors, the finest partition that concords with both national IO table and firm-level datasets.\textsuperscript{17} Tables 9 and 10 provide some descriptive statistics, from which I highlight two features.

### Table 9: Descriptive statistics: sectoral policies vary significant across Chinese sectors

<table>
<thead>
<tr>
<th>Sectoral Means (in Percentage Points)</th>
<th>Min</th>
<th>1st Quartile</th>
<th>Median</th>
<th>3rd Quartile</th>
<th>Max</th>
<th>Average</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective interest rate</td>
<td>1.85</td>
<td>3.39</td>
<td>4.12</td>
<td>5.00</td>
<td>12.33</td>
<td>4.45</td>
<td>1.67</td>
</tr>
<tr>
<td>Debt ratio</td>
<td>40.91</td>
<td>51.54</td>
<td>54.78</td>
<td>57.04</td>
<td>65.39</td>
<td>54.45</td>
<td>4.82</td>
</tr>
<tr>
<td>Fraction of firms with tax incentives</td>
<td>8.70</td>
<td>24.88</td>
<td>30.81</td>
<td>36.55</td>
<td>61.33</td>
<td>31.23</td>
<td>9.84</td>
</tr>
<tr>
<td>Effective corporate income tax rate</td>
<td>9.08</td>
<td>15.13</td>
<td>17.48</td>
<td>19.45</td>
<td>24.78</td>
<td>17.29</td>
<td>2.94</td>
</tr>
<tr>
<td>Subsidies / revenue</td>
<td>0.60</td>
<td>0.98</td>
<td>1.36</td>
<td>1.79</td>
<td>4.74</td>
<td>1.57</td>
<td>0.83</td>
</tr>
<tr>
<td>SOE Share of sectoral value-added</td>
<td>0.66</td>
<td>4.76</td>
<td>10.67</td>
<td>24.40</td>
<td>74.50</td>
<td>17.32</td>
<td>17.04</td>
</tr>
</tbody>
</table>

### Table 10: Descriptive statistics: SOEs receive more favorable policies

<table>
<thead>
<tr>
<th>Variable</th>
<th>Means By Ownership</th>
<th>Private Firms</th>
<th>SOEs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effective interest rate</td>
<td>4.63</td>
<td>2.23</td>
<td></td>
</tr>
<tr>
<td>Debt ratio</td>
<td>54.38</td>
<td>63.49</td>
<td></td>
</tr>
<tr>
<td>Fraction of firms with tax incentives</td>
<td>31.93</td>
<td>31.48</td>
<td></td>
</tr>
<tr>
<td>Effective corporate income tax rate</td>
<td>17.29</td>
<td>14.98</td>
<td></td>
</tr>
<tr>
<td>Fraction of firms receiving subsidies</td>
<td>11.46</td>
<td>22.41</td>
<td></td>
</tr>
<tr>
<td>Subsidies / revenue</td>
<td>1.56</td>
<td>2.78</td>
<td></td>
</tr>
</tbody>
</table>

First, industrial policies in China vary substantially across sectors. Row 1 of Table 9 shows sectoral means for effective interest rates paid by private manufacturing firms. Interest rates for producers in the median sector are 4.12%, whereas producers in sectors with the highest and lowest interest rates pay as much as 12.33% and as little as 1.85% on average. Row 2 shows that firms in the most-indebted sector have an average debt-to-asset ratio that is over one-and-a-half times that of firms in the least-indebted sector. Likewise, rows 3 through 6 show considerable variations in the fraction of firms that receive tax incentives from the tax authority, effective corporate income tax rates, the fraction of firms receiving subsidies from the government, and the average amount of subsidies (as a share of revenue) conditioned on having received any. All variables in rows 1 through 6 are based on the sample of domestic, privately owned firms. Row 7 shows Chinese SOEs account for sectoral value-added that ranges from 0.66% to 74.5%, highlighting their heterogeneous presence across sectors.

Second, SOEs receive significantly more-favorable policies than private firms, as shown in Table 10. On average, the effective interest rate paid by SOEs is half that paid by private firms, despite the

\textsuperscript{17}I exclude the tobacco sector from the policy analysis because it is heavily regulated and entirely state-owned in China.
former’s debt ratios being 9 percentage points (17%) higher than the latter’s. SOEs are also twice as likely to receive production subsidies from the government, and conditioned on having received any, SOEs receive more subsidies (as a share of revenue) than private firms.

**Reduced-Form Evidence**

I now show that distortion centrality predicts sectoral interventions in China. I first examine sectoral policy outcomes for the sample of private firms, performing cross-sector regressions of the form

\[
\text{Outcome}_i = a + b \times \bar{\xi}_{i10\%} + \text{controls}_i + \epsilon_i.
\]

Each observation \(i\) is a sector, and \(\text{Outcome}_i\) is the sectoral mean for the corresponding policy variable for non-SOEs, measured in percentage points. In accordance with my later application of Proposition 2, each observation is weighted by sectoral value-added. \(\bar{\xi}_{i10\%}\) is the benchmark distortion centrality standardized to unit-variance. Note that, because of standardization, the regression results are insensitive to the choice of distortion centrality measures. The results should be read as, for instance, “one standard deviation higher in distortion centrality above the mean is associated with \(b\) percentage points higher in the policy outcome.” I control for several sectoral characteristics in order to partial out non-network reasons for state interventions, and I also standardize these control variables.

Regression results (Table 11) show that private firms in high distortion centrality sectors receive more-favorable policies. Based on columns (2), (4), (6), and (8), a one standard deviation higher sectoral distortion centrality is associated with having a 0.99 percentage points lower effective interest rate for firms, a 2.73 percentage points higher debt-to-capital ratio, a 2.91 percentage points higher likelihood of receiving tax incentives, and a 1.59 percentage points lower effective corporate income tax rate. These variations in the policy variables are economically significant: one standard deviation in distortion centrality translates into policy differences of between 0.30 and 0.59 standard deviations of the respective policy variables (c.f. the last column in Table 9). These specifications control for a variety of sectoral characteristics, including capital intensity (fixed asset over output), Lerner index (operating profits over output), average log-fixed capital of firms during the first year of operation (a proxy for the minimum scale of operation), and export intensity (exports over output). Together, these variables serve to partial out other, non-network predictors for state interventions. Some of these control variables do have predictive power over certain intervention measures, although none is as consistently predictive as the distortion centrality measure. Also note that coefficients on distortion centrality remain almost unaffected after including the controls. Appendix Table D.8 shows that coefficients remain quantitatively robust after controlling for various estimates of sectoral wedges. The only policy variables for which distortion centrality lacks predictive power relate to direct subsidies from the government. As shown in Table 10, private firms tend to receive few subsidies to begin with, as compared to SOEs.
Table 11: Private firms in Chinese manufacturing sectors with high distortion centrality receive more-favorable policies

<table>
<thead>
<tr>
<th></th>
<th>Effective Interest Rate</th>
<th>Debt Ratio</th>
<th>Tax Break</th>
<th>Effective Tax Rate</th>
<th>Recipient of Subsidies</th>
<th>Subsidies Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>ξ_{10%}</td>
<td>-0.895*** (-0.222)</td>
<td>2.961*** (0.556)</td>
<td>2.861** (1.323)</td>
<td>-1.595*** (0.396)</td>
<td>-0.556 (0.593)</td>
<td>-0.210 (0.127)</td>
</tr>
<tr>
<td>Capital intensity</td>
<td>-0.425** (0.199)</td>
<td>-0.390 (0.556)</td>
<td>0.759 (1.263)</td>
<td>-0.253 (0.385)</td>
<td>1.403*** (0.517)</td>
<td>0.284** (0.113)</td>
</tr>
<tr>
<td>Lerner index</td>
<td>-0.0247 (0.173)</td>
<td>0.146 (0.481)</td>
<td>-0.559 (1.092)</td>
<td>0.0958 (0.333)</td>
<td>0.166 (0.447)</td>
<td>0.00943 (0.0975)</td>
</tr>
<tr>
<td>Log(fixed assets in starting year)</td>
<td>-0.0273 (0.204)</td>
<td>0.511 (0.568)</td>
<td>-0.559 (1.290)</td>
<td>-0.643 (0.394)</td>
<td>1.075** (0.528)</td>
<td>0.147 (0.115)</td>
</tr>
<tr>
<td>Export intensity</td>
<td>-0.682*** (0.172)</td>
<td>0.284 (0.487)</td>
<td>2.824** (1.105)</td>
<td>-0.375 (0.337)</td>
<td>1.186** (0.452)</td>
<td>-0.0977 (0.0986)</td>
</tr>
</tbody>
</table>

adj. $R^2$ 0.163 0.301 0.260 0.231 0.045 0.097 0.164 0.176 -0.002 0.209 0.022 0.198

The table examines correlations between standardized benchmark distortion centrality $ξ_{10%}$ and measures of government interventions. The benchmark distortion centrality is constructed by assuming imperfections $χ_{ij} \equiv 0.1$ for all $i, j$. Industry averages of firm-level variables are computed after dropping outliers at 1%. Standard errors are in parentheses.
Chinese manufacturing sectors were predominantly state-owned in the 1990s. Through several subsequent waves of market reform, small and unproductive SOEs were privatized or closed, and large and relatively successful SOEs were corporatized as market participants (Hsieh and Song (2015)). Consequently, today SOEs are large and perhaps overly profitable corporations (Bai et al. (2014), Li et al. (2015)). The predominant view in the literature is that these SOEs are over capitalized, and their existence impedes the efficient allocation of resources within sectors (Song et al. (2011)). I do not dispute this view, but I highlight that, in a world with many policy constraints, SOEs might serve as a means to implement sectoral policies, and strategically placing SOEs in selected sectors might expand sectoral production. This latter view is not new to economic historians, especially in the context of East Asian economies such as Taiwan and Singapore (see Hernandez (2004), Chang (2007, 2009) for overviews).

Table 12 shows that distortion centrality predicts the sectoral presence of SOEs. In 2007, in sectors with distortion centrality one standard deviation above the mean, SOEs had is 7.81 percentage points (0.46 standard deviations) higher share of sectoral value-added. Moreover, this correlation is not driven by historical legacy: columns (3) through (6) examine sectoral value-added shares of SOEs that were established after the year 2000, and the correlations remain significant.

| Table 12: Sectors with high distortion centrality have larger SOE presence |
|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|---------------------------------|
|                                | (1)                             | (2)                             | (3)                             | (4)                             | (5)                             | (6)                             |
| ξ_{10%}                        | 7.577**                         | 7.808***                        | 2.960***                        | 2.549***                        | 2.123***                        | 1.545**                        |
|                                | (2.963)                         | (2.834)                         | (1.059)                         | (0.886)                         | (0.725)                         | (0.619)                         |
| Capital intensity              | 0.914                           | 0.774                           | 0.717                           | 0.602                           | 0.199                           |
|                                | (2.535)                         | (0.947)                         | (0.792)                         | (0.649)                         | (0.554)                         |
| Lerner index                   | −4.622**                        | −2.191***                       | −1.997***                       | −1.611***                       | −1.148**                        |
|                                | (2.193)                         | (0.820)                         | (0.685)                         | (0.561)                         | (0.479)                         |
| Log(fixed assets in starting year) | 6.974***                       | 2.042**                         | 1.632**                         | 1.245*                          | 1.028*                          |
|                                | (2.590)                         | (0.968)                         | (0.809)                         | (0.663)                         | (0.565)                         |
| Export intensity               | −5.660**                        | −2.013**                        | −1.810**                        | −1.484**                        | −1.145**                        |
|                                | (2.218)                         | (0.829)                         | (0.693)                         | (0.568)                         | (0.484)                         |
| adj. R²                        | 0.066                           | 0.290                           | 0.269                           | 0.284                           | 0.276                           | 0.220                           |
| # Obs.                         | 79                              | 79                              | 79                              | 79                              | 79                              | 79                              |

The table examines correlations between standardized benchmark distortion centrality ξ_{10%} and SOE’s share of sectoral value-added. SOEs are identified following Hsieh and Song (2015). The benchmark distortion centrality is constructed by assuming imperfections χ_{ij} ≡ 0.1 for all i, j. Standard errors are in parentheses.
Policy Evaluations

The reduced-form evidence suggests that Chinese sectors with high distortion centrality—i.e., the upstream sectors—tend to receive favorable policies. I now apply Proposition 2 and compute the covariance between policy expenditure $s_i$ and distortion centrality $\xi_i$ in order to quantitatively evaluate these sectoral policies’ aggregate impact. Note the covariance can be calculated using a bivariate regression: let $\bar{\xi}_i \equiv \xi_i / sd(\xi)$ denote distortion centrality standardized to unit variance; then $\text{Cov}(s_i, \xi_i) = b \cdot sd(\bar{\xi})$, where $b$ is the slope coefficient from regressing $s_i$ on $\bar{\xi}_i$. Higher coefficient $b$ indicates better sectoral targeting, meaning that sectors with high distortion centrality are more heavily subsidized. Higher dispersion in distortion centrality, $sd(\xi)$, implies more misallocations and thus more room for welfare-improving policies. The residual variation in $s_i$, after partialling out $\bar{\xi}_i$, has no first-order impact on output $Y$.

To proceed, I compute policy spending $\{s_i\}$ separately for 1) subsidized credit, 2) tax incentives based on the sample of private firms, and 3) policy incentives to SOEs. For subsidized credit, I proxy the market interest rate $r$ by the highest sectoral average interest rate, and I calculate policy spending in each sector as the difference between private firms’ total interest payments and the nominal payments implied by debt obligations and the market rate $((r - r_i) \times \text{debti})$. The choice of market rate $r$ is an unimportant normalization because uniform cross-sector spending has no aggregate effect. I compute policy spending on tax incentives using the difference between the statutory corporate income tax rate and the effective tax rate at the sector level $(25\% \times \text{Profits}_i - \text{TaxesPaid}_i)$. Finally, I compute policy spending on SOEs as the sum of credit subsidies, tax incentives, and direct government subsidies received by SOEs in each sector. Because intervention measures are available only for manufacturing sectors, the reported gains can be seen as extrapolations that project in-sample policies onto sectors outside manufacturing, while maintaining the same covariances between distortion centrality and policy spending. Alternatively, the reported numbers can be interpreted as the proportional gains in net manufacturing output.

As Table 13 shows, sectoral interventions in all three categories generate positive aggregate effects in China. The gains in output across these categories are on the same order of magnitude, with credit subsidies playing a somewhat stronger role than funds given to SOEs, which are in turn more effective than tax incentives. For instance, under specification B1, differential sectoral interest rates lead to 3.1% aggregate gains, while tax incentives and funds to SOEs generate 1.2% and 2.4% gains, respectively. The pattern is qualitatively robust across various specifications of distortion centrality.

Quantitatively, the magnitude of output gains depends on the standard deviation of the corresponding distortion centrality measure (reported in the first column). Specification B1, which follows De Loecker and Warzynski (2012) and structurally estimate generic wedges based on firm-level data, is my preferred specification for policy evaluation. Results show that in China, industrial policies
together generate 6.7% first-order gains in output. These gains are sizable given the scale of the interventions: policy expenditures are, on average, only 6% of sectoral revenue and 23% of sectoral value-added (c.f. Table D.3); this means that every dollar of subsidies generates 29 cents of output gains. These gains are entirely due to the positive selection of policy expenditures in sectors with high distortion centrality; gains would have been precisely zero if subsidies were uncorrelated with distortion centrality.

The output gains are smaller under the other specifications (B2–B4) because these strategies recover smaller imperfection wedges (c.f. Table C.1). This is unsurprising: by construction, strategy B2 recovers imperfections faced by private firms relative to those faced by foreign firms operating in China; to the extent that foreign firms are also subject to imperfections, the strategy leads to underestimates. Likewise, specifications B3 and B4 each capture only a single source of market imperfections—financial frictions and profits that arise from non-competitive conduct, respectively—and therefore miss other sources of imperfections. Smaller wedges imply a lesser degree of cross-sectoral misallocations; output gains are thus smaller under these specifications and should be seen as conservative lower bounds for the aggregate policy impact. Appendix Tables C.5 computes an additional specification that captures both financial frictions and markups, with sectoral wedges computed as the sum of wedges from B3 and B4. Interestingly, based on this specification, sectoral policies in China generate 5.01% aggregate gains, which is of comparable magnitude to estimates based on B1.

Table 13: Evaluating sectoral interventions in modern-day China

<table>
<thead>
<tr>
<th>Distortion centrality specification</th>
<th>Aggregate gains ($\Delta \ln Y$) by intervention (in percentage points)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$sd(\xi)$</td>
</tr>
<tr>
<td>Benchmark ($\xi^{10%}$)</td>
<td>0.22</td>
</tr>
<tr>
<td>B1 De Loecker and Warzynski</td>
<td>0.42</td>
</tr>
<tr>
<td>B2 Foreign firms as controls</td>
<td>0.25</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>0.11</td>
</tr>
<tr>
<td>B4 Sectoral profit share</td>
<td>0.17</td>
</tr>
</tbody>
</table>

Policy Counterfactuals

I now conduct policy counterfactuals for China. Each policy experiment evaluates the aggregate impact of a hypothetical vector of sectoral subsidies. In order to keep the exercise tractable and transparent, I proceed as follows. Recall $b$ is the slope coefficient from regressing actual subsidy expenditure $s_i$ on $\bar{\xi}_i$, the distortion centrality measure standardized to unit variance. I first answer questions of the type, “if a regression of counterfactual subsidy expenditure $\tilde{s}_i$ on [a sectoral characteristic] has coefficient $\tilde{b}$, what would the aggregate effects be?”
For instance, consider the Domar weight (standardized to unit variance, $\tilde{\gamma}_i = \gamma_i / sd(\gamma)$) as a counterfactual policy target. Instead of specifying subsidies sector-by-sector, I specify that counterfactual policy spending $\tilde{s}_i$ projects linearly onto the Domar weight with a slope coefficient $\tilde{b}$, and that the residual $u_i$ is independent of both the Domar weight and the distortion centrality (i.e., $\tilde{s}_i = \tilde{a} + \tilde{b} \cdot \tilde{\gamma}_i + u_i$ and $u \perp \xi, \gamma$). The coefficient $\tilde{b}$ captures the sensitivity of subsidies $\{\tilde{s}_i\}$ to the policy target. To first-order, the general equilibrium impact of counterfactual policy spending $\{\tilde{s}_i\}$ is

$$\Delta \ln Y (\{\tilde{s}_i\}) \approx Cov(\tilde{s}_i, \tilde{\xi}) = \rho_{\tilde{\xi}, \tilde{\gamma}} \cdot \frac{\tilde{b}}{\tilde{b}} \times \Delta \ln Y (\{s_i\}),$$

where $\rho_{\tilde{\xi}, \tilde{\gamma}}$ is the correlation between distortion centrality $\tilde{\xi}$ and the Domar weight $\tilde{\gamma}$. Intuitively, subsidizing sectors with high Domar weights can raise output $Y$ only to the extent that $\tilde{\gamma}$ correlates positively with $\tilde{\xi}$; hence, by construction, the counterfactual $\{\tilde{s}_i\}$ is always less effective than the actual policy spending $\{s_i\}$ when $\tilde{b} = b$. Policymakers can achieve different aggregate impacts by varying the policy sensitivity $\tilde{b}$.

Following this procedure, I conduct policy experiments using various alternative measures as policy targets, and I repeat each counterfactual across various specifications of distortion centrality. For each specification and counterfactual scenario, I standardize the policy target to unit variance, and I normalize policy sensitivity to $\tilde{b} = b$. Counterfactuals under alternative policy sensitivity $\tilde{b}$ can be obtained by proportionally rescaling the numbers reported in Table 14.

Table 14: Policy counterfactuals for modern-day China

<table>
<thead>
<tr>
<th>Specification for $\xi$</th>
<th>Total output gains across interventions (in percentage points)</th>
<th>Output gains relative to real-world interventions (correlation between $\xi$ and the counterfactual policy target)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\xi^{10%}$</td>
<td>B1</td>
</tr>
<tr>
<td>Real-world interventions</td>
<td>3.60</td>
<td>6.65</td>
</tr>
<tr>
<td>Counterfactual policy target</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CF1</td>
<td>Domar weight $\gamma$</td>
<td>-1.42</td>
</tr>
<tr>
<td>CF2</td>
<td>Consumption share $\beta$</td>
<td>-2.56</td>
</tr>
<tr>
<td>CF3</td>
<td>Export intensity</td>
<td>1.13</td>
</tr>
<tr>
<td>CF4</td>
<td>Sectoral value-added</td>
<td>-1.30</td>
</tr>
<tr>
<td>CF5</td>
<td>Intern. exp. share</td>
<td>1.34</td>
</tr>
<tr>
<td>CFO</td>
<td>Optimal assignment</td>
<td>5.33</td>
</tr>
</tbody>
</table>

Table 14 shows that using Domar weights (CF1), consumption share (CF2), or sectoral value-added (CF4) as policy targets leads to aggregate losses. Among observable sectoral measures, only two would be good policy targets: export-intensity (CF3) and intermediate expenditure shares (CF5). Interestingly, these are also the two measures that work well for South Korea. Promoting sectors with high intermediate shares using policy sensitivity $\tilde{b} = b$, for instance, generates between 29% and 39% of the gains relative to real-world interventions across different specifications of distortion.
centrality. Put another way, for policy target CF5 to be as effective as real-world interventions, the policy sensitivity ($\tilde{b}$) has to be two or three times as large as $b$, the sensitivity of $s_i$ on $\xi_i$. This means higher cross-sector dispersions in policy spending: sectors with high intermediate shares need to receive two or three times higher subsidies under the counterfactual, relative to funds spent in high-distortion-centrality sectors under real-world policies. Overall, for each counterfactual and across distortion centrality specifications, welfare numbers on the left panel are qualitatively robust, and the relative gains on the right panel are quantitatively stable; the stability reflects high correlations across various distortion centrality measures.

How much better could China have done? My theory concerns the first-order impact of interventions and does not address policy optimality; nevertheless, the last row of Table 14 (CFO) computes the counterfactual output gains under the optimal reassignment of subsidies across sectors while holding fixed the vector of policy expenditures as measured from real-world data.\(^{18}\) Results show that sectoral interventions in China could have been more effective by 48–67% if the same vector of policy expenditures was reassigned optimally across sectors.

4.3 Robustness of Empirical Findings

Appendix D conducts extensive empirical robustness tests, and I provide a brief summary here.

**Data Aggregation** In Section 2.4.1, I discussed a condition under which distortion centrality is sector-specific and inference based on sectoral data is appropriate. Nevertheless, there could still be a mismatch between the level of aggregation in IO tables and the level of product differentiation at which my theory applies, either because a sectoral aggregator over varieties does not exist or because data are mismeasured due to firms’ operating across industries and conducting multi-stage production in-house. While I cannot conclusively verify empirical robustness when the underlying product differentiation is finer than the data available, I can indeed conduct the robustness check in reverse, testing distortion centrality’s stability when I use *even coarser* data than those available. This is done in Appendix D.1, where I merge sectors and progressively create coarser sectoral partitions over several iterations, and I recompute distortion centrality using the collapsed IO tables at each iteration. Table D.1 shows that, at all levels of aggregation for both economies, the benchmark distortion centrality computed from the collapsed IO tables almost perfectly correlates with the benchmark measure computed from the original, disaggregated tables. The stability is once again due to the hierarchical property of the collapsed IO tables, as shown in Figure D.1.

**Policy Endogeneity and Systematic Specification Errors** In the main text, I construct distortion centrality using real-world data, yet both the IO demand matrix $\Theta$ and market imperfections $\chi$ could

\(^{18}\)Specifically, row (CFO) of Table 14 shows the covariance between $s_{(i)}$, the $i^{th}$ highest sectoral policy spending per value-added, and $\xi_{(i)}$, the $i^{th}$ highest distortion centrality.
be contaminated by existing policy interventions and other errors. Here I demonstrate that my empirical findings are quantitatively robust and discuss the underlying intuitions.

Policy endogeneity in Θ could arise from either 1) endogenous changes in production elasticities or 2) failing to account for subsidies in observed input-output structure. As Lemma 2 shows, both sources of error are second order; hence, it is conceptually appropriate to ignore them in my first-order analysis. In Appendix D.2, I show that correctly accounting for subsidies in observed input-output structures does not quantitatively affect any of my findings (Table D.2) and that policy spending accounts for only a small fraction—about 6% (Table D.3)—of sectoral revenue, thereby providing empirical support for conducting policy evaluations as first-order approximations.

Policy-induced measurement errors in χ can arise because some estimated specifications (B1 and B2) misattribute imperfections net of subsidies (χ − τ) as true imperfections χ. These errors are also second order; more importantly, they bias ξ against my findings. Intuitively, because imperfections accumulate through backward demand linkages, systematic underspecification of χ’s in promoted sectors, which tend to have high ξ, compress cross-sector ξ’s towards the mean, causing upstream (downstream) distortion centrality to be biased downwards (upwards). These errors in χ therefore weaken any positive correlations between subsidies and ξ, and correcting for the errors should strengthen my findings. Appendix D.2 conducts error corrections and shows that my findings remain quantitatively unchanged, and, if anything, become slightly stronger.

Indeed, for my findings to be spurious, the systematic errors in χ must be perverse. Intuitively, false positives arise when ξ is biased negatively for downstream sectors, meaning χ must be underspecified for buying downstream goods as production inputs and, conversely, overspecified for buying upstream goods. In practice, the scope for false positives is very limited in hierarchical networks. Consider the “shoemaking” sector, which has low estimated ξ because it appears downstream and is not an important supplier to upstream sectors. In order for “shoemaking” to have high actual ξ, it is necessary for shoes to be an important input for producing upstream goods, such as machinery and chemicals, and for “shoemaking” to appear downstream only because of the enormous market imperfections that upstream producers face when buying shoes. As implausible as it is, the condition may still be insufficient, since imperfections over buying shoes eventually also accumulate into upstream sectors’ distortion centrality. Appendix D.3 verifies these intuitions by showing that my findings are robust even with substantial specification errors of the most perverse kind.

Appendix D.4 contains additional robustness tests for my analysis of China. Table D.6 shows that endogeneity-corrected distortion centrality measures remain almost perfectly correlated with the respective uncorrected measures. Table D.7 reproduces the reduced-form regressions in Tables 11 and 12, using the “upstreamness” measure from Antras et al. (2012) as an instrument variable for the benchmark distortion centrality measure. The instrument variable should purge specification errors
in distortions insofar as “upstreamness” captures non-policy features of the input-output relationship; results show that coefficients remain quantitatively unchanged. Table D.8 shows my reduced-form findings are also robust after including estimated market imperfections as control variables.

5 Conclusion

I do not wish to imply that South Korea and China adopted optimal policies. My nonparametric sufficient statistics capture welfare effects to the first order but do not address optimality. Further, my analysis does not address the decision process behind policy adoption, as my model abstracts away from various political economy factors that affect policy choices in these economies.

The key takeaways from my analysis and findings are as follows.

First, interventions should begin with sectors that have high distortion centrality. Well-meaning interventions need not target the most-distorted sectors, and promoting undistorted sectors need not exacerbate misallocation. Qualitatively, these findings echo the theory of the second best; yet, distortion centrality succinctly and quantitatively summarizes how misallocative effects of imperfections accumulate through input-output linkages in a production network.

Second, proposition 2 provides a simple formula for policy evaluations and counterfactuals. To the first-order, economic gains are higher if more subsidies are given to high-distortion-centrality sectors, and the aggregate effect can be summarized by the covariance between sectoral policy spending and distortion centrality. It is usually difficult for empirical studies to shed light on sectoral interventions’ aggregate effects, as the answer inevitably hinges on general equilibrium reallocate effects. My results overcome this difficulty.

Third, the misallocative effects of imperfections accumulate through backward demand linkages and, as a result, upstream sectors—those that supply directly or indirectly to many sectors—become sinks for imperfections and tend to have higher distortion centrality. Moreover, in South Korea and China, sectors follow a hierarchical production structure. In these economies, sectors with high distortion centrality tend to be the upstream heavy industries and chemical sectors; conversely, light manufacturing sectors tend to have low distortion centrality. This conclusion is insensitive to underlying imperfections because of the hierarchical structure of sectoral production.

Fourth, and finally, distortion centrality predicts sectoral interventions in these economies. According to market imperfections recovered from firm-level data, sectoral variations in credit availability, tax incentives, and policy funds to SOEs raise aggregate consumption in China by 3.5-6.7%; in South Korea, policy spending in sectors targeted by the HCI drive also generated positive net effects.

There are several important caveats: my results concern marginal interventions and do not address
when are subsidies becoming too high; I analyze the economic effects of reallocation and omit political economy aspects of policy implementation; I assume market imperfections are policy invariant, though the former could be directly influenced by the latter; I study static effects of interventions and omit dynamic considerations. I leave these areas for future research.
References


United Nations Department of Economic and Social Affairs (1999). *Handbook of Input-Output Table Compilation and Analysis*.


Appendix

A Theory: Extensions, Microfoundations, and Discussions

In this appendix, I discuss some extensions and a few additional issues relating to my theory. First, I show how within-sector heterogeneity can be incorporated into the model. Second, I provide other microfoundations for market imperfections, including markups and Marshallian externalities. Third, I discuss the issue of multiple factors. Fourth, I characterize the distinctions between market imperfections and iceberg costs. Fifth, I discuss an extension in which policy instruments have an advantage over market transactions and can directly counteract deadweight losses. Sixth, I discuss the role of social welfare functions. In Section A.7 I solve for expressions in the vertical network example of 2.2; in Section A.8, I provide an additional example to highlight intuitions for how distortionary effects of market imperfections accumulate through backward demand linkages.

A.1 Within-Sector Heterogeneity

The model in the main text features constant-returns-to-scale (CRTS) sectoral production and market imperfections \( \chi_{ij} \) at the sector-pair level. I now incorporate within-sector heterogeneity into the model. In what follows, I maintain the use “intermediate good” when referring to output aggregated at the sector level, and I use “variety” when referring to differentiated products within each sector. I show that, under a reasonable condition, distortion centrality remains sector-specific (rather than variety-specific), so that \( \xi_i \) captures the social value of government subsidies to any firms in sector \( i \). In this case, using sectoral input-output data to compute distortion centrality is without loss of generality.

Consider modifying the model such that each intermediate good \( i \) is combined from a continuum of varieties \( v \in [0, 1] \) using a CRTS aggregator

\[ Q_i = G_i(\{q_i(v)\}) . \]

Producers of variety \( v \) in sector \( i \) have a CRTS production function \( f_i^v \):

\[ q_i(v) = \bar{z}_i z_i(v) f_i^v \left( \ell_i(v), \{m_{ij}(v)\}_{j=1}^S \right) , \]

where \( \bar{z}_i \) represents a sector-specific productivity shifter that affects all varieties in sector \( i \), \( z_i(v) \) is a variety-specific productivity shifter, and \( \ell(v) \) and \( m_{ij}(v) \) represent variety-specific input quantities. The fact that cross-sector demand must go through an aggregator \( G_i(\cdot) \) implies that different buyers of each intermediate good purchase the same bundle of underlying varieties; this is an important
Suppose market imperfections and subsidies are variety-specific, i.e. a producer of variety $v$ in sector $i$ faces imperfection wedge $\chi_{ij}(v)$ and subsidy $\tau_{ij}(v)$. Given that each variety features CRTS in production, one can relabel each variety as a sector and compute variety-specific distortion centrality $\xi_i(v)$. My theoretical results in Section 2 trivially extend to this case, and $\xi_i(v)$ captures the social value of policy expenditures on subsidizing variety $v$ in sector $i$. More interestingly, distortion centrality remains sector-specific in this environment: $\xi_i(v) = \xi_i$ for all $v$, where $\xi_i$ is the distortion centrality computed by treating good $i$ as a homogeneous sectoral good, with price index

$$P_i \equiv \min_{\{q_i(v)\}} \int p_i(v) q_i(v) \, dv \quad \text{s.t.} \quad G_i(\{q_i(v)\}) \geq 1.$$ 

The equivalence $\xi_i(v) = \xi_i$ implies that $\xi_i$ captures the social value of policy expenditure in sector $i$, regardless of which variety $v$ is being subsidized.

To prove this, note that it is cumbersome to write out the notations for sectoral influence based on nonparametric production elasticities with respect to individual variety of inputs. That being said, Lemma 1 implies that influence can be re-defined using factor price elasticity with respect to productivity shocks. Hence, distortion centrality of variety $v$ must equal

$$\xi_i(v) = \frac{d \ln W / d \ln z_i(v)}{p_i(v) q_i(v)}.$$ 

On the other hand, sector-specific distortion centrality equals

$$\xi_i = \frac{d \ln W / d \ln z_i}{\int_0^1 p_i(v) q_i(v) \, dv}.$$ 

The existence of a sectoral aggregator $G_i(\cdot)$ implies

$$\frac{d \ln W / d \ln z_i(v)}{d \ln W / d \ln z_i} = \frac{\partial \ln P_i}{\partial \ln p_i(v)} = \frac{p_i(v) q_i(v)}{\int p_i(v) q_i(v) \, dv}. \tag{A.1}$$

The first equality states that the impact of a variety-level productivity shock $z_i(v)$ on the factor price, relative to a sectoral-level common shock $z_i$, can be summarized by the partial derivative of the sectoral price index $P_i$ with respect to the price of variety $v$. This is a direct consequence of the aggregator $G_i(\cdot)$, through which cross-sector transactions take place. The second inequality follows by applying the envelope theorem to the definition of sectoral price index. Equation (A.1) implies $\xi_i(v) = \xi_i$, proving the claim.

Intuitively, the restriction that cross-sector transactions must take place through sectoral aggrega-
tors, implies that all buyers of good $j$ must purchase the same bundle of varieties within sector $j$, which in turn implies each buyer must be subject to a common market imperfection wedge when purchasing varieties produced by a common sector (i.e. buyer $\nu$ in sector $i$ faces the same market imperfection $\chi_{ij}(\nu)$ when buying different varieties in sector $j$). Without this restriction, imperfections can be variety-pair-specific, in which case the notion of variety indeed coincides with the notion of sector in the baseline model, and distortion centrality would become variety-specific.

Note that the formulation normalizes the measure of varieties to one but does not impose any restriction on the measure of firms within each sector. Indeed, the notion of variety is the level of differentiation at which heterogeneity is defined and could differ from the notion of firm. For instance, the framework can nest microfoundations with endogenous entry, in which case output per firm of variety $v$, $\tilde{q}_i(\nu)$, might differ from variety-level total output $q(v)$; the two objects relate by the density $\lambda(v)$ of firms for variety $v$, with $q(v) = \lambda(v) \tilde{q}(v)$. This distinction is conceptually important because my theoretical results rely on CRTS at the level of differentiation (variety), yet models with endogenous entry can feature firm-level production functions without constant returns (e.g., in an earlier version of this paper, I adopted convex-concave production functions as in Buera et al. (2011)).

Lastly, the fact that social value of policy expenditures is independent of within-sector heterogeneity is a feature of the first-order effects that my theory concerns; the selection of firms within each sector does matter for higher-order effects.

A.2 Microfoundations

I provide additional microfoundations to market imperfections. All microfoundations below emit a “wedge” representation with two features: wedges raise production costs, and payments associated with imperfection wedges are quasi-rents that are competed away as deadweight losses in terms of the consumption good.

A.2.1 Financial Frictions

The first microfoundation expands on the running narrative in the main text, i.e. financial frictions. This microfoundation takes the form of working capital requirements on intermediate transactions. Specifically, orders for intermediate inputs must be placed before production and, to prevent hold-up, seller $j$ requires buyer $i$ to pay $\delta_{ij} \geq 0$ fraction of transactional value up front in the form of working capital. Producer $i$ borrows working capital loans $\Gamma_i$ from a lender at interest rate $\lambda$, solving the following profit maximization problem:

$$\max_{\Gamma_i, L_i, \{M_{ij}\}_{j=1}^S} P_z \xi_i F_i \left(L_i, \{M_{ij}\}_{j=1}^S\right) - \left( \sum_{j=1}^S \left(1 - \tau_{ij}\right) P_j M_{ij} + (1 - \tau_{iL}) W L_i + \lambda \Gamma_i \right) \text{ s.t. } \sum_{j=1}^S \delta_{ij} P_j M_{ij} \leq \Gamma_i,$$
where \( \delta_{ij} P_j M_{ij} \) is the working capital required for input \( j \), and \( \lambda \Gamma_i \) is the total financial costs. Because the producer flexibly chooses how much to borrow, the working capital constraint always binds, and financial costs can be represented by reduced-form proportional wedges \( \chi_{ij} \equiv \lambda \delta_{ij} \). For every unit of input \( j \), producer \( i \) makes interest payments of \( \chi_{ij} P_j \) to the lender; equilibrium prices solve the cost-minimization in (3).

Issuing working capital is costly to the lender because producers cannot commit to repay and instead have an incentive to default that increases with loan size. In order to monitor and enforce repayment, the lender incurs a proportional disutility cost of \( \lambda \geq 0 \) for every dollar of loans issued. The lender charges a competitive interest rate on loans, earning total income \( \Pi \equiv \lambda \sum_{i=1}^{S} \Gamma_i \) as compensation. He spends the income on consumption but earns zero utility net of monitoring costs. The interest payments can therefore be seen as total consumption lost due to the imperfection.

### A.2.2 Other Transaction Costs

Note that the financial friction formulation can also be interpreted more broadly as other transaction costs. For instance, if market imperfections arise due to contracting frictions, one can interpret \( \lambda \) as the disutility cost of contract enforcement, incurred by an arbitrator, and \( \delta_{ij} \) as the fraction of transaction value to be arbitrated.

### A.2.3 Markups

Consider sectoral production as a two-stage entry game. In the first stage, a large measure of potential entrepreneurs decide whether to enter each sector \( i \). Entry requires each entrepreneur \( x \) to pay a disutility cost \( \kappa_i \) in exchange for a constant returns to scale production function:

\[
q_i(x) = z_i F_i \left( \ell_i(x), \{ m_{ij}(x) \} \right).
\]

For notational simplicity, I assume firms are identical within each sector. The extension that allows for within-sector heterogeneity, as outlined in Appendix A.1, can be easily integrated into this microfoundation.

Suppose buyers’ demand for firm-level output by sector \( j \) can be represented by the aggregator

\[
Q_i = N_i^{\frac{1}{\sigma - 1}} \left( \int_0^{N_i} q_i(x) \frac{\sigma - 1}{\sigma} \ dx \right)^{\frac{\sigma}{\sigma - 1}}, \tag{A.2}
\]

where \( N_i \) is the measure of firms that entered. The multiplicative term \( N_i^{\frac{1}{\sigma - 1}} \) in the aggregator neutralizes the taste-for-variety effect, so that sectoral production features constant-returns-to-scale in sectoral inputs. Firms behave identically and monopolistically, charging a constant markup \( \frac{\sigma_i}{\sigma_i - 1} \) over
marginal costs. Let $M_{ij} \equiv N_i m_{ij}$ and $L_i \equiv N_i \ell_i$ denote the total inputs used in the sector. Simple substitution shows that sectoral production features CRTS, with total output equal to

$$Q_i = z_i F_i \left( L_i, \{M_{ij}\} \right).$$

Entrepreneurs receive accounting profits from markups and spend the income on the consumption good, compensating for their disutility entry cost. In equilibrium, free-entry condition pins down the measure of firms in each sector:

$$\kappa_i N_i = \frac{1}{\sigma_i} \frac{P_i Q_i}{\text{accounting profits}}.$$

Entrepreneurs earn zero utility net of entry costs, and no economic profits remain in the economy.

The baseline version of this microfoundation generates, for each seller $j$, a uniform price wedge $\frac{\sigma_j}{\sigma_{j-1}}$ over marginal cost of production. This environment is allocationally equivalent to one in which producers set prices equal to marginal costs, but all buyer $i$’s of good $j$ incur proportional cost $\chi_{ij} = \frac{\sigma_j}{\sigma_{j-1}}$, which is deadweight loss in terms of the consumption good. Under this transformation, the microfoundation maps into the accounting convention, used in the main text, that using factor inputs does not directly generate deadweight losses.

Lastly, note that one can always microfound buyer-seller-pair specific imperfections $\chi_{ij}$ using markups, by generalizing the aggregator in (A.2) to be buyer-specific aggregator functions, causing sellers in sector $j$ to charge buyer-specific markups $\frac{\sigma_{ij}}{\sigma_{ij-1}}$ and, correspondingly, proportional deadweight losses that vary across buyer-seller pairs.

### A.2.4 Marshallian Externality

Under the previous microfoundation, firms’ entry effectively imposes negative externalities upon one another through the aggregator in (A.2). I now show that non-negative imperfection wedges can also represent Marshallian externalities, under which firms impose positive spillovers to each other and underproduce relative to the first-best. Conceptually, the sign restriction $\chi_{ij} \geq 0$ does not assume the direction of spillovers but instead assumes that, holding input-prices constant, sectoral output prices are higher when imperfections are present than if they are not.

Specifically, consider again the two-stage entry game, in which a large measure of potential entrants choose whether to incur disutility cost $\kappa_i$ to enter each sector. Upon entry, each firm $x$ in sector $i$ competitively produces an identical good $i$ according to the production function

$$q_i(x) = z_i \left( \frac{Q_i}{N_i} \right)^{1-\alpha_i} F_i \left( \ell_i(x), \{m_{ij}(x)\} \right)^{\alpha_i},$$

56
where $F_i(\cdot)$ features CRTS and $\alpha_i \in (0, 1)$. $N_i$ is again the measure of firms in sector $i$. The term $\left(\frac{Q_i}{N_i}\right)^{1-\alpha_i}$ represents Marshallian externalities; it captures the component of productivity that each firm takes as exogenous but nevertheless depends on the average firm output in the sector. The exponent $(1 - \alpha_i)$ controls the strength of Marshallian externality. In any equilibrium, firms within a sector make identical production decisions, and sectoral production emits a CRTS representation despite positive externalities. Firms underproduce relative to the first-best, and despite being price-takers, firms earn accounting profits because they take $\frac{Q_i}{N_i}$ as exogenous while optimizing over a strictly concave production function. There is no pure economic profit due to disutility entry cost. In equilibrium, firms set prices to be private marginal costs and are higher than sectoral marginal costs, thereby generating a seller-specific sectoral wedge that is common to all buyers, $\chi_{ij} \equiv \left(1 - \alpha_j\right) / \alpha_j$. As with markups, this environment is allocationally equivalent to one in which producers set prices equal to sectoral marginal costs, and buyers incur deadweight losses proportional to $\chi_{ij}$, thus mapping into the accounting convention in the main text.

A.3 Multiple Factors

The baseline model features a single, composite factor $L$ in fixed supply. This, together with the CRTS assumption, implies an important property in input-output economies: demand changes and variations in production quantity do not affect production costs. Consequently, policy interventions’ price effects can be fully summarized by local elasticities, a key property underlying Lemma 1 and my subsequent results. This property is first noted by Samuelson (1951) as the “no substitution” theorem, derived when there is a single factor in the economy.

Now suppose there are multiple factors, $L_1, \ldots, L_K$. To extend my results to this environment, an important assumption is that all factors must enter production only through an aggregator $H(L_1, \ldots, L_K)$ that is common across sectors. When this is the case, one can re-define a composite factor through the aggregator $L \equiv H(L_1, \ldots, L_K)$ and define the price $W$ of $L$ as the price index of the aggregator. Relative prices of various factors $L_1, \ldots, L_K$ are unaffected by production quantities; the “no substitution” theorem holds, and so do my subsequent results. On the other hand, if intermediate sectors use factors in varying intensities, then relative factor prices will be affected by production quantities. In this case, resource reallocation induced by policy interventions will generate indirect effects on all prices, and the size of these effects depends on parametric production structures in all sectors of the economy; from this perspective, “no substitution” and my subsequent results fail to hold.

A.4 Imperfections $\neq$ Iceberg Costs

In this appendix, I further distinguish between market imperfections and iceberg costs. I first solve for closed-form allocations in a simple example, and I compare allocations under market imperfections with those under iceberg costs. I then show that distortion centrality is always equal to one in
Comparing Allocations Under Market Imperfections and Iceberg Costs

I compare a decentralized economy with imperfections to an economy with iceberg costs, maintaining the same wedge size across the two economies. From the set of cost-minimization problems (3) and (5), it is easy to see that equilibrium prices coincide under these economies. In what follows, I provide closed-form solutions to show:

1. Factor allocations in the imperfection economy do not coincide with those under the first-best. By redistributing resources, policy interventions can raise output $Y$ in the imperfection economy.

2. Factor allocations in the iceberg economy coincide with those under the first best, and output cannot be improved by interventions.

To maximize transparency, I exposit through a simple Cobb-Douglas example.

First, consider an economy with imperfections. Sectors 1 and 2 produce linearly from the factor and sell their entire output to sector 3, which faces imperfections $\chi > 0$ for buying input 1 and no imperfection regarding input 2. The consumption good is produced linearly from good 3.

Following the notations in the paper,

(production functions) \[ Q_1 = L_1, \quad Q_2 = L_2, \quad Q_3 = M_3^\alpha M_3^{1-\alpha}, \quad Y^G = Y_3, \]

(market clearing conditions) \[ Q_1 = M_{31}, \quad Q_2 = M_{32}, \quad Q_3 = Y_3, \quad L_1 + L_2 = L, \quad Y = Y^G - \chi P_1 M_{31}. \]

(A.3)

Absent interventions, factor allocations and output in this distorted economy follow

\[ L_1 = \frac{\alpha}{\alpha + (1 - \alpha)(1 + \chi)} L, \quad L_2 = \frac{(1 - \alpha)(1 + \chi)}{\alpha + (1 - \alpha)(1 + \chi)} L. \]

\[ Y^G = L_1^\alpha L_2^{1-\alpha}, \quad Y = L_1^\alpha L_2^{1-\alpha} \left( 1 - \frac{\alpha \chi}{1 + \chi} \right). \]

Compare these with allocations and output in a first-best economy, without any wedges:

\[ L_1^* = \alpha L, \quad L_2^* = (1 - \alpha) L, \quad Y^* = (L_1^*)^\alpha (L_2^*)^{1-\alpha}. \]
I make two observations. First, relative to the first-best, imperfections cause factor inputs to be underallocated to sector 1 and, conversely, overallocated to sector 2 ($L_1 < L_1^*, L_2 > L_2^*$). Second, output under imperfections is lower than the first-best output $Y^* > Y$. The decline in output is due to two effects from imperfections: $Y^* > Y^G$ due to misallocation, and $Y^G > Y$ due to deadweight losses associated with quasi-rents.

Now consider policy interventions that reallocate factor inputs across sectors. Specifically, factor inputs in sector 1 receive a proportional subsidy $\frac{1}{1-\tau_1L} = \alpha + (1 - \alpha)(1 + \chi)$; those in sector 2 receive $\frac{1}{1-\tau_2L} = \frac{\alpha+(1-\alpha)(1+\chi)}{1+\chi}$. Under these policies, factor allocations become aligned with those under the first-best, and output becomes

$$Y^G(\tau_1L, \tau_2L) = (L_1^*)^\alpha (L_2^*)^{1-\alpha} = Y^*, \quad Y(\tau_1L, \tau_2L) = Y^* \left(1 - \frac{\alpha \chi}{1+\chi}\right).$$

The subsidies correct factor input misallocations and consequently improve both $Y$ and $Y^G$. In fact, in this example, $Y^G$ under the subsidies prescribed above becomes equal to the first-best output, because misallocation is eliminated entirely. Nevertheless, $Y < Y^G$, as subsidies do not counteract deadweight losses. Note that the level of these subsidies is chosen to align with distortion centrality, following Proposition 3.

Interventions can improve output in the imperfection economy because the size of deadweight losses depends on relative prices. In this example, the total deadweight losses are $\chi P_1 Q_1$ and always equal to a constant fraction $(\frac{\alpha \chi}{1+\chi})$ of gross output. By manipulating relative prices and reallocate productive resources, the level of deadweight losses can be minimized if allocative inefficiency is corrected.

Next, consider an iceberg economy, in which $\chi$ units of good 1 are lost for every unit delivered to sector 3 as a production input. The relevant equations become

(production functions) \quad Q_1 = L_1, \quad Q_2 = L_2, \quad Q_3 = M_{31}^G M_{32}^{1-\alpha}, \quad Y^{IB} = Y_3,

(market clearing conditions) \quad Q_1 = (1+\chi)M_{31}, \quad Q_2 = M_{32}, \quad Q_3 = Y_3, \quad L_1 + L_2 = L, \quad (A.4)

where $Y^{IB}$ is the output of consumption good, and there is no distinction between gross and net output in an iceberg economy. Note how iceberg wedge $\chi$ enters market-clearing conditions differently than do imperfections (compare A.3 and A.4).

Equilibrium allocations follow:

$$L_1^{IB} = \alpha L, \quad L_2^{IB} = (1-\alpha) L, \quad Y^{IB} = \left(\frac{L_1^{IB}}{1+\chi}\right)^\alpha \left(L_2^{IB}\right)^{1-\alpha}.$$
Factor allocations are therefore efficient this iceberg economy. Iceberg cost is isomorphic to a negative technology shocks \((\frac{1}{1+\chi})\) to sector 1, and there is no room for interventions to improve output.

In fact, one can show that aggregate consumption coincides in an iceberg economy and in an imperfection economy without interventions:\(^{19}\)

\[ Y^* > Y^G > Y = Y^{IB}. \]

As discussed earlier, the decline in output \(Y^* > Y\) in an imperfection economy is due to two effects: \(Y^* > Y^G\) due to misallocation and \(Y^G > Y\) due to deadweight losses associated with quasi-rents. By contrast, the entire output loss in an iceberg economy \(Y^* > Y^{IB}\) is due to deadweight losses associated with iceberg costs, and there is no misallocation of resources.

To summarize, the following observations hold more broadly in arbitrary networks with CRTS production functions:

1. Market imperfections and iceberg costs generate identical effects on equilibrium prices and aggregate consumption.

2. The two formulations generate different sectoral and factor allocations.

3. The imperfection economy is inefficient, and interventions can raise aggregate consumption by affecting equilibrium prices. The iceberg economy is efficient.

The reason the two formulations differ in terms of sectoral and input allocations is as follows. While both formulations depress input demand, iceberg costs do so by raising the technological production cost of inputs, and demand remain undistorted given prices. By contrast, rather than changing inputs’ technological costs, market imperfections distort input demand given prices. Hence, by affecting prices, subsidies can have first-order aggregate effects.

Allocations cannot be solved in closed-form in a nonparametric production network. Nevertheless, observation #1 follows from cost-minimizations (3) and (5), while observation #2 can be demonstrated from the two equations in (12). Below, I demonstrate observation #3 by showing that influence and Domar weights are always equal; thus, Lemma 2 and Proposition 1 imply that, starting from an iceberg economy, policy subsidies have no first-order effects on aggregate output, consistent with the First Welfare Theorem.

**Distortion Centrality Is Always One In Iceberg Economies** Recall that influence is defined as \(\mu' \equiv \beta' (I - \Sigma)^{-1}\). Moreover, Lemma 1 holds, and influence captures factor price elasticity with

\(^{19}\)That \(Y = Y^{IB}\) follows from 1) absent interventions, \(Y = WL\) in the imperfection economy, and \(Y^{IB} = W^{IB}L\) in the iceberg economy and 2) iceberg costs and my imperfections wedges have identical effects on equilibrium prices, \(W = W^{IB}\).
respect to sectoral TFP shocks.

I now show that sectoral Domar weights, defined as \( \gamma_i \equiv \frac{P_i Q_i}{WL} \), are always equal to influence. I start from the market clearing condition for good \( j \) in an iceberg economy:

\[
Q_j = Y_j + \sum_i M_{ij} (1 + \chi_{ij}),
\]

where \( \chi_{ij} \) represents the proportional loss in good \( j \) during transportation to sector \( i \). In the iceberg economy, expenditure shares on inputs are always equal to production elasticities; hence, \( P_j M_{ij} (1 + \chi_{ij}) = \sigma_{ij} P_i Q_i \) for all \( i \) and \( j \). By multiplying both sides of (A.5) by \( \frac{P_j}{WL} \) and applying the substitution for \( P_j M_{ij} (1 + \chi_{ij}) \), one derives

\[
\frac{P_j Q_j}{WL} = \frac{P_j Y_j}{WL} + \sum_i \sigma_{ij} \frac{P_i Q_i}{WL}.
\]

In the iceberg economy, \( WL = Y^{IB} \); thus, \( P_j Y_j/WL = \beta_j \). In matrix notation, the set of equations becomes

\[
\gamma' = \beta' + \gamma' \Sigma = \beta' (I - \Sigma)^{-1},
\]

establishing that \( \xi_i \equiv \mu_i/\gamma_i = 1 \) for all \( i \) and that policy interventions have no first-order effect on output in iceberg economies.

A.5 Extension: Subsidies Counteract Deadweight Losses

In my model, subsidies redistribute resources but do not counteract deadweight losses. Specifically, given subsidy \( \tau_{ij} \), deadweight losses are \( \chi_{ij} P_j M_{ij} \) and not \( \chi_{ij} (1 - \tau_{ij}) P_j M_{ij} \): the former scales with transactions’ market value, whereas the latter scales with transactions’ subsidized value. In the main text, I adopt the first formulation because it effectively subjects policy spending to the same imperfections faced by market-based transactions, thereby isolating only the reallocative effects of policy interventions. Under the latter “subsidized value” formulation, the government has an advantage over private market participants and can directly reduce deadweight losses in the economy by subsidizing all inputs. Policy expenditures’ social value in the latter formulation is \( SV_{ij} = \xi_i \times (1 + \chi_{ij}) \) and consists of two parts: 1) the reallocative effect captured by sectoral distortion centrality, and 2) the efficiency gained by directly canceling out sectoral imperfections. My model in the main text isolates the first effect. An earlier version of this paper (available upon request) adopts the alternative formulation.

Tables A.1 and A.2 demonstrate that my findings in the main text are qualitatively robust under the alternative formulation, but, because policy spending has an additional advantage in canceling out
imperfections, the quantitative welfare gains from policy interventions become even larger. Specifically, Table A.1 reproduces regressions in Tables 11 and 12, replacing the main variable of interest on the right-hand-side from the benchmark distortion centrality measure to the product between estimated distortion centrality and imperfection wedges under various specifications. Because estimated imperfection wedges necessarily include noise and estimation errors, I use the upstreamness measure from Antras et al. (2012) as an instrument for the main right-hand-side variable in order to correct for attenuation bias in the regressions. All regressions include the full set of sectoral control variables, but only coefficients on the main variable of interest are reported. Table A.2 conducts policy evaluations in China under the alternative formulation. Results show that all three sectoral intervention categories (credit markets, tax policies, and funds to SOEs) generated positive aggregate gains, and the gains are somewhat larger relative to results reported in the main text’s Table 13 (note that this exercise is unaffected by the potential attenuation bias and thus needs no correction).

Table A.1: Reduced form coefficients under the alternative specification in Appendix A.5

<table>
<thead>
<tr>
<th>Specification</th>
<th>Effective Interest Rate</th>
<th>Debt Ratio</th>
<th>Tax Break</th>
<th>Effective Tax Rate</th>
<th>SOE Share of Value-Added</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>-0.946</td>
<td>2.788</td>
<td>2.287</td>
<td>-1.560</td>
<td>5.771</td>
</tr>
<tr>
<td>B2</td>
<td>-0.954</td>
<td>2.813</td>
<td>2.308</td>
<td>-1.575</td>
<td>5.824</td>
</tr>
<tr>
<td>B3</td>
<td>-0.847</td>
<td>2.496</td>
<td>2.047</td>
<td>-1.397</td>
<td>5.167</td>
</tr>
<tr>
<td>B4</td>
<td>-1.474</td>
<td>4.345</td>
<td>3.564</td>
<td>-2.431</td>
<td>8.996</td>
</tr>
</tbody>
</table>

Table A.2: Policy evaluation under the alternative specification in Appendix A.5

<table>
<thead>
<tr>
<th>Specification</th>
<th>Subsidized credit</th>
<th>Tax incentive</th>
<th>SOEs</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>5.60</td>
<td>2.05</td>
<td>4.14</td>
<td>11.79</td>
</tr>
<tr>
<td>B2</td>
<td>3.17</td>
<td>1.19</td>
<td>2.03</td>
<td>6.40</td>
</tr>
<tr>
<td>B3</td>
<td>1.78</td>
<td>0.70</td>
<td>1.00</td>
<td>3.48</td>
</tr>
<tr>
<td>B4</td>
<td>2.07</td>
<td>0.80</td>
<td>1.49</td>
<td>4.36</td>
</tr>
</tbody>
</table>

A.6 Normative Implications and the Role of A Social Welfare Function

The normative interpretation of my positive characterizations in Propositions 1 and 2 implicitly assumes a social welfare function $U(C, G)$ that places equal marginal value on private and public consumption (for instance, $U(C, G) = C + G$). This is without loss of generality when the government has unrestricted access to lump-sum taxes, which enable one-for-one transfers between private and public consumption. That said, my results are still useful when lump-sum taxes are restricted: the
generic welfare impact of a subsidy $\tau_{ik}$ financed by marginally cutting back $G$ is

$$\left. \frac{dU/d\tau_{ik}}{dG/d\tau_{ik}} \right|_{\tau=0,T\text{ constant}} = -\frac{\partial U}{\partial G} + \frac{\partial U}{\partial C} \times SV_{ik}.$$  

The social value of policy expenditures, as characterized in Proposition 1, directly translates into a preference ordering over policy instruments under $U(\cdot)$.

### A.7 Solving For the Example in Section 2.2

The elasticity and expenditure share matrices in the example are, respectively,

$$\Sigma = \begin{bmatrix} 0 & 0 & 0 \\ \sigma_2 & 0 & 0 \\ 0 & \sigma_3 & 0 \end{bmatrix}, \quad \Omega = \begin{bmatrix} 0 & 0 & 0 \\ \frac{\sigma_2}{1+\chi_2} & 0 & 0 \\ 0 & \frac{\sigma_3}{1+\chi_3} & 0 \end{bmatrix}$$

The consumption share vector is $\beta' = (0, 0, 1)$, and the sectoral factor share is $\omega_L' = (1, (1 - \sigma_2), (1 - \sigma_3))$. Thus, influence follows $\mu' = \beta'(I - \Sigma)^{-1} = (\sigma_2\sigma_3, \sigma_3, 1)$, and Domar weight follows

$$\gamma' = c_1 \cdot \left( \frac{\sigma_2\sigma_3}{(1+\chi_2)(1+\chi_3)}, \frac{\sigma_3}{1+\chi_3}, 1 \right)$$

for some constant $c_1$ such that factor income share sums to one: $\gamma'\omega_L = 1$. Factor allocation in the economy follows

$$(L_1, L_2, L_3) = c_2 \cdot \left( \frac{\sigma_2\sigma_3}{(1+\chi_2)(1+\chi_3)}, \frac{\sigma_3}{1+\chi_3}(1 - \sigma_2), 1 - \sigma_3 \right)$$

for some constant $c_2$ that ensures the factor market clearing condition holds with $L_1 + L_2 + L_3 = L$.

### A.8 Another Example Network

To gain further intuitions for Proposition 4, consider another example with three types of intermediate sector: black ($B$), grey ($G$), and white ($W$). $B$’s and $G$’s produce from the factor and supply to a single white sector. The white produces from black and grey inputs with imperfections $\chi^B$ and $\chi^G$, respectively, and feeds into the final sector.
Imperfections depress white’s demand for black and grey inputs. The relative distortion centrality of the black and grey sectors depends solely on relative imperfections faced by these inputs’ buyer—the white sector—and is not affected by other fundamentals such as productivities: \(\chi^B > \chi^G \iff \xi^B > \xi^G\). When demand for black inputs is more severely depressed, too little factor is allocated to \(B\)’s and too much to \(G\)’s; in this case, subsidizing \(B\)’s generates higher social value because the policy channels productive resources from sectors that are too large to ones that are too small.

## B Proofs

### B.1 Derivation for Domar weight

The market clearing condition for good \(j\) is

\[
Q_j = Y_j + \sum_{i=1}^{N} M_{ij}.
\]

By multiplying both sides by \(P_j/WL\) and substituting for Domar weight \(\gamma_j \equiv \frac{P_jQ_j}{WL}\), consumption expenditure share \(\beta_j \equiv \frac{P_jY_j}{YG}\), and intermediate expenditure share \(\omega_{ij} \equiv \frac{P_jM_{ij}}{P_iQ_i}\), we obtain

\[
\gamma_j = \frac{Y^G}{WL} \beta_j + \sum_{i=1}^{N} \omega_{ij}\gamma_i
\]

or, in matrix notation,

\[
\gamma' = \frac{Y^G}{WL} \beta' (I - \Omega)^{-1}.
\] (B.1)

Factor payments in sector \(i\) is

\[
WL_i = WL\gamma_i\omega_{iL}
\]

By the labor market clearing condition, it must be the case that

\[
\sum_{i=1}^{N} WL_i = WL\sum_{i=1}^{N} \gamma_i\omega_{iL}
\]

\[
\iff \sum_{i=1}^{N} \gamma_i\omega_{iL} = 1,
\]

which pins down the proportionality constant \(\frac{Y^G}{WL}\) in equation (B.1), deriving

\[
\gamma' = \frac{\beta' (I - \Omega)^{-1}}{\beta' (I - \Omega)^{-1}\omega L}.
\]
B.2 Proof of Lemma 1

The equilibrium prices \( \{P_i\} \) and \( W \) form the fixed point in the system of equations implied by the cost-minimization problems (3) and (5). Totally differentiating these equations, we obtain

\[
d \ln P_i = -d \ln z_i + \sigma_{iL} d \ln W + \sum_{j=1}^{N} \sigma_{ij} d \ln P_j
\]

\[
0 = \sum_{j=1}^{N} \beta_j d \ln P_j
\]

or in matrix form,

\[
d \ln P = (I - \Sigma)^{-1} (-d \ln z + \sigma_L \cdot d \ln W) \quad \text{(B.2)}
\]

\[
0 = \beta' d \ln P. \quad \text{(B.3)}
\]

A key property used to derive results in this paper is that production elasticities \( \{\sigma_L, \Sigma, \beta\} \) are sufficient statistics to characterize how prices respond to economic shocks, such as the productivity shocks summarized in equation (B.2) and (B.3): one needs not know how these production elasticities change in response to productivity shocks. This follows from the fact that, even with market imperfections and policy subsidies in the economy, producers engage in cost-minimization; accordingly, the envelope theorem can be applied.

From equations (B.2) and (B.3), deriving Lemma 1 is a matter of re-arranging and solving for \( d \ln W / d \ln z_i \). In particular, equation (B.2) implies

\[
\frac{d \ln P}{d \ln z_i} = (I - \Sigma)^{-1} \left( \sigma_L \cdot \frac{d \ln W}{d \ln z_i} - e_i \right)
\]

where \( e_i \) is the vector with \( i \)-th element equal to one and zero otherwise; plug this into the equation (B.3),

\[
\frac{d \ln W}{d \ln z_i} = \frac{\beta'(I - \Sigma)^{-1} \cdot e_i}{\beta'(I - \Sigma)^{-1} \sigma_L} = \mu_i.
\]

The last equality follows from the fact that the numerator is simply the influence vector, and the denominator is equal to one under constant-returns-to-scale. Specifically, CRTS implies production elasticities within each sector must sum to one: \( \sum_j \sigma_{ij} + \sigma_{iL} = 1 \), which, in matrix notation,

\[
\Sigma 1 + \sigma_L = 1 \iff (I - \Sigma)^{-1} \sigma_L = 1,
\]
hence

$$\beta' (I - \Sigma)^{-1} \sigma_L = \beta' 1 = \sum_i \beta_i = 1.$$  

Furthermore, note that market imperfections and subsidies affect prices in ways similar to input-augmenting productivity shocks; thus, we have the following Lemma.

**Lemma 4.** \(d \ln W \over d \tau_{ij} = \mu_i \omega_{ij}\) for all \(i = 1, \ldots, N\) and \(j = 1, \ldots, N, L\).

### B.3 Proof of Lemma 2

Using the income accounting identity (10), we derive

$$d \frac{\ln Y}{d \tau_{ij}} = \frac{1}{Y} \left( d \frac{WL}{d \tau_{ij}} - \frac{d}{d \tau_{ij}} \left( \sum_{i=1}^{N} S_i \right) \right)$$

$$= \frac{1}{Y} \left( WL \cdot \mu_i \omega_{ij} - \frac{d}{d \tau_{ij}} \left( \sum_{n=1}^{N} \left( \sum_{n=1}^{N} \tau_{kn} P_n M_{kn} + \tau_{kL} WL_k \right) \right) \right),$$

in which I have applied Lemma 4 from Appendix B.2 to derive \(dW_L / d \tau_{ij} = WL \cdot \mu_i \omega_{ij}\) and used the definition of policy spending \(S_i\) to expand the second term.

Note that \(d \ln Y / d \tau_{ij}\) generically cannot be characterized by reduced-form sufficient statistics and depends instead on structural features of the economy, which govern how production elasticities respond to policy shocks \(\tau_{ij}\). The difficulty, as explained in the main text, arises because of the indirect budgetary effects in the second term below:

$$d \left( \sum_{i=1}^{N} S_i \right) / d \tau_{ij} = P_j M_{ij} \quad \text{direct impact from targeted input}$$

$$+ \sum_{k,n=1}^{N} \tau_{kn} \frac{d}{d \tau_{ij}} (P_n M_{kn}) + \sum_{k=1}^{N} \tau_{kL} \frac{dW_L}{d \tau_{ij}} \quad \text{indirect effects due to endogenous changes in network structure.}$$

However, in the decentralized economy, these indirect effects are zero; hence

$$\left. d \ln Y \over d \tau_{ij} \right|_{\tau=0} = \frac{1}{Y} \left( WL \cdot \mu_i \omega_{ij} - P_j M_{ij} \right).$$

Further, note that even though output differs generically from total factor income \((Y = WL - \sum_i S_i)\), they coincide in the decentralized economy, when subsidy expenditures are zero. Accordingly, the equation above can be further simplified to:

$$\left. d \ln Y \over d \tau_{ij} \right|_{\tau=0} = \omega_{ij} (\mu_i - \gamma_i),$$

as desired. Note that the same derivation applies to value-added subsidies \(\{\tau_{iL}\}_{i=1}^{N}\), establishing also
that \( \frac{d \ln Y}{d \tau_{il}} \bigg|_{\tau=0} = \omega_i L (\mu_i - \gamma_i) \).

**B.4 Proof of Proposition 1**

From the proof of Lemma 2, we see that

\[
\frac{d W_L}{d \tau_{ij}} = W_L \cdot \mu_i \omega_{ij}, \quad \left. \frac{\sum_{i=1}^{N} S_i}{d \tau_{ij}} \right|_{\tau=0} = P_j M_{ij} = W_L \cdot \gamma_i \omega_{ij}.
\]

When lump-sum taxes \( T \) are held constant, the first term \( d W_L / d \tau_{ij} \) captures the marginal gain in private consumption per unit of subsidy \( \tau_{ij} \), and the second term \( d \left( \sum_{i=1}^{N} S_i \right) / d \tau_{ij} \) captures the required marginal deduction in public consumption per unit subsidy. The social value of policy expenditures is defined as their ratio in the decentralized economy, thus

\[
SV_{ij} \equiv - \left. \frac{d C}{d \tau_{ij}} \right|_{\tau=0, T \text{ constant}} = \frac{d W_L}{d \tau_{ij}} \left|_{\tau=0, T \text{ constant}} \right. = \xi_i, \quad \text{as desired.}
\]

**B.5 Proof of Proposition 2**

Under constant returns to scale, production elasticities within each sector must sum to one: \( \sum_j \sigma_{ij} + \sigma_{iL} = 1 \), which, in matrix notation, implies

\[
\Sigma 1 + \sigma_L = 1 \iff (I - \Sigma)^{-1} \sigma_L = 1,
\]

so that \( \mu' \sigma_L = \beta' (I - \Sigma)^{-1} \sigma_L = \beta' 1 = 1 \). This equality can be rewritten as

\[
\sum_{i=1}^{N} \mu_i \sigma_{iL} = \sum_{i=1}^{N} \frac{\mu_i}{\gamma_i} \gamma_i \sigma_{iL} = 1. \quad (B.4)
\]

I have chosen the accounting convention that using factor inputs does not directly incur deadweight losses, so that total factor endowment accurately represents the total value of resources. Accordingly, at the decentralized economy, factor allocations follow

\[
\frac{W_{Li}}{WL} = \frac{P_i Q_i \cdot \sigma_{iL}}{WL} = \gamma_i \sigma_{iL},
\]
reflecting the fact that production elasticities with respect to factor input is equal to factor expenditure share. Equation (B.4) can therefore be re-written as

\[ \sum_{i=1}^{N} \xi_{i} \frac{L_i}{L} = 1, \]

establishing that distortion centrality averages to one when weighted by sectoral value-added.

Next, consider the aggregate impact of subsidies \( \{ \tau_{ij}, \tau_{iL} \} \). It follows from Lemma 2 that, as a first-order expansion around the decentralized economy, \( \Delta \ln Y \equiv \frac{Y|\{ \tau_{ij}, \tau_{iL} \} - Y|\{ \tau_{ij}, \tau_{iL} \} = 0}{Y|\{ \tau_{ij}, \tau_{iL} \} = 0} \) can be characterized as

\[
\Delta \ln Y \approx \sum_{i=1}^{N} \left( \sum_{j=1}^{N} \frac{d \ln Y}{d \tau_{ij}} \tau_{ij} + \frac{d \ln Y}{d \tau_{iL}} \tau_{iL} \right) \\
= \sum_{i=1}^{N} (\mu_{i} - \gamma_{i}) \left( \sum_{j=1}^{N} \tau_{ij} \omega_{ij} + \tau_{iL} \omega_{iL} \right) \\
= \sum_{i=1}^{N} (\xi_{i} - 1) \left( \sum_{j=1}^{N} \tau_{ij} \gamma_{i} \omega_{ij} + \tau_{iL} \omega_{iL} \right)
\]

From the definition of sectoral policy spending in equation (6), we see

\[ s_{i} \equiv \frac{S_{i}}{W L_{i}} \equiv \left( \sum_{j=1}^{N} \tau_{ij} \gamma_{i} \omega_{ij} + \tau_{iL} \omega_{iL} \right) \frac{L}{L_{i}} \]

Hence

\[ \Delta \ln Y \approx \sum_{i=1}^{N} (\xi_{i} - 1) s_{i} L_{i} / L \]

The covariance between \( \xi_{i} \) and \( s_{i} \), using relative sectoral value-added as the distribution, can be written as

\[
\text{Cov}(\xi_{i}, s_{i}) \equiv \mathbb{E} [\xi_{i} s_{i}] - \mathbb{E} [\xi_{i}] \mathbb{E} [s_{i}] \\
= \sum_{i=1}^{N} \xi_{i} s_{i} L_{i} / L - \sum_{i=1}^{N} s_{i} L_{i} / L \\
= \sum_{i=1}^{N} (\xi_{i} - 1) s_{i} L_{i} / L,
\]

thereby establishing that \( \Delta \ln Y \approx \text{Cov}(\xi_{i}, s_{i}) \), as desired.
The corollary follows directly from properties of bivariate regressions.

B.6 Proof of Proposition 3

The solution to the problem \( \{ \arg\max_{\{ \tau, k \}_{i=1}^N} Y \} \) can be characterized by the set of first-order conditions \( \{ \frac{dY}{d\tau_i} = 0 \} \). To derive \( \frac{dY}{d\ln \tau_i} \), note

\[
\frac{dY}{d\tau_i} = \frac{dWL}{d\tau_i} - \frac{d}{d\tau_i} \left( \frac{\sum_{k=1}^N S_k}{WL} \right)
\]

We perform a substitution to express \( \frac{dS_k}{d\tau_i} \) using \( \frac{d}{d\tau_i} \left( \frac{S_k}{WL} \right) \) and \( \frac{dWL}{d\tau_i} \), noting that

\[
\frac{dS_k}{d\tau_i} = \frac{WL \frac{d(S_k/WL)}{d\tau_i}}{d\tau_i} + S_k \frac{d\ln WL}{d\tau_i}
\]

Substitute for \( \frac{dS_k}{d\tau_i} \) in equation (B.5),

\[
\frac{dY}{d\tau_i} = \frac{dWL}{d\tau_i} - \frac{\sum_{k=1}^N d(S_k/WL)}{d\tau_i} - \frac{\sum_{k=1}^N \frac{d(S_k/WL)}{d\tau_i}}{d\tau_i}
\]

the last equality follows from Lemma 4 in Appendix B.2. The second term inside the curly brackets of (B.6) can also be written as

\[
\frac{\sum_{k=1}^N d(S_k/WL)}{d\tau_i} = \frac{d}{d\tau_i} \left( \sum_{k=1}^N \frac{\tau_{kn}}{\gamma_k \omega_{kn}} + \frac{\tau_{iL}}{\gamma_k \omega_{iL}} \right)
\]

To characterize this, note that under Cobb Douglas, \( \frac{d\omega_{kn}}{d\tau_i} = 0 \) for all \( kn \neq iL \), and the numerator in Domar weight \( \gamma' \equiv \left( \frac{\beta'(I-\Omega)^{-1}}{\beta' (I-\Omega)^{-1} \omega_L} \right) \) is invariant to value-added subsidies; thus,

\[
\frac{d\gamma_k}{d\tau_{ij}} = -\gamma_k \frac{d\ln \beta' (I-\Omega)^{-1} \omega_L}{d\tau_{ij}}
\]

and

\[
\frac{d\tau_{iL} \omega_{iL}}{d\tau_i} = \frac{\omega_{iL}}{1 - \tau_{iL}}.
\]
Using these expressions, we can simplify the second term inside the curly brackets of (B.6):

\[
\sum_{k=1}^{N} \frac{d}{d\tau_{IL}} \left( \frac{S_k}{WL} \right) = \frac{d}{d\tau_{IL}} \left( \sum_{k=1}^{N} \left( \sum_{n=1}^{N} \tau_{kn} \omega_{nk} + \tau_{kL} \omega_{kL} \right) \right)
\]

\[
= \frac{\gamma_i \omega_{iL}}{1 - \tau_{iL}} \sum_{k=1}^{N} \left( \sum_{n=1}^{N} \tau_{kn} \omega_{nk} + \tau_{kL} \omega_{kL} \right) \]

\[
= \frac{\gamma_i \omega_{iL}}{1 - \tau_{iL}} \left( 1 - \frac{\sum_{k=1}^{N} S_k}{WL} \right) \tag{B.7}
\]

The first-order condition (setting the RHS of equation B.6 to zero) can therefore be written as

\[
0 = \mu_i \omega_{iL} \left( 1 - \sum_{k=1}^{N} \frac{S_k}{WL} \right) - \gamma_i \omega_{iL} \left( 1 - \frac{\sum_{k=1}^{N} S_k}{WL} \right)
\]

The solution features

\[
\frac{1}{1 - \tau_{iL}} = \frac{\mu_i}{\gamma_i},
\]

as desired.

To see that the same levels of subsidies also solve \( \{ \arg \max_{\tau_{IL}} Y^G \} \), use the definition \( Y \equiv Y^G - \Pi \) and the income accounting identity \( Y \equiv WL - \sum_{k=1}^{N} S_k \) to obtain

\[
\frac{dY^G}{d\tau_{IL}} = \frac{dWL}{d\tau_{IL}} + \frac{d\Pi}{d\tau_{IL}} - \frac{d}{d\tau_{IL}} \left( \sum_{k=1}^{N} S_k \right).
\]

We apply the following substitutions

\[
\frac{dS_k}{d\tau_{IL}} = WL \frac{d}{d\tau_{IL}} \left( \frac{S_k}{WL} \right) + S_k \frac{d\ln WL}{d\tau_{IL}}, \quad \frac{d\Pi}{d\tau_{IL}} = WL \frac{d}{d\tau_{IL}} \left( \frac{\Pi}{WL} \right) + \Pi \frac{d\ln WL}{d\tau_{IL}}
\]

to obtain:

\[
\frac{dY^G}{d\tau_{IL}} = WL \left( \frac{d\ln WL}{d\tau_{IL}} + \left( \frac{d}{d\tau_{IL}} \left( \frac{\Pi}{WL} \right) + \Pi \frac{d\ln WL}{d\tau_{IL}} \right) - \left( \frac{\sum_{k=1}^{N} d(S_k/WL)}{d\tau_{IL}} + \frac{d\ln WL}{d\tau_{IL}} \sum_{k=1}^{N} \frac{S_k}{WL} \right) \right)
\]

\[
= WL \left( \frac{d\ln WL}{d\tau_{IL}} \left( 1 + \frac{\Pi}{WL} - \sum_{k=1}^{N} \frac{S_k}{WL} \right) + \frac{d}{d\tau_{IL}} \left( \frac{\Pi}{WL} \right) - \sum_{k=1}^{N} \frac{d(S_k/WL)}{d\tau_{IL}} \right)
\]

Following the same steps that preceded equation (B.7), we can show

\[
\sum_{k=1}^{N} \frac{d}{d\tau_{IL}} \left( \frac{S_k}{WL} \right) = \frac{\gamma_i \omega_{iL}}{1 - \tau_{iL}} \left( 1 - \frac{\sum_{k=1}^{N} S_k}{WL} \right)
\]
\[
\frac{d \left( \Pi/WL \right)}{d \tau_{iL}} = -\frac{\gamma_i \omega_{iL}}{1 - \tau_{iL}} \Pi
\]

Hence the first-order condition is

\[
0 = \left( \mu_i \omega_{iL} \left( 1 + \frac{\Pi}{WL} - \sum_{k=1}^{N} S_k/WL \right) - \frac{\gamma_i \omega_{iL}}{1 - \tau_{iL}} \left( 1 + \frac{\Pi}{WL} - \sum_{k=1}^{N} S_k/WL \right) \right)
\]

with solution

\[
\frac{1}{1 - \tau_{iL}} = \frac{\mu_i}{\gamma_i}
\]

as desired.

**B.7 Proof of Proposition 4**

Let \(\delta \equiv \frac{WL}{\gamma G} \). We write out both influence \(\mu_j\) and Domar weight \(\gamma_j\) in their scalar form:

\[
\mu_j = \beta_j + \sum_{i=1}^{N} \mu_i \sigma_{ij},
\]

\[
\gamma_j = \beta_j/\delta + \sum_{i=1}^{N} \gamma_i \omega_{ij},
\]

where \(\beta_j \equiv \frac{p_j Y_j}{Y_G}\) is the consumption expenditure share, \(\omega_{ij} \equiv \frac{p_j M_{ij}}{p_i Q_i}\) is the intermediate expenditure share, and \(\sigma_{ij}\) is the intermediate production elasticity. Dividing both influence by the Domar weight of sector \(j\), we get

\[
\xi_j = \frac{\beta_j}{\gamma_j} + \sum_{i=1}^{N} \frac{\mu_i \sigma_{ij}}{\gamma_j} = \frac{p_j Y_j/Y_G}{p_j Q_j/WL} + \sum_{i=1}^{N} \frac{\mu_i \sigma_{ij}}{\gamma_i \omega_{ij}} \frac{\gamma_i}{\gamma_j} \omega_{ij} \frac{p_j M_{ij}}{p_i Q_i} = \theta_j^F \cdot \delta + \sum_{i=1}^{N} \xi_i \left( 1 + \chi_{ij} - \tau_{ij} \right) \theta_{ij},
\]

where, recall, \(\theta_j^F \equiv \frac{Y_j}{Q_j}\) is the fraction of good \(j\) used to produce the consumption good, and \(\theta_{ij} \equiv \frac{M_{ij}}{Q_j}\) is the fraction of good \(j\) used to produce good \(i\). In deriving the last equality, we have used the property that \(\frac{\gamma_j}{\theta_{ij}} \omega_{ij} = \frac{p_j Q_i}{p_j Q_j} \frac{p_j M_{ij}}{p_i Q_i} = \theta_{ij}\) and that intermediate elasticities and expenditure shares relate by \(\frac{\sigma_{ij}}{\omega_{ij}} = (1 + \chi_{ij} - \tau_{ij})\).

Let \(D \equiv [\chi_{ij}]\) be the matrix of market imperfections. In the decentralized economy, \(\tau_{ij} = 0\); thus,
distortion centrality can be written in matrix form as:

$$
\xi' = \delta \cdot (\Theta^F)' (I - (\Theta + D \circ \Theta))^{-1},
$$

as desired.

### B.8 A Few Properties of Hierarchical Matrices

I use the term “hierarchical” to describe a square matrix if the matrix has non-increasing partial column sums. That is, a $N \times N$ square matrix $A \equiv [a_{ij}]$ is hierarchical iff

$$
\sum_{k=1}^{K} a_{ki} \geq \sum_{k=1}^{K} a_{kj} \quad \text{for all } i < j \text{ and } K \leq N.
$$

**Lemma 5.** Let $A$ be a hierarchical matrix. If $\{b_m\}_{m=1}^{N}$ is a non-increasing and non-negative sequence, then

$$
\sum_{m=1}^{N} a_{mi} b_m \geq \sum_{m=1}^{N} a_{mj} b_m \quad \text{for all } i < j.
$$

**Proof.** Note

$$
\sum_{m=1}^{N} a_{mi} b_m = \sum_{m=1}^{N} a_{mi} b_N + \sum_{m=1}^{N-1} a_{mi} (b_m - b_N)
$$

$$
= \sum_{m=1}^{N} a_{mi} b_N + \sum_{m=1}^{N-1} a_{mi} (b_N - b_{N-1}) + \sum_{m=1}^{N-2} a_{mi} (b_m - b_{N-1})
$$

$$
\vdots
$$

$$
= b_N \left( \sum_{m=1}^{N} a_{mi} \right) + \sum_{k=1}^{N-1} \left( b_{N-k} - b_{N-(k-1)} \right) \sum_{m=1}^{N-k} a_{mi}
$$

$$
\geq b_N \left( \sum_{m=1}^{N} a_{mj} \right) + \sum_{k=1}^{N-1} \left( b_{N-k} - b_{N-(k-1)} \right) \sum_{m=1}^{N-k} a_{mj}
$$

$$
= \sum_{m=1}^{N} a_{mj} b_m,
$$

the inequality follows from the fact that $A$ is hierarchical and that $b_{N-k} - b_{N-(k-1)} \geq 0$ for all $k = 1, \ldots, N-1$.

**Lemma 6.** If $A$ and $B$ are two $N \times N$ non-negative hierarchical matrices, then $C \equiv B \times A$ is hierarchical.
Proof. By definition, \( C_{mi} = \sum_{k=1}^{N} B_{mk} A_{ki} \). Let \( i < j \). Note

\[
\sum_{m=1}^{M} C_{mi} = \sum_{m=1}^{M} \sum_{k=1}^{N} B_{mk} A_{ki} \\
= \sum_{k=1}^{N} \left( \sum_{m=1}^{M} B_{mk} \right) A_{ki} \\
\geq \sum_{k=1}^{N} \left( \sum_{m=1}^{M} B_{mk} \right) A_{kj} \\
= \sum_{m=1}^{M} C_{mj}.
\]

The inequality follows from the fact that \( \left( \sum_{m=1}^{M} B_{mk} \right) \) forms a non-increasing sequence in \( k \); accordingly, we can apply Lemma 5. Because \( \sum_{m=1}^{M} C_{mi} \geq \sum_{m=1}^{M} C_{mj} \) for any \( i < j \) and \( M \), we conclude that \( C \) is hierarchical, as desired. \( \square \)

B.9 Proof of Lemma 3

Let \( \Theta \) be a hierarchical input-output demand matrix. Let \( U \equiv 1'(I - \Theta)^{-1} \) be the upstreamness measure. The goal is to show \( U_i \geq U_j \) for all \( i < j \).

First, note that \( \theta^F_j + \sum_{i=1}^{N} \theta_{ij} = 1 \); that is, the share of good \( j \) supplied as an input to the consumption good and other intermediate goods should sum to one. Stacking the equations for all intermediate goods into vector form,

\[
(\theta^F)' + 1'\Theta = 1' \\
\iff (\theta^F)'(I - \Theta)^{-1} = 1'.
\]

Let \( \eta \) be the vector with \( j \)-th element \( \eta_j \equiv \sum_{i=1}^{N} \theta_{ij} \). The fact that \( \Theta \) is hierarchical implies that \( \eta_i \geq \eta_j \) for all \( i < j \). The upstreamness measure can be re-written as

\[
U = 1' + \eta'(I - \Theta)^{-1} = 1' + \eta' \sum_{k=0}^{\infty} \Theta^k.
\]

\( U_i \) can be written as \( 1 + \sum_{k=0}^{\infty} \sum_{m=1}^{N} \eta_m [\Theta^k]_{mi} \). We now apply the Lemmas in Appendix B.8. Lemma 6 implies \( \Theta^k \) is hierarchical for all \( k \). Furthermore, Lemma 5 implies \( \sum_{m=1}^{N} \eta_m [\Theta^k]_{mi} \geq \sum_{m=1}^{N} \eta_m [\Theta^k]_{mj} \) for all \( k \) and \( i < j \). Thus, we have \( U_i \geq U_j \), as desired.
B.10 Proof of Proposition 5

The model in my paper assumes market imperfection wedges \( \chi_{ij} \)'s are all non-negative. We now prove a slightly stronger version of Proposition 5: under case 2, we model market imperfections as random, and we exchange the strict non-negativity of \( \chi_{ij} \)'s for the weaker condition that imperfections are on average non-negative.

**Proposition 6.** Consider a hierarchical production network with input-output demand matrix \( \Theta \).

**Case 1.** (Deterministic imperfections) If \( D \circ \Theta \) is non-negative and hierarchical, then

\[
\xi_i \geq \xi_j \text{ for all } i < j \text{ in the decentralized economy.}
\]

**Case 2.** (Random imperfections) Suppose \( \Theta \) is lower-triangular. If cross-sector imperfections \( \{ \chi_{ij} \} \) are i.i.d. and \( \mathbb{E} [ \chi_{ij} ] \geq 0 \), then

\[
\mathbb{E} [ \xi_i ] \geq \mathbb{E} [ \xi_j ] \text{ for all } i < j \text{ in the decentralized economy,}
\]

where the expectation is taken with respect to the distribution of \( \chi_{ij} \)'s.

**Proof of Case 1 (deterministic imperfections)**

The plan is to derive a matrix representation of distortion centrality—different from the representation in Proposition 4—so that we can easily apply Lemmas 5 and 6 to show that the distortion centrality is non-increasing under the assumption that \( D \circ \Theta \) is hierarchical.

Note that \( \mu' = \beta'(I - \Sigma)^{-1} \) and \( \delta \cdot \gamma' = \beta'(I - \Omega)^{-1} \), where \( \delta \equiv \frac{\text{WL}}{\gamma \sigma} \). We have

\[
\mu'(I - \Sigma) = \delta \cdot \gamma'(I - \Omega)
\]

\[
\iff \mu' - \delta \cdot \gamma' = \mu' \Sigma - \delta \cdot \gamma' \Omega.
\]

We write out the \( j \)-th entry of the equation above and divide both sides by \( \delta \cdot \gamma_j \):

\[
\frac{\mu_j - \delta \cdot \gamma_j}{\delta \cdot \gamma_j} = \sum_{i=1}^{N} \frac{\mu_i \sigma_{ij} - \delta \cdot \gamma_i \omega_{ij}}{\delta \cdot \gamma_j} \gamma_i
\]

\[
= \sum_{i=1}^{N} \frac{\mu_i \sigma_{ij} - \delta \cdot \gamma_i \sigma_{ij} + \delta \cdot \gamma_i (\sigma_{ij} - \omega_{ij})}{\delta \cdot \gamma_i} \gamma_i
\]
In the decentralized economy, \( \sigma_{ij} = \omega_{ij} (1 + \chi_{ij}) \); thus,

\[
\frac{\mu_j - \delta \cdot \gamma_j}{\delta \cdot \gamma_j} = \sum_{i=1}^{N} \left( \frac{\mu_i - \delta \gamma_i}{\delta \cdot \gamma_i} \right) \omega_{ij} \left(1 + \chi_{ij}\right) + \delta \cdot \gamma_i \omega_{ij} \chi_{ij} \gamma_i \gamma_j
\]

\[
= \sum_{i=1}^{N} \left( \frac{\mu_i - \delta \gamma_i}{\delta \cdot \gamma_i} \right) \theta_{ij} \left(1 + \chi_{ij}\right) + \delta \cdot \gamma_i \theta_{ij} \chi_{ij} \gamma_i
\]

where we have used the substitution that \( \omega_{ij} \gamma_i \gamma_j = \frac{P_i M_{ij}}{P_j Q_{ij}} = \frac{M_{ij}}{Q_j} \equiv \theta_{ij} \). In matrix form, we have

\[
\frac{\xi' \delta - 1}{\delta} = \left( \frac{\xi' \delta - 1}{\delta} \right) (\Theta + D \circ \Theta) + 1' (D \circ \Theta)
\]

\[
= 1' (D \circ \Theta) (I - (\Theta + D \circ \Theta))^{-1}
\]

\[
= 1' (D \circ \Theta) \sum_{k=0}^{\infty} (\Theta + D \circ \Theta)^k
\]

Because the sum of two hierarchical matrices is hierarchical, \( \Theta + D \circ \Theta \) is hierarchical. Lemma 6 implies \((D \circ \Theta) (\Theta + D \circ \Theta)^k\) is hierarchical for any \( k \), and so is \((D \circ \Theta) \sum_{k=0}^{\infty} (\Theta + D \circ \Theta)^k\). Premultiplying by \( 1' \) generates the vector of column sums, which form a non-decreasing sequence by the hierarchical property; hence, \( \xi'_i \geq \xi'_j \) for all \( i < j \), as desired.

**Proof of Case 2 (random imperfections)**

Suppose \( \Theta \) is hierarchical and lower-triangular, i.e. \( \theta_{ij} = 0 \) for all \( j \geq i \). Let \( d_i \equiv \frac{1}{\delta} \xi_i \), \( \theta_{N+1,i} \equiv \theta_i^{F} \), and \( \bar{\gamma} = \mathbb{E}[\chi] > 0 \) to simplify notation; we now use induction to show \( \mathbb{E}[d_i] \geq \mathbb{E}[d_j] \) for all \( i < j \).

From Theorem (4) and the fact that \( \Theta \) is lower-triangular, we have \( d_N = \theta_N^{F} = 1 \), and

\[
\mathbb{E}[d_{N-1}] = \theta_{N+1,N-1} + \theta_{N,N-1} d_N (1 + \mathbb{E}[\chi_{N,N-1}])
\]

\[
= 1 + \theta_{N,N-1} \bar{\chi}
\]

\[
\geq \mathbb{E}[d_N].
\]

We next apply mathematical induction: suppose we know \( \mathbb{E}[d_i] \geq \mathbb{E}[d_j] \) for all \( s+1 \leq i < j \leq N \); we now show \( \mathbb{E}[d_s] \geq \mathbb{E}[d_{s+1}] \).

By independence of \( \chi_{ij} \)'s, we know \( \mathbb{E}[d_n (1 + \chi_{n,m})] = \mathbb{E}[d_n] (1 + \bar{\chi}) \) for all \( m < n \). By Proposition (4),

\[
d_{s+1} = \theta_{N+1,s+1} + \sum_{n=s+2}^{N} \theta_{n,s+1} d_n (1 + \chi_{n,s+1})
\]
\[ d_s = \theta_{N+1,s} + \sum_{n=s+1}^{N} \theta_{n,s} d_n (1 + \chi_{n,s}) \]

Taking expectation over \( d_{s+1} \), we get

\[
\mathbb{E}[d_{s+1}] = \theta_{N+1,s+1} + \sum_{n=s+2}^{N} \theta_{n,s+1} \mathbb{E}[d_n] (1 + \bar{\chi})
\]

\[
= \theta_{N+1,s+1} + \sum_{n=s+1}^{N} \theta_{n,s+1} \mathbb{E}[d_n] (1 + \bar{\chi}) \]

\[
\leq \theta_{N+1,s} + \sum_{n=s+1}^{N} \theta_{n,s} \mathbb{E}[d_n] (1 + \bar{\chi}) \]

\[
= \theta_{N+1,s} + \sum_{n=s+1}^{N} \theta_{n,s} \mathbb{E}[d_n (1 + \chi_{n,s})] \]

\[
= \mathbb{E}[d_s].
\]

The second equality follows from the fact that the matrix \( \Theta \) is lower triangular (thus \( \theta_{s+1,s+1} = 0 \)).

The inequality follows from Lemma 5, exploiting the fact that

\( \{ \mathbb{E}[d_{s+1}] (1 + \bar{\chi}), \mathbb{E}[d_{s+2}] (1 + \bar{\chi}), \ldots, \mathbb{E}[d_N] (1 + \bar{\chi}), 1 \} \) forms a non-increasing sequence and that \( \Theta \) is a lower-triangular hierarchical matrix. The third equality follows from the fact that \( d_n \) is independent from \( \chi_{n,s} \) for all \( n \geq s + 1 \) (\( d_n \) is not a function of imperfections within sector \( n \)). Hence, by induction, we have \( \mathbb{E}[d_i] \geq \mathbb{E}[d_j] \) for all \( i < j \), as desired.
C  Empirical Exercise: Data and Estimation Strategies

C.1  Data Sources and Variable Construction

My empirical analysis relies on four data sources. My first source is the 1970 input-output table of South Korea, which is published by the Bank of Korea, translated from Korean into English, and then digitized into a machine-readable format by Nathaniel Lane, who graciously shared the data with me. My second source is the 2007 Chinese input-output table, published by the National Bureau of Statistics of China.

The third dataset I use is the Chinese Annual Survey of Manufacturing (ASM), an extensive yearly survey of Chinese manufacturing firms, also published by the National Bureau of Statistics of China. The ASM is weighted towards medium and large firms, and includes all Chinese manufacturing firms with total annual sales of more than 5 million RMB (approximately $800,000), as well additional state-owned firms with lower sales. The years covered include 1998 through 2007. The data provide detailed information on production, including real and nominal output, assets, number of workers, wages, inputs, public ownership, foreign ownership, and sales revenue. The dataset also contains information on manufacturing firms’ balance sheets, including external liabilities, interest payments, and production subsidies received from the government. The ASM dataset is well-studied in the literature; for instance, detailed descriptions of the data appear in Brandt et al. (2012) and Du et al. (2014). I use this panel data for production function estimation, and I extract policy variables including debt-to-capital ratio (defined as total external liabilities relative to total assets), effective interest rates (ratio of interest payments to total external liabilities, conditioned on reporting positive interest payments), government subsidies, and SOEs’ sectoral value-added shares from the 2007 cross-section. Following Hsieh and Song (2015), I identify SOEs as either firms that are legally registered as state-owned or firms for which the state is the controlling shareholder.

My fourth data source is the administrative enterprise income tax records, which contain detailed tax rate information for individual manufacturing firms. The data are collected by the Chinese State Administration of Taxation, which is China’s counterpart to the IRS and is responsible for collecting tax, auditing, and supervising tax incentive programs. Descriptive statistics of the administrative tax records can be found in Chen et al. (2018). From the 2008 edition of this data, I compute effective corporate income tax rates for each firm and extract information on whether a firm received tax incentives and tax breaks in the fiscal year.

All policy variables extracted from the two firm-level datasets have outliers removed at 1% above and below. Sectors in both ASM and the administrative tax records are coded at the four-digit CIC (Chinese industrial codes) level, which I harmonize to the 135 sector input-output tables.
C.2 Estimating Market Imperfections

I estimate market imperfections using five strategies:

1. Specification B1 follows the methodology and code of De Loecker and Warzynski (2012). The strategy first estimates sectoral-level translog production functions using the “control function” approach (Olley and Pakes (1996), Levinsohn and Petrin (2003), Ackerberg et al. (2015)) and then recovers firm-level “wedges” between production elasticities and expenditure shares over flexible inputs, which I then average to sector-level.

2. Specification B2 employs the approach outlined by Gandhi et al. (2017), who estimate production elasticities from dynamic panels by exploiting first-order conditions over flexible inputs. Compared to the “control function” approach, this strategy requires less stringent assumptions about information sets and timing of production decisions, but it does require a sample of “control” firms that are not subject to market imperfections and choose input quantities to equate input expenditure shares to production elasticities. I use foreign firms (defined as firms with over 50% foreign equity share) operating in China as the control group, under the assumption that foreign firms are subject to fewer market imperfections (such as financial and contracting frictions) than domestic firms in China. Based on foreign firms’ dynamic input choices, I estimate flexible translog production functions, from which I recover “wedges” between production elasticities and expenditure shares for private firms.

3. Specification B3 relies on Rajan and Zingales (1998)’s measure of external financial dependence and applies to both South Korea and China. The measure captures the fraction of external financing required for capital expenditures in U.S. industries and is likely a lower bound on financial dependence in the two developing economies that I study. To convert the measure into proportional wedges over input costs, I winsorize the measure from below at zero (because financial costs should not be negative) and then interact with the prevailing interest rate in the respective economies: 12.33% for China in 2007, based on the highest sectoral average interest rate from the manufacturing survey data, as reported in Table 9, and 22% for South Korea in 1970, based on International Financial Statistics released by the International Monetary Fund.20

4. Specification B4 uses accounting profits’ sectoral revenue share (i.e. Lerner index) recorded in the national IO tables as the sectoral wedge; the estimates are available for both economies.

Table C.1 reports summary statistics for market imperfections across specifications. The vast majority of sectoral wedges are positive; this is not mechanical except for B3. For instance, because specification B2 estimates production functions from foreign firms that operate in China, positive wedges in

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20International Monetary Fund, Interest Rates, Discount Rate for Republic of Korea [INTDSRKRM193N], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/INTDSRKRM193N.
this case reflect the fact that foreign firms use inputs more intensively then domestic, non-state-owned firms, suggesting the latter face greater market imperfections. Likewise, specification B1 estimates production functions based on the Olley-Pakes method and does not mechanically guarantee $\chi \geq 0$. Table C.1 therefore supports my assumption that $\chi \geq 0$. Moreover, by Proposition 5, upstream sectors tend to have higher distortion centrality in expectation as long as the market imperfection wedges are non-negative on average, which holds true under all specifications.21

Table C.1: Mean and dispersion of estimated market imperfections

<table>
<thead>
<tr>
<th>Specifications</th>
<th>South Korea in 1970</th>
<th>China in 2007</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean($\chi$)</td>
<td>$sd(\chi)$</td>
</tr>
<tr>
<td>Benchmark measure $\xi^{10%}$</td>
<td>0.1</td>
<td>0</td>
</tr>
<tr>
<td>B1 De Loecker and Warzynski</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>B2 Foreign firms as controls</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>0.07</td>
<td>0.05</td>
</tr>
<tr>
<td>B4 Sectoral profit share</td>
<td>0.18</td>
<td>0.17</td>
</tr>
</tbody>
</table>

When constructing distortion centrality, I winsorize the estimated wedges from below at zero—in accordance with my modeling assumption—and, because B1-B3 only recover wedges for manufacturing sectors, I specify wedges in the missing sectors to be the average wedge among manufacturing sectors. Table C.2 reports distortion centrality’s range and standard deviation across estimated specifications, and Table C.3 reports the pair-wise correlations. Table C.4 shows the high correlations are insensitive to either winsorization or to setting wedges in missing sectors to zero. Table C.5 conducts policy evaluation using additional specifications of distortion centrality. The first row computes distortion centrality using sectoral wedges specified as the sum of wedges from B3 and B4—the goal is to capture both financial frictions and markups. Based on this specification, sectoral policies in China generate 5.01% aggregate gains, which is of comparable magnitude to estimates based on B1 and B2. The remaining rows rerun policy evaluation using specifications B1–B4 without adjusting international trade, i.e., distortion centrality are computed under the assumption that China is a closed economy. The table shows that adjusting for trade does not significantly change my quantitative policy evaluation results.

21A potential issue with strategies B1 and B2 is that they confound government interventions as part of market imperfections, measuring $\chi - \tau$ as $\chi$. First, this suggests that wedges are positive even net of subsidies, further supporting my assumption that $\chi \geq 0$. Second, I argue and present evidence in Section 4.3 and D that my findings are quantitatively robust to the mismeasurement.
Table C.2: Dispersion and range of estimated distortion centrality

<table>
<thead>
<tr>
<th>Specifications</th>
<th>South Korea in 1970</th>
<th>China in 2007</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>sd(ξ)  min  max</td>
<td>sd(ξ)  min  max</td>
</tr>
<tr>
<td>Benchmark measure ξ_{i}^{10%}</td>
<td>0.08  0.92  1.41</td>
<td>0.22  0.56  1.47</td>
</tr>
<tr>
<td>B1  De Loecker and Warzynski</td>
<td>-      -     -</td>
<td>0.42  0.19  1.96</td>
</tr>
<tr>
<td>B2  Foreign firms as controls</td>
<td>-      -     -</td>
<td>0.25  0.51  1.60</td>
</tr>
<tr>
<td>B3  Rajan and Zingales</td>
<td>0.06  0.93  1.25</td>
<td>0.11  0.78  1.27</td>
</tr>
<tr>
<td>B4  Sectoral profit share</td>
<td>0.16  0.81  2.31</td>
<td>0.17  0.64  1.37</td>
</tr>
</tbody>
</table>

Table C.3: Pair-wise correlation of distortion centrality based on estimated imperfections

<table>
<thead>
<tr>
<th></th>
<th>South Korea</th>
<th>China</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>B3  B5</td>
<td>B1  B2  B3  B4</td>
</tr>
<tr>
<td>B1</td>
<td>-  -</td>
<td>1</td>
</tr>
<tr>
<td>B2</td>
<td>-  -</td>
<td>0.97  1</td>
</tr>
<tr>
<td>B3</td>
<td>1  0.90</td>
<td>0.98  0.95  1</td>
</tr>
<tr>
<td>B4</td>
<td>0.90 1</td>
<td>0.99  0.95  0.97  1</td>
</tr>
</tbody>
</table>

Table C.4: Correlation between baseline and alternative specifications

<table>
<thead>
<tr>
<th>Specifications</th>
<th>no winsorization</th>
<th>setting χ = 0 for missing sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>South Korea</td>
<td>China</td>
</tr>
<tr>
<td>B1  De Loecker and Warzynski</td>
<td>-</td>
<td>1.00</td>
</tr>
<tr>
<td>B2  Foreign firms as controls</td>
<td>-</td>
<td>0.95</td>
</tr>
<tr>
<td>B3  Rajan and Zingales</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>B4  Sectoral profit share</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

D Empirical Exercise: Robustness and Additional Results

D.1 Robustness: Data Aggregation

In Section 4.3, I acknowledge the possibility of a mismatch between the level of aggregation in IO tables and the level of product differentiation at which my theory applies, either because a sectoral aggregator over varieties fails to exist or because data are mismeasured due to firms operating across industries and conducting multi-stage production in house.\(^{22}\) While I cannot conclusively verify distortion centrality stability when underlying product differentiation is finer than the data available, I

\(^{22}\)Orr (2018) documents a high fraction of vertically integrated firms in Indian manufacturing sectors. Conceptually, vertical integration could arise endogenously to minimize frictions associated with inter-firm trade (Williamson (1985)), but such joint-production arrangements could also generate new sources of market imperfections—for instance, through low-powered incentives (Grossman and Hart (1986)).
Table C.5: Evaluating sectoral interventions in modern-day China using an additional specification

<table>
<thead>
<tr>
<th>Distortion centrality specification</th>
<th>Aggregate gains ($\Delta \ln Y$) by intervention (in percentage points)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>sd ($\xi$)</td>
</tr>
<tr>
<td>Based on the sum of wedges from B3 and B4</td>
<td>0.31</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>Without accounting for international trade</td>
<td></td>
</tr>
<tr>
<td>B1</td>
<td>0.36</td>
</tr>
<tr>
<td>B2</td>
<td>0.21</td>
</tr>
<tr>
<td>B3</td>
<td>0.10</td>
</tr>
<tr>
<td>B4</td>
<td>0.16</td>
</tr>
</tbody>
</table>

Table C.5: Evaluating sectoral interventions in modern-day China using an additional specification

Table D.1: Distortion centrality based on coarse IO tables correlates highly with benchmark measure

<table>
<thead>
<tr>
<th>Average correlation with benchmark $\xi_{10%}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of sectors ($N$)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>$N^{SK} = 54$, $N^{CN} = 57$</td>
</tr>
<tr>
<td>$N^{SK} = 25$, $N^{CN} = 28$</td>
</tr>
<tr>
<td>$N^{SK} = 16$, $N^{CN} = 17$</td>
</tr>
</tbody>
</table>

Table D.1 shows that, at all aggregation levels, benchmark distortion centrality computed from the collapsed IO tables almost perfectly correlates with the benchmark measure computed from the
Figure D.1: Collapsed IO demand matrices are hierarchical in South Korea (left) and China (right)

original, disaggregated tables. The stability is once again due to the hierarchical property of the collapsed IO tables. Figure D.1 visualizes the IO demand matrix for collapsed tables with 25 and 28 sectors for South Korea and China, respectively. Comparing figures 2 and D.1 reveals an interesting, fractal-like property of these networks: linkages across broad sector categories seem to follow a hierarchical structure, as do linkages within each broad category and across more narrowly defined sectoral definitions.

D.2 Robustness: Policy-Induced Measurement Errors

In Section 4.3, I acknowledge the possibility of policy-induced measurement errors in the IO demand matrix $\Theta$ and market imperfections $\chi$. I argue that these errors are second-order, and, if anything, correcting for errors in $\chi$ would strengthen my findings. I now quantitatively verify these intuitions in the Chinese context by correcting for policy-induced measurement errors using actual policy variations. For simplicity, I compute sector-specific policy wedges $\tau_i$ as the total policy spending in each sector relative to sectoral revenue. I normalize $\tau_i$’s to mean zero, assume $\tau_i$ applies equally to all inputs in sector $i$, and correct separately and jointly for errors in $\Theta$ and $\chi$. Correspondingly, I

---

23Policy-induced errors in $\chi$ can arise in specifications B1 and B2 because they misattribute imperfections net of subsidies $(\chi - \tau)$ as true imperfections $\chi$. Specifications B3 and B4 are, in principle, not subject to this issue; nevertheless, my robustness tests below can be seen as sensitivity analysis with respect to systematic errors in $\chi$.

24Distortion centrality in the main text is computed as

$$\xi' \propto (\theta^F)' \left( I - \Theta \circ (1 + \chi) \right)^{-1}$$

Error correction for $\chi$ simply replaces $\chi$ in the formula with $\chi - \tau$. Because high-$\xi$ sectors tend to receive more subsidies, this correction effectively raises wedges in high-$\xi$ sectors and lowers wedges in low-$\xi$ sectors.
recompute every distortion centrality specification and replicate the welfare evaluation exercise using the corrected measure.

Table D.2: Policy evaluations are robust to policy-induced endogeneity and specification errors

<table>
<thead>
<tr>
<th>Distortion centrality specification</th>
<th>Uncorrected</th>
<th>With Correction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark ($\xi^{10%}$)</td>
<td>3.60</td>
<td>3.58</td>
</tr>
<tr>
<td>B1 De Loecker and Warzynski</td>
<td>6.64</td>
<td>6.61</td>
</tr>
<tr>
<td>B2 Foreign firms as controls</td>
<td>3.47</td>
<td>3.43</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>2.02</td>
<td>2.01</td>
</tr>
<tr>
<td>B4 Sectoral profit share</td>
<td>2.62</td>
<td>2.61</td>
</tr>
</tbody>
</table>

Table D.2 uses the corrected measures to recalculate total output gain $\Delta \ln Y$ from sectoral interventions. As a comparison, the first column reports gains based on uncorrected measures, reproducing the last column of Table 13. Results show that aggregate gains remain quantitatively unchanged, and, as my discussion suggests, output gains become slightly stronger when specification errors in $\chi$ are corrected. These results also empirically validate that second-order errors due to policy endogeneity are indeed small.

Table D.3 reports cross-sector means of gross policy expenditure as a share of sectoral revenue and value-added. Total policy spending on subsidized credit, tax incentives, and funds to SOEs account for, on average, 6.14% of sectoral revenue and 23.1% of sectoral value-added.

D.3 Stress-Test: Systematic Errors in Market Imperfections

My evidence suggests that industrial policy in both South Korea and China favored sectors with high distortion centrality over those with low distortion centrality. Can these findings be driven by systematic specification errors in imperfections? I demonstrate that false positives are unlikely given

Correcting for subsidies in $\Theta$ is more involved. I abuse the notation and let $1 + \chi - \tau$ be the $N \times N$ matrix with $i$-th element $1 + \chi_{ij} - \tau_{ij}$, and let $\frac{1 + \chi - \tau}{1 + \chi}$ be the matrix with elements $\frac{1 + \chi_{ij} - \tau_{ij}}{1 + \chi_{ij}}$. Let variables with tilde-overhead denote pre-intervention variables, and those without are post-intervention variables. I maintain the assumption that elasticities are locally policy-invariant, i.e., $\mu_i = \tilde{\mu}_i$. One would like to measure $\tilde{\xi}_i \equiv \mu_i / \gamma_i$ for welfare calculations but can only measure $\xi_i = \mu_i / \gamma_i$ in the data. Following the proof for Proposition 4, one can show that the vectors with elements $\mu_i / \gamma_i$ and $\tilde{\gamma}_i / \gamma_i$ respectively follow

$$[\mu_i / \gamma_i]' \propto (\theta^F)' \left( I - \Theta \circ \frac{1 + \chi - \tau}{1 + \chi} \right)^{-1}$$

$$[\tilde{\gamma}_i / \gamma_i]' \propto (\theta^F)' \left( I - \Theta \circ \left( \frac{1 + \chi - \tau}{1 + \chi} \right) \right)^{-1}.$$ 

Hence, given imperfections and subsidies, pre-intervention distortion centrality $\mu_i / \gamma_i$ can be recovered by first taking the element-wise ratio between the two vectors $[\mu_i / \tilde{\gamma}_i]$ and $[\gamma_i / \tilde{\gamma}_i]$ and then normalizing so that it averages to one across sectors.
Table D.3: Policy spending as a share of sectoral revenue

<table>
<thead>
<tr>
<th></th>
<th>Average ratio between policy expenditure and sectoral revenue</th>
<th>sectoral value-added</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subsidized credit</td>
<td>3.14%</td>
<td>11.85%</td>
</tr>
<tr>
<td>Tax incentive</td>
<td>1.04%</td>
<td>3.90%</td>
</tr>
<tr>
<td>SOEs</td>
<td>1.96%</td>
<td>7.39%</td>
</tr>
<tr>
<td>Total</td>
<td>6.14%</td>
<td>23.1%</td>
</tr>
</tbody>
</table>

the hierarchical nature of these production networks.

Intuitively, false positives arise when \( \xi \) is biased negatively for downstream sectors, meaning \( \chi \) must be underspecified for purchasing downstream goods as production inputs, and, conversely, overspecified for purchasing upstream goods. Such misspecification is a priori counterintuitive because, in contrast to capital goods produced by upstream sectors, downstream sectors tend to produce consumption goods that are more tradable, less durable, and generally less frequently used as intermediate inputs. Most importantly, the scope of false positives is severely limited in hierarchical networks, as imperfections over buying downstream goods eventually accumulate into upstream sectors’ distortion centrality.

I demonstrate these intuitions by conducting exercises that are specifically designed to put stress on my empirical findings.

**South Korea** For each specification of imperfections \( \{ \chi_{ij} \} \), I assume true imperfections \( \tilde{\chi} \) follow

\[
\tilde{\chi}_{ij} = \begin{cases} 
(1 - \kappa) \chi_{ij} & \text{if sector } j \text{ is HCI,} \\
(1 + \kappa) \cdot \chi_{ij} & \text{if sector } j \text{ is non-HCI.}
\end{cases}
\]

I correct for specification errors and correspondingly re-compute distortion centrality using \( \tilde{\chi} \). The parameter \( \kappa \in [0, 1] \) tunes the degree of misspecification. The case \( \kappa = 1 \) is designed to minimize HCI distortion centrality, by doubling imperfections for non-HCI inputs and setting imperfections over HCI inputs to zero. Under this case, HCI sectors can have high distortion centrality only by supplying to other high-distortion-centrality sectors. The specification errors are therefore chosen to maximize the scope for false positives.

Table D.4 shows that HCI sectors’ distortion centrality remain consistently above one for the entire range of \( \kappa \in [0, 1] \), even in the extreme case of \( \kappa = 1 \). My finding that HCI sectors tend to have higher distortion centrality is therefore unlikely to be driven by specification errors.
China  For each version of distortion centrality, I hypothetically assume the corresponding market imperfections are underspecified by 10 percentage points for purchasing downstream goods (i.e. those produced by sectors with below-median distortion centrality) and are symmetrically overspecified for purchasing upstream goods. These errors are specifically assigned to maximize the scope of false positives, and the magnitude of errors is liberally chosen to be significantly higher than the full range of policy variations (see Table 9). Correcting for these hypothetical errors should significantly weaken total gains in output, but any positive gains should be seen as very conservative lower bounds and can be used to vindicate my findings from being false positives. I redo policy evaluations using the corrected measures, reported in Table D.5. Results show that, after corrections, the variance of distortion centrality significantly decreases across specifications; consequently, welfare gains are smaller. Yet output gains remain consistently positive even after accounting for significant specification errors. This stress test lends credence to my earlier inference.

### Table D.5: Qualitative conclusion survives stress-testing

<table>
<thead>
<tr>
<th>Distortion centrality specification</th>
<th>Aggregate gains ($\Delta Y/Y$) by intervention (in percentage points)</th>
<th>sd ($\xi$)</th>
<th>Subsidized credit</th>
<th>Tax incentive</th>
<th>SOEs</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark ($\xi_{10%}$)</td>
<td></td>
<td>0.09</td>
<td>0.18</td>
<td>0.07</td>
<td>0.11</td>
<td>0.36</td>
</tr>
<tr>
<td>B1 De Loecker and Warzynski</td>
<td></td>
<td>0.25</td>
<td>1.28</td>
<td>0.51</td>
<td>1.01</td>
<td>2.80</td>
</tr>
<tr>
<td>B2 Foreign firms as controls</td>
<td></td>
<td>0.15</td>
<td>0.60</td>
<td>0.22</td>
<td>0.36</td>
<td>1.18</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td></td>
<td>0.05</td>
<td>0.21</td>
<td>0.07</td>
<td>0.10</td>
<td>0.39</td>
</tr>
<tr>
<td>B4 Sectoral profit share</td>
<td></td>
<td>0.09</td>
<td>0.32</td>
<td>0.11</td>
<td>0.24</td>
<td>0.67</td>
</tr>
</tbody>
</table>

### D.4 Additional Robustness Results for China

Table D.2 reports policy evaluations after correcting distortion centrality measures for policy-induced endogeneity in $\Theta$, $\chi$, or both; Table D.5 reports welfare evaluations after correcting for hypothetical extreme measurement errors in $\chi$ (underspecified by 10 percentage points for purchasing downstream goods and symmetrically overspecified by 10 percentage points for purchasing upstream goods). In Table D.6, I report various distortion centrality measures’ Pearson correlation coefficients before and after these error corrections. Columns 1 through 3 show that $\xi$ remains almost perfectly
correlated after correcting for endogeneity in $\Theta$, $\chi$, or both, using subsidies computed from real-world policy spending. The last column shows that distortion centrality corrected for extreme errors in $\chi$ remains highly correlated with the uncorrected measures.

Table D.7 replicates selected reduced-form regressions from Tables 11 and 12, using the “upstreamness” measure from Antras et al. (2012) as an instrument variable for the benchmark distortion centrality measure. All specifications in Table D.7 include the full set of controls. Results show that coefficients on policy outcomes remain quantitatively unchanged from OLS to IV specifications.

Table D.8 replicates selected reduced-form regressions from Tables 11 and 12, using various estimated distortion centrality as the main right-hand-side variables and adding the corresponding estimated sectoral imperfections as a control variables. All specifications include the full set of other sectoral controls. I report coefficient only on the main variable of interest, i.e. distortion centrality. For instance, the entry in column 1 row 1 should be read as “one standard deviation increase in distortion centrality specification B1 is associated with a 0.58 percentage points decrease in sectoral effective interest rate”. Results show that coefficients on policy outcomes remain quantitatively unchanged, with few exceptions.

Table D.6: Policy evaluations are robust to policy-induced endogeneity and specification errors

<table>
<thead>
<tr>
<th>Distortion centrality specification</th>
<th>$\Theta$</th>
<th>$\chi$</th>
<th>Both</th>
<th>Correcting for extreme errors in $\chi$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark ($\xi^{10%}$)</td>
<td>1.0000</td>
<td>0.9982</td>
<td>0.9987</td>
<td>0.7238</td>
</tr>
<tr>
<td>B1 De Loecker and Warzynski</td>
<td>1.0000</td>
<td>0.9994</td>
<td>0.9996</td>
<td>0.9552</td>
</tr>
<tr>
<td>B2 Foreign firms as controls</td>
<td>1.0000</td>
<td>0.9983</td>
<td>0.9991</td>
<td>0.9220</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>1.0000</td>
<td>0.9940</td>
<td>0.9949</td>
<td>0.6686</td>
</tr>
<tr>
<td>B4 Sectoral profit share</td>
<td>1.0000</td>
<td>0.9973</td>
<td>0.9978</td>
<td>0.8523</td>
</tr>
</tbody>
</table>

Table D.7: Replicating Tables 11 and 12 using “upstreamness” as instrument variable

<table>
<thead>
<tr>
<th></th>
<th>Effective Interest Rate</th>
<th>Debt Ratio</th>
<th>Tax Break</th>
<th>Effective Tax Rate</th>
<th>SOEs’ Share of Value-Added</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\xi^{10%}$</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td></td>
<td>$-0.958^{***}$</td>
<td>2.679***</td>
<td>2.812**</td>
<td>$-1.591^{***}$</td>
<td>6.589***</td>
</tr>
<tr>
<td></td>
<td>(0.216)</td>
<td>(0.603)</td>
<td>(1.369)</td>
<td>(0.418)</td>
<td>(2.752)</td>
</tr>
</tbody>
</table>

D.5 Additional Tables and Figures
Table D.8: Replicating Tables 11 and 12 using estimated distortion centrality as main explanatory variable and adding the corresponding estimated imperfections as control variables

<table>
<thead>
<tr>
<th>Specification</th>
<th>Effective Interest Rate</th>
<th>Debt Ratio</th>
<th>Tax Break</th>
<th>Effective Tax Rate</th>
<th>SOE Share of Value-Added</th>
</tr>
</thead>
<tbody>
<tr>
<td>B1</td>
<td>-0.675</td>
<td>2.385</td>
<td>1.218</td>
<td>-1.325</td>
<td>7.633</td>
</tr>
<tr>
<td>B2</td>
<td>-0.902</td>
<td>2.777</td>
<td>1.940</td>
<td>-1.463</td>
<td>4.131</td>
</tr>
<tr>
<td>B3</td>
<td>-0.835</td>
<td>2.377</td>
<td>2.079</td>
<td>-1.122</td>
<td>4.339</td>
</tr>
<tr>
<td>B4</td>
<td>-1.004</td>
<td>2.771</td>
<td>2.593</td>
<td>-1.399</td>
<td>8.647</td>
</tr>
</tbody>
</table>

Figure D.2: Visualizing IO demand matrix Θ (sectors sorted by original 3-digit industrial codes)
Left: South Korea in 1970; Right: China in 2007
Table D.9: Distortion centrality is highly correlated across specifications (cont’d)

<table>
<thead>
<tr>
<th>Distribution of $\chi_{ij}$’s</th>
<th>South Korea in 1970</th>
<th>China in 2007</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pearson</td>
<td>Spearman</td>
</tr>
<tr>
<td><strong>Constant distortion</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\chi_{ij} = 0.15$</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>$\chi_{ij} = 0.2$</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td><strong>Log-Normal</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log-$N(0.09, 0.05)$</td>
<td>0.98</td>
<td>0.97</td>
</tr>
<tr>
<td>log-$N(0.15, 0.05)$</td>
<td>0.99</td>
<td>0.99</td>
</tr>
<tr>
<td>log-$N(0.15, 0.1)$</td>
<td>0.97</td>
<td>0.97</td>
</tr>
<tr>
<td><strong>Normal</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$N(0.05, 0.05)$</td>
<td>0.99</td>
<td>0.98</td>
</tr>
<tr>
<td>$N(0.1, 0.05)$</td>
<td>0.95</td>
<td>0.93</td>
</tr>
<tr>
<td>$N(0.2, 0.05)$</td>
<td>1.00</td>
<td>0.99</td>
</tr>
<tr>
<td>$N(0.2, 0.1)$</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td><strong>Truncated Normal</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$(\max { 0, \text{Norm} [\mu, \sigma^2] })$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\mu = 0.05, \sigma^2 = 0.05$</td>
<td>0.97</td>
<td>0.95</td>
</tr>
<tr>
<td>$\mu = 0.05, \sigma^2 = 0.1$</td>
<td>0.94</td>
<td>0.93</td>
</tr>
<tr>
<td>$\mu = 0.15, \sigma^2 = 0.1$</td>
<td>0.98</td>
<td>0.97</td>
</tr>
<tr>
<td>$\mu = 0.15, \sigma^2 = 0.2$</td>
<td>0.94</td>
<td>0.95</td>
</tr>
<tr>
<td><strong>Uniform</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$U[0, 0.3]$</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td>$U[0, 0.4]$</td>
<td>0.98</td>
<td>0.98</td>
</tr>
<tr>
<td><strong>Exponential</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Scale = 0.05</td>
<td>0.95</td>
<td>0.94</td>
</tr>
<tr>
<td>Scale = 0.2</td>
<td>0.91</td>
<td>0.93</td>
</tr>
</tbody>
</table>

Note: This table reports the average Pearson and Spearman-rank correlation between the benchmark distortion centrality $\xi_{i10\%}$ and simulated distortion centrality. The benchmark distortion centrality constructed by assuming imperfections $\chi_{ij} \equiv 0.1$ for all $i, j$. Simulated distortion centrality is constructed by randomly and independently drawing imperfections $\chi_{ij}$ drawn from the listed distribution. Each specification is simulated 10,000 times, and the correlation between $\xi_{i10\%}$ and simulated distortion centrality, averaged over 10,000 draws, is reported.
### Table D.10: Three-digit industries targeted by the Heavy-Chemical Industry drive

<table>
<thead>
<tr>
<th>Industry Name</th>
<th>Industry Name</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sulfuric acid and hydrochloric acid</td>
<td>Ferroalloys</td>
</tr>
<tr>
<td>Carbide</td>
<td>Steel rolling</td>
</tr>
<tr>
<td>Caustic soda products</td>
<td>Pipe and plated steel</td>
</tr>
<tr>
<td>Industrial compressed gases</td>
<td>Steel casting</td>
</tr>
<tr>
<td>Other inorganic basic chemicals</td>
<td>Non-ferrous metals</td>
</tr>
<tr>
<td>Petrochemical based products</td>
<td>Primary non-ferrous metal products</td>
</tr>
<tr>
<td>Acyclic intermediate</td>
<td>Construction metal products</td>
</tr>
<tr>
<td>Cyclic intermediate</td>
<td>Other metal products</td>
</tr>
<tr>
<td>Other organic basic chemicals</td>
<td>Prime movers, boilers</td>
</tr>
<tr>
<td>Chemical fertilizer</td>
<td>Machine tool</td>
</tr>
<tr>
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<tr>
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<td>General purpose machinery and equipment</td>
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<td>Chemical Fiber</td>
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<td>Explosives</td>
<td>Industrial electrical machinery and apparatus</td>
</tr>
<tr>
<td>Paints</td>
<td>Electronics and telecommunications equipment</td>
</tr>
<tr>
<td>Other chemical products</td>
<td>Other electrical equipment</td>
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<tr>
<td>Petroleum products</td>
<td>Shipbuilding and ship repair</td>
</tr>
<tr>
<td>Pig iron</td>
<td>Railroad transportation equipments</td>
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<tr>
<td>Crude iron</td>
<td>Cars and parts</td>
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