INDUSTRIAL POLICIES IN PRODUCTION NETWORKS*

Ernest Liu

Many developing economies 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. *JEL* Codes: C67, O11, O25, O47.

I. Introduction

Many developing economies 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 article, 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

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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 policy makers seem to view as important targets for intervention in historical South Korea and modern-day China,[1] 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, nonpolicy 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 are 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 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.

1. Public 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), and Yang (1993) for Taiwan; Kim (1997) for Korea; State Development Planning Commission of China (1995) for China.

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 1, and there is no role for intervention. With market imperfections, as I show, distortion centrality averages to 1 across sectors; thus, uniformly promoting all sectors generates no aggregate gains. Effective interventions must disproportionally 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 where 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 Antràs 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, because 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 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 Antràs 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 nontargeted 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, nonnetwork 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. Furthermore, 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 and World Bank 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, Storesletten, and Zilibotti (2011) study resource reallocation between state-owned enterprises and private firms during China's recent economic transition. Itskhoki and Moll (2019) study optimal Ramsey policies in a multisector growth model with financial frictions. Also related is Aghion et al. (2015), who show that 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, 1991), Deaton (1987), and Dixit (1985), regarding marginal policy reforms in the different context of commodity taxation. More broadly, my article contributes to a large literature on the aggregate implications of micro imperfections, including 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, Kaboski, and Shin (2011, 2015), Midrigan and Xu (2014), Rotemberg (2018), and Cheremukhin et al. (2015, 2016) among many others.

Methodologically, my article builds on the production networks literature. Papers on efficient networks include Hulten (1978), Acemoglu et al. (2012), Acemoglu, Akcigit, and Kerr (2016), Acemoglu, Ozdaglar, and Tahbaz-Salehi (2017), and Baqaee and Farhi (2019); on inefficient networks, see Bartelme and Gorodnichenko (2015), Caliendo, Parro, and Tsyvinski (2017), Grassi (2017), Altinoglu (2018), Baqaee (2018), Boehm (2018), and Boehm and Oberfield (2019), among others.[2] Particularly related to my theoretical results are works that study properties of inefficient networks with generic "wedges," including Jones (2011, 2013), and Bigio and La'O (2019), who study Cobb-Douglas networks, and, more recently, Baqaee and Farhi (forthcoming), 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 preexisting 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 ex ante, nonparametric sufficient statistic that 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 (forthcoming) are ex post in nature, requiring allocations to be measured from both the pre- and postshock economies. Those results are therefore useful for ex post accounting but cannot be used for policy evaluation and prescription.

II. Model

There is a composite production factor L in fixed supply and a numeraire consumption good that is endogenously produced.

2. Also see Long and Plosser (1983), Horvath (1998, 2000), Dupor (1999), Shea (2002), Atalay (2017), and Oberfield (2018). For the active literature on input-output linkages and international trade, see di Giovanni and Levchenko (2010), Antràs et al. (2012), Chaney (2014), Caliendo and Parro (2014), Carvalho et al. (2016), Antràs and de Gortari (2017), Kikkawa, Magerman, and Dhyne (2017), Redding and Rossi-Hansberg (2017), and Auer, Levchenko, and Sauré (2019).

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

$$Y^G = \mathcal{F}(Y_1, \cdots, Y_N), \tag{1}$$

where Y_1 is the intermediate good i used for consumption. Intermediate good i is produced by

$$Q_i = z_i F_i \left(L_i, \{M_{ij}\}_{j=1}^{N} \right), \tag{2}$$

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.

II.A. 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 nonpolicy 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" χ 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 $\chi_{ij} \geqslant 0$ fraction of the transaction value. Second, these payments represent "quasi-rents," meaning they are competed away and can 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 τ. My goal is to analyze how policy interventions τ affect aggregate efficiency, taking market imperfections χ 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, Kaboski, and Shin 2011). A more elaborated microfoundation is provided in Online Appendix A.2, where I also show that imperfection wedges χ with the aforementioned two features can be microfounded by various other imperfections, including monopoly markups (with profits dissipated by entry), contracting frictions, and externalities.

1. Producer Problem. Suppose market imperfections arise because seller j requires each buyer i to pay a fraction δ_{ij} of transaction value up front. Buyers can achieve this by borrowing working capital, which carries an interest rate λ. 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 τ_{ij} and τ_{iL} proportional to input expenditures. Producers otherwise behave competitively, and equilibrium prices solve the following cost-minimization problem:

$$P_i \equiv \min_{\ell_i, \{m_{ij}\}_{j=1}^N} \left(\sum_{j=1}^{N} \left(1 - \tau_{ij} + \chi_{ij}\right) P_j m_{ij} + (1 - \tau_{iL}) W \ell_i \right)$$

$$\text{s.t. } z_i F_i \left(\ell_i, \{m_{ij}\}_{j=1}^N\right) \geqslant 1, \tag{3}$$

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

2. Imperfections Generate Deadweight Losses. Lenders receive interest payments in proportion to loan size but incur the disutility cost of financial monitoring 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

$$\Pi \equiv \sum_{i=1}^{N} \sum_{j=1}^{N} \chi_{ij} P_j M_{ij}. \tag{4}$$

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.

3. 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

$$1 \equiv \min_{\{Y_j\}_{j=1}^{N}} \sum_{j=1}^{N} P_j Y_j \qquad \text{s.t. } \mathcal{F}(Y_1, \cdots, Y_N) = 1. \tag{5}$$

II.B. 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:

$$S_i \equiv \sum_{j=1}^{N} \tau_{ij} P_j M_{ij} + \tau_{iL} W L_i. \tag{6}$$

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:

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

1. Consumer. The representative consumer spends posttax factor income on consumption C:

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

II.C. Aggregation

The expenditure accounting identity follows:

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

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 Π). Since lenders earn zero utility and their consumption Π 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 equation (9):

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

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 $\chi_{ij} \geqslant 0$, subsidies $\{\tau_{ij}, \tau_{iL}\}$, 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 Π, such that (i) producers choose allocations to solve cost-minimization problems (3) and (5), setting prices to production costs; (ii) government and consumer budget constraints (7) and (8) are satisfied; (iii) the income accounting identity (10) holds; and (iv) 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.

1. Model Summary. This is a canonical model of a constant-returns-to-scale, nonparametric production network augmented by two types of wedges: market imperfections χ and subsidies τ. The goal of my theory is to derive a set of empirically measurable objects to capture how changes in subsidies τ affect output Y, holding imperfections χ 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 Π in the form of the consumption good.[3] Note that 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

3. The treatment of wedges varies in the literature. Caliendo, Parro, and Tsyvinski (2017) also use factor income as the aggregate variable and discard Π as deadweight losses. By contrast, Jones (2013), Bigio and La'O (2019), and more recently, Baqaee and Farhi (forthcoming), rebate Π 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 III.D.

(Greenwald and Stiglitz 1986). In Online Appendix A.2, I provide additional microfoundations for market imperfections, including monopoly markups (with profits dissipated by entry), contracting frictions, and externalities.

2. *Notations for the Rest of the Article.* Throughout the article, 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 ($\tau = \mathbf{0}$) 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 $\Omega \equiv \left[\omega_{ij}\right] \equiv \left[\frac{P_j M_{ij}}{P_i Q_i}\right]$ 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 β 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 μ be the $N \times 1$ 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, that is, how productivity shocks to one sector affect prices in another, taking all higher-order effects into account (Acemoglu et al. 2012).

Let $\gamma_i \equiv \frac{P_i Q_i}{WL}$ be sector i's Domar weight, which is an expenditure-based centrality measure of 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 $\gamma' = \frac{\beta'(I-\Omega)^{-1}}{\beta'(I-\Omega)^{-1}\omega_L}$.[4] In efficient economies, γ_i's are used as sectoral weights for growth accounting (Domar 1961).

The ratio between influence μ and Domar weight γ is the key object of this article.

DEFINITION 2. The distortion centrality ξ_i of sector i is defined as $\xi_i \equiv \frac{\mu_i}{\gamma_i}$.

Influence and Domar weights coincide in an efficient economy ($\mu = \gamma$) but differ in distorted economies; influence can thus be seen as a local measure of potential sectoral size under optimal production. ξ_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 1 across all sectors in an efficient economy. In the decentralized economy, distortion centrality differs from 1 because of market imperfections.

The rest of the article revolves around distortion centrality ξ. Section III shows its economic significance: policy makers should first subsidize sectors with higher ξ, and the cross-sector covariance between ξ and policy spending on subsidies reveals the aggregate effect of interventions. Section IV analyzes how ξ depends on network structures and shows why ξ tends to be higher in upstream sectors. In Section V, I measure distortion centrality, show that it predicts sectoral interventions in South Korea and China, and quantify the aggregate impact of interventions in these economies. All proofs are in Online Appendix B.

4. The expression follows from market clearing (see Online Appendix B). The denominator equals 1 in an efficient economy.

III. 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 III.B, I demonstrate that distortion centrality differs substantively from other notions of sectoral importance. I discuss various interpretation and robustness issues in Section III.D.

To begin, note that the income accounting identity (equation (10); reproduced below) maps aggregate consumption Y into total factor income net of policy expenditures:

$$Y = WL - \sum_{i=1}^{N} S_i. \tag{10}$$

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 preintervention 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 then apply the income accounting identity to obtain net effects on output Y.

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

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 μ' 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 ($\frac{d\ln Y}{d\ln z_i} = \gamma_i$). By contrast, Lemma 1 shows that 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: (i) influence differs from Domar weights, and (ii) 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]

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

$$\left.\frac{d\ln Y}{d\tau_{ij}}\right|_{\tau=\mathbf{0}} = \omega_{ij}\left(\mu_i - \gamma_i\right) \quad \text{for } j = 1, \cdots, N, L. \tag{11}$$

5. Jones (2013) and Bigio and La'O (2019) analyze Cobb-Douglas networks, rebating quasi-rents Π to the consumer. Aggregate output in these papers is equivalent to gross output in mine ($Y^G = Y + \Pi$). These publications show $\frac{d\ln Y^G}{d\ln z_i} = \mu_i \neq \gamma_i$, but their equality sign relies crucially on the Cobb-Douglas assumption. Generically, $\frac{d\ln Y^G}{d\ln z_i} \neq \frac{d\ln Y}{d\ln z_i} \neq \frac{d\ln WL}{d\ln z_i} = \mu_i \neq \gamma_i$.

By the income accounting identity, the aggregate impact of subsidies on Y is the net effect on 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 μ_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 γ_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 equation (11) is scaled by intermediate expenditure share, ω_{ij}, because the subsidy τ_{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 (ω_{ij}), influence (μ_i), and Domar weights (γ_i) are all reduced-form objects in the local equilibrium and are, in principle, observable. The formula holds in the decentralized economy. As noted already, 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, that is, the second term in equation (10):

$$\frac{d\left(\sum_{i=1}^N S_i\right)}{d\tau_{ij}} = \underbrace{P_j M_{ij}}_{\text{direct impact from targeted input}} + \underbrace{\sum_{k,n=1}^N \tau_{kn} \frac{d\left(P_n M_{kn}\right)}{d\tau_{ij}} + \sum_{k=1}^N \tau_{kL} \frac{dWL_k}{d\tau_{ij}}}_{\text{indirect effects due to endogenous changes in network structure}}.$$

6. Baqaee and Farhi (forthcoming) 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, productivities, 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 preintervention economy.

Subsidy τ_{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 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.

III.A. 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, that is, 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:

$$\underbrace{C = WL - T,}_{\text{consumer budget constraint}} \qquad \underbrace{G + \sum_{i=1}^{N} S_i = T.}_{\text{government budget constraint}}$$

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 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 τ_{ij} *is*

$$SV_{ij} \equiv -\frac{dC/d\tau_{ij}}{dG/d\tau_{ij}}\bigg|_{\tau=\mathbf{0},\, T \text{ constant}} = \xi_i \quad \text{for } j = 1, \cdots, N, L.$$

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 τ_{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, that is, distortion centrality ξ_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, that is, 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. $\frac{dY/d\tau_{ij}}{dT/d\tau_{ij}}\Big|_{\tau=\mathbf{0},\, G\,\text{constant}} = \xi_i - 1.$

$(\xi_i - 1)$ 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 1.

In an efficient economy, distortion centrality is always 1, 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 1, 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 $\left\{\tau_{ij}, \tau_{iL}\right\}_{i,j=1}^{N}$, and let $s_i \equiv \frac{S_i}{WL_i}$ denote policy spending per value added in each sector.

PROPOSITION 2. (i) In the decentralized economy, distortion centrality averages to 1 ($\mathbb{E}[\xi] = 1$). (ii) 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]

$$\Delta \ln Y \approx Cov(\xi, s_i).$$

The expectation and covariance are taken across sectors using relative sectoral value added as the distribution, for example, $\mathbb{E}[\xi] \equiv \sum_i \left(\xi_i \cdot \frac{L_i}{L}\right)$.

Part (i) of the result shows that distortion centrality averages to 1 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 by 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.

Even though distortion centrality always averages to 1, 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 1 in all sectors. Conversely, severe imperfections lead to significant cross-sector dispersion in distortion centrality.

Part (ii) 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

7. Formally, $\Delta \ln Y \equiv \frac{Y|_{\{\tau_{ij},\tau_{iL}\}} - Y|_{\tau=\mathbf{0}}}{Y|_{\tau=\mathbf{0}}}$.

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 postintervention economy, as the differences therein have only second-order impact on the covariance term.

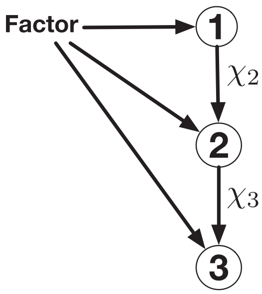
Proposition 2 enables econometricians and policy makers to conduct nonparametric policy evaluations and perform counterfactuals to compare alternative interventions. The result is useful, because it is usually difficult for empirical before-after studies that compare across sectors (the difference-in-differences 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—that is, 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 V, I apply Proposition 2 to evaluate industrial policies in South Korea and China.

III.B. Distortion Centrality $\neq$ 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, whereas 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,



$$Q_1 = z_1 L_1$$
$$Q_2 = z_2 L_2^{1-\sigma_2} M_{21}^{\sigma_2}$$
$$Q_3 = L_3^{1-\sigma_3} M_{32}^{\sigma_3}$$
$$Y^G = Y_3$$

FIGURE I

A Vertical Production Network with Three Intermediate Sectors

influential, or very distorted sectors can indeed amplify—rather than attenuate—misallocations and lead to aggregate losses. I now turn to a simple example to illustrate how distortion centrality relates to these other measures. In Section V, I also empirically demonstrate that distortion centrality differs substantially from these other measures in real-world networks.

1. 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 in Figure I, omitting the final sector.

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

$$\begin{array}{lccccc} & & & \text{Upstream} & \text{Midstream} & \text{Downstream} \\ \text{(Influence)} & \left(\mu_1,\ \mu_2,\ \mu_3\right) & \propto & \Big(\quad \sigma_2\sigma_3, & \sigma_3, & 1 \quad \Big), \\ \text{(Domar weights)} & \left(\gamma_1,\ \gamma_2,\ \gamma_3\right) & \propto & \Big(\quad \frac{\sigma_2}{(1+\chi_2)}\cdot\frac{\sigma_3}{(1+\chi_3)}, & \frac{\sigma_3}{1+\chi_3}, & 1 \quad \Big), \\ \text{(Distortion centrality)} & \left(\xi_1,\ \xi_2,\ \xi_3\right) & \propto & \Big(\quad (1+\chi_2)(1+\chi_3), & (1+\chi_3), & 1 \quad \Big). \end{array}$$

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 Online Appendix A.7.

2. Downstream Is Large and Influential, But Upstream Has High Distortion Centrality. I want 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 that contribute to its distortion centrality, but imperfections in sectors 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.

2. 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 1, 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:

$$
\begin{array}{ll}
 & \qquad\quad \text{Upstream} \qquad\quad \text{Midstream} \qquad \text{Downstream} \\
\left(L_1^*,\ L_2^*,\ L_3^*\right) \propto & \left(\qquad \sigma_2\sigma_3, \qquad\quad \sigma_3\,(1-\sigma_2), \qquad (1-\sigma_3) \qquad \right), \\
\left(L_1,\ L_2,\ L_3\right) \propto & \left(\frac{\sigma_2}{(1+\chi_2)}\cdot\frac{\sigma_3}{(1+\chi_3)},\ \frac{\sigma_3}{1+\chi_3}\,(1-\sigma_2), \qquad (1-\sigma_3) \qquad \right),
\end{array}
$$

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. Next I characterize nonmarginal 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 III.D. Section IV analyzes how network structure generally shapes distortion centrality, formalizing the intuition that distortionary effects accumulate through backward demand linkages.

III.C. 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, $\frac{dY}{d\tau_{ij}}$ 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 $\left\{\tau_{iL}^*\right\}_{i=1}^N$ to the problem $\left\{\arg\max_{\{\tau_{iL}\}_{i=1}^N} Y\right\}$ 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

$$\text{(12)} \quad \text{(first best)} \quad L_i^* = \mu_i \sigma_{iL} L, \qquad \text{(distorted)} \quad L_i = \frac{\gamma_i}{1-\tau_{iL}} \sigma_{iL} L.$$

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 $\frac{\gamma_i \sigma_{iL}}{1-\tau_{iL}}$ 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 nonmarginal 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 (i) elasticities are constant under Cobb-Douglas and (ii) 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 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.

III.D. Discussions and Extensions

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

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 Online Appendix A.1 that ξ 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. 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

$$\max_{\Gamma_i Q_i, L_i, \{M_{ij}\}_{j=1}^{S}} P_i Q_i - \left(\sum_{j=1}^{N} P_j M_{ij} + W L_i + (\lambda - u_i)\,\Gamma_i \right)$$

$$\text{s.t. (2) and } \sum\nolimits_{j=1}^{N} \delta_{ij} P_j M_{ij} \leqslant \Gamma_i.$$

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.

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 χ_{ij} generates deadweight losses $\chi_{ij}P_jM_{ij}$ instead of $\chi_{ij}(1-\tau_{ij})P_jM_{ij}$: 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 on in Online Appendix A.5.

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 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.

5. Market Imperfections $\neq$ 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.[8] I elaborate on this issue in Online Appendix A.4, where I demonstrate (i) allocations in my economy do not coincide with allocations under the first-best economy, and

8. Contracting frictions in Boehm and Oberfield (2019) feature pecuniary externalities of the same nature.

by redistributing resources, policy interventions can raise output Y; (ii) factor allocations under an iceberg economy coincide with those under the first best; and (iii) distortion centrality is always equal to 1 in an iceberg economy, so policy interventions have no first-order effects.

IV. Theory: Distortion Centrality and Network Structure

How does distortion centrality relate to network structure? The vertical-network example in Section III.B 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, the ranking of distortion centrality is insensitive to underlying imperfections. This last result is useful for my empirical analysis later.

To proceed, let $\theta_{ij} \equiv \frac{M_{ij}}{Q_j}$ 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 $\theta_j^F = \frac{Y_j}{Q_j}$ capture the importance of consumer demand for intermediate good j. The market-clearing condition for good j implies that $\theta_j^F + \sum_{i=1}^N \theta_{ij} = 1$. Note that θ_{ij} is different from intermediate expenditure share ω_{ij}: the latter captures the importance of sector j as a supplier to i, and the two objects relate by $\theta_{ij} = \frac{P_j M_{ij}}{P_i Q_i} \frac{P_i Q_i}{P_j Q_j} = \omega_{ij} \frac{\gamma_i}{\gamma_j}$. 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 Θ is the relevant representation for computing distortion centrality.

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

$$\xi_j = \theta_j^F \cdot \delta + \sum_{i=1}^{N} \xi_i \cdot \left(1 + \chi_{ij}\right) \cdot \theta_{ij} \tag{13}$$

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

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

where $\mathbf{D} \equiv \left[\chi_{ij}\right]$ 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 ξ_j; the effect is magnified by ξ_i and weighted by the importance of the demand relationship θ_{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 δ ensures distortion centrality averages to 1 across sectors.

IV.A. Distortion Centrality and the "Upstreamness" Measure

The "upstreamness" measure by Antràs et al. (2012) ("upstreamness" henceforth) is

$$U' = \mathbf{1}'(I - \Theta)^{-1}. \tag{14}$$

The formulation in equation (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 $\xi' = \left(\theta^F\right)'(I - \Theta)^{-1}$, which always collapses to the identity vector $\mathbf{1}'$.

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 Θ has nonincreasing partial column sums:

$$\sum_{k=1}^{K} \theta_{ki} \geqslant \sum_{k=1}^{K} \theta_{kj} \quad \text{for all } i < j \text{ and } K \leqslant N. \tag{15}$$

LEMMA 3. Let U_i denote "upstreamness" as in equation (14). In a hierarchical network, $U_i \geqslant U_j \Leftrightarrow i \leqslant j$.

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 II visualizes the IO demand matrix Θ of a hierarchical network, with entry size drawn in proportion to the strength of the demand linkages θ_{ij}. The condition that partial column sums are nonincreasing 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 III.B. 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 Θ.

9. A sufficient (but unnecessary) condition for an IO demand matrix Θ to satisfy the hierarchical property is for its entries θ_{im} to exhibit log-supermodularity in (i, m), that is, $\theta_{im}\theta_{jn} \geqslant \theta_{in}\theta_{jm}$ for $i \leqslant j$, $m \leqslant n$.

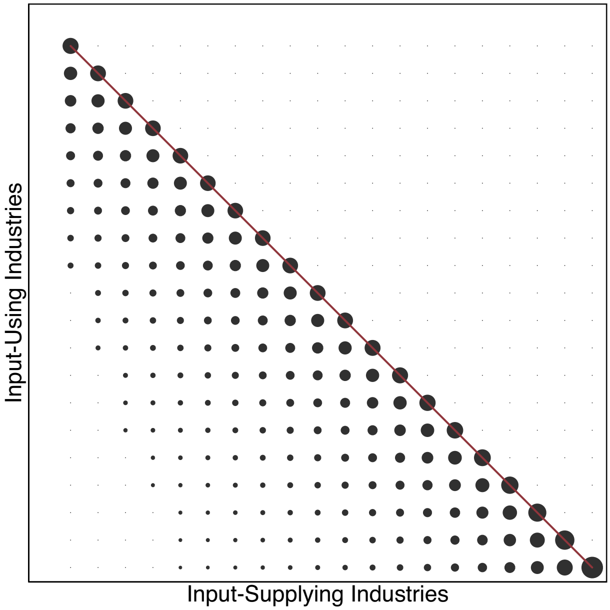


FIGURE II

An Illustrative Input-Output Demand Matrix of a Hierarchical Network

CASE 1. *(Deterministic imperfections) If* $\mathbf{D} \circ \Theta$ *satisfies the hierarchical property, then*

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

CASE 2. *(Random imperfections) Suppose* Θ *is lower-triangular. If cross-sector imperfections* $\{\chi_{ij}\}$ *are i.i.d. and* $\mathbb{E}^{\chi}\left[\chi_{ij}\right] \geqslant 0$, *then*

$$\mathbb{E}^{\chi}\left[\xi_i\right] \geqslant \mathbb{E}^{\chi}\left[\xi_j\right] \quad \text{for all } i < j \text{ in the decentralized economy,}$$

where the expectation is taken with respect to the distribution of χ_{ij}*'s.*

Case 1 shows that distortion centrality aligns with upstreamness if $\mathbf{D} \circ \Theta$ 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 $i \geqslant j$ and $m \geqslant n$). This condition is reasonable because, as I show later, upstream sectors in real-world economies tend to be heavy manufacturing sectors, which use more intermediate inputs and 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 Θ 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, 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 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—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

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

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

In this hierarchical (but nonvertical) 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 ($\xi_1 \geqslant \xi_2 \geqslant \xi_3$), a necessary condition is $y > \frac{10x}{1-0.9x}$, that is, 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 1. By contrast, distortion centrality also depends on market imperfections (the $\mathbf{D}$ matrix), as the measure captures the degree to which distortionary effects in the network accumulate to each sector. Distortion centrality always averages to 1.

V. 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 V.A, and I conduct policy evaluations and counterfactuals in Section V.B. I conduct extensive robustness tests in Section V.C and Online Appendix D.

V.A. *Recovering Distortion Centrality*

To measure distortion centrality, I apply the formula in Proposition 4, which expresses ξ as a function of (i) the network structure and (ii) 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 V.C and Online 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 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.

1. 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.[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 $\Theta \equiv \left[\frac{M_{ij}}{Q_j}\right]$ and vector $\theta^F \equiv \left[\frac{Y_j}{Q_j}\right]$ from the IO table by dividing appropriate entries by the total output of input-supplying sectors.

To illustrate the hierarchical property, I 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, $\xi_i^{10\%}$, by assuming imperfections to be 10% across all sectors and all inputs, and I reorder sectors to descend in $\xi_i^{10\%}$. 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 III visualizes the input-output demand matrices Θ of South Korea and China, with sectors arranged to descend in the benchmark distortion centrality $\xi_i^{10\%}$. For ease of visualization, entries are drawn in proportion to the strength of demand linkages θ_{ij} and are truncated below at 5%, so that only important linkages are shown.

This figure shows a striking pattern of cross-sector linkage structures in these economies. Once sectors are arranged by $\xi_i^{10\%}$, both matrices bear remarkable resemblance to the hierarchical network depicted in Figure II. 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

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).

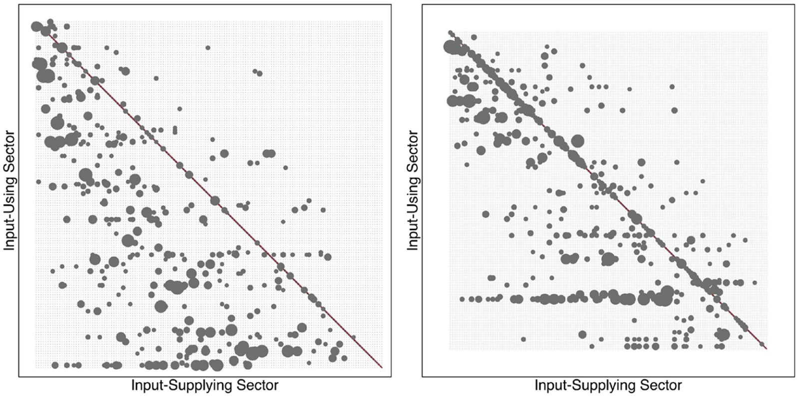


FIGURE III

The IO Demand Matrices of South Korea (Left) and China (Right) Are Hierarchical

magnitude larger than the upper-triangular ones.[11] More important, the matrices are hierarchical: the bottom-left area is sparse but gets denser toward 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 (Online Appendix Figure D.2).

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, 85.0% of which hold true for South Korea and 86.0% for China, as shown in Table I. 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.

11. For 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%.

TABLE I
Testing the Hierarchical Property of Input-Output Demand Matrices in South Korea and China

Relax inequalities by ε $\left(\sum_{k=1}^{K}\theta_{ik} \geqslant \sum_{k=1}^{K}\theta_{jk} - \varepsilon\right)$	Fraction of partial-column-sum comparisons (in Definition 3) that hold true: South Korea	China
0	85.0%	86.0%
0.001	87.0%	87.4%
0.005	89.0%	88.9%

2. Recovering Market Imperfections. Because 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 IV 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 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 2019; Baqaee and Farhi forthcoming) approaches to specify imperfections. I use a variety of specifications based on both of these approaches. For every specification, I overlay the input-output demand matrix Θ 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 χ_{ij} independently across ij from a wide range of distributions, as listed in Table II and Online Appendix Table 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

TABLE II
DISTORTION CENTRALITY IS HIGHLY CORRELATED ACROSS SPECIFICATIONS

		Average correlation with benchmark $\xi_i^{10\%}$			
		South Korea in 1970		China in 2007	
Specifications		Pearson's r	Spearman's ρ	Pearson's r	Spearman's ρ
Upstreamness by Antràs et al. (2012)		0.96	0.96	0.98	0.97
Panel A: Simulated χ_{ij}'s					
A1	constant $\chi_{ij} = 5\%$	1	1	1	1
A2	log-$N(0.09, 0.1)$	0.94	0.92	0.99	0.99
A3	$N(0.1, 0.1)$	0.95	0.93	0.99	0.99
A4	$N(0.2, 0.2)$	0.93	0.94	0.95	0.97
A5	$\max\{N(0.1, 0.1), 0\}$	0.97	0.96	0.99	0.99
A6	$U[0, 0.1]$	0.98	0.97	1	1
A7	$U[0, 0.2]$	0.98	0.97	0.99	0.99
A8	$Exp(0.1)$	0.95	0.94	0.98	0.99
A9	$Exp(0.15)$	0.94	0.94	0.96	0.97
(more simulated specifications in Online Appendix Table D.9)					
Panel B: Estimated imperfections					
B1	De Loecker and Warzynski	–	–	1.00	1.00
B2	Foreign firms as controls	–	–	0.97	0.98
B3	Rajan and Zingales	0.98	0.97	0.98	0.97
B4	Sectoral profit share	0.91	0.91	0.99	0.98

(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 Online 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, Navarro, and Rivers (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. Last, B4 assumes imperfections arise from noncompetitive conduct (see Online Appendix A.2 for microfoundation) and uses sectoral profit shares to proxy for imperfection wedges.[12]

For specifications that recover firm-level imperfections, I compute sectoral averages according to the within-sector heterogeneity analysis in Online Appendix A.1, so that every specification results in one wedge per sector. My baseline analysis assumes that 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 because they recover generic wedges and might confound subsidies as part of market imperfections. I suppress these issues for now and will return to them in Section V.C, where I address policy endogeneity

12. 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.

and conduct extensive sensitivity analysis to specification errors in imperfection wedges.

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

3. 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 (ρ) between these alternative measures and the benchmark measure $\xi_i^{10\%}$. The results are reported in Table II. 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 upstreamness measure by Antràs 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 rank stable ($\rho \approx 1$) and 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 nonhierarchical, the correlation between simulated distortion centrality and the benchmark measure would have been precisely 0 by construction.

The finding in Table II 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 1, various distortion centrality measures differ in ranges and scales (as reported in Online 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 1 in all sectors; conversely, severe imperfections lead to significant distortion centrality dispersion across sectors.

4. 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 $\xi_i^{10\%}$. For the scale-dependent welfare analysis, 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.

5. 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.

Guided by this extension, I map the fictitious "intermediary" sector into IO tables and rerun my estimations. Table III 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

TABLE III

Distortion Centrality after Open-Economy Adjustments

	Correlation (Pearson's r) before and after open-economy adjustments		Fraction of sectors with distortion centrality below the fictitious trade intermediary sector	
ξ specification	South Korea	China	South Korea	China
Benchmark	0.95	0.98	63%	77%
B1	–	0.98	–	76%
B2	–	0.98	–	79%
B3	0.95	0.98	64%	79%
B4	0.97	0.98	56%	73%

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.

6. Distortion Centrality Weakly Correlates with Other Sectoral Measures. Table IV 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 β) 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.

7. Which Sectors Have High Distortion Centrality? In 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 V and VI list the top 10 and the bottom 10 manufacturing sectors ranked by the benchmark measure in these economies.

TABLE IV

DISTORTION CENTRALITY DOES NOT STRONGLY CORRELATE WITH OTHER SECTORAL MEASURES

		Correlation with benchmark $\xi_i^{10\%}$			
		South Korea		China	
Specification		Pearson's r	Spearman's ρ	Pearson's r	Spearman's ρ
C1	Domar weight γ	−0.20	−0.32	−0.40	−0.16
C2	Consumption share β	−0.42	−0.66	−0.71	−0.71
C3	Export intensity	0.31	0.22	0.31	0.37
C4	Sectoral value added	−0.25	−0.52	−0.36	0.09
C5	Expenditure share on intermediate inputs	0.45	0.23	0.37	0.32

TABLE V

South Korean Manufacturing Sectors with High and Low Distortion Centrality

Top 10	$\xi_i^{10\%}$	Bottom 10	$\xi_i^{10\%}$
Pig iron	1.43	Tobacco	0.91
Crude steel	1.38	Condiments	0.91
Iron alloy	1.35	Bread and pastry	0.92
Steel forging	1.26	Cosmetics and toothpaste	0.92
Explosives	1.26	Slaughter, meat, and dairy products	0.93
Acyclic intermediates	1.25	Leather goods	0.93
Construction clay products	1.25	Furniture	0.93
Carbides	1.25	Soaps	0.95
Nonferrous metals	1.24	Other miscellaneous food products	0.95
Machine tools	1.23	Drugs	0.96

TABLE VI

Chinese Manufacturing Sectors with High and Low Distortion Centrality

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

V.B. 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.

1. South Korea in the 1970s. Between 1973 and 1979, South Korea implemented a government-led industrialization program, officially called 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

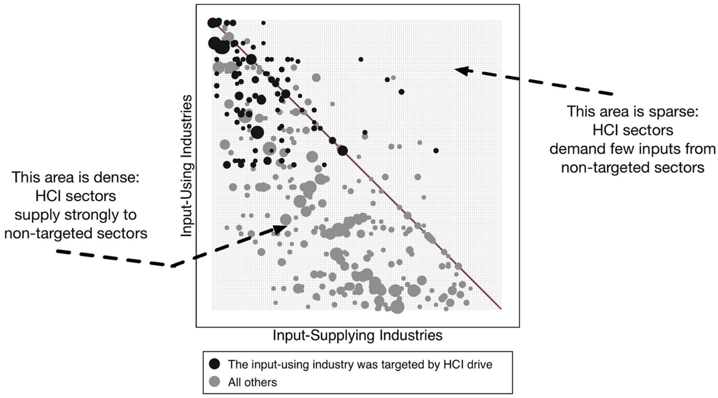


FIGURE IV

South Korea's IO Demand Matrix, with HCI Sectors Darkened

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.[13] Online Appendix Table D.10 shows the full list of 38 targeted three-digit industries.

2. HCI Sectors Are Upstream and Have High Distortion Centrality. That HCI sectors are upstream can be clearly visualized. In Figure IV, I reproduce South Korea's IO demand matrix with sectors ranked by the benchmark measure, as in Figure II, but with one small change: cells are now darkened if the corresponding input-using sectors were promoted by the HCI drive. Note the ith 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 $\xi_i^{10\%}$. The targeted sectors supply strongly to nontargeted 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 10 high-ξ sectors in

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.

TABLE VII

HCI Sectors Have Higher Distortion Centrality than Nontargeted Ones

	ξ Specification	$sd(\xi)$	ξ_i of HCI sectors	Share of sectors with $\xi_i > 1$	
				HCI	Non-HCI
	Benchmark	0.09	1.16	100%	47.8%
B3	Rajan and Zingales	0.06	1.12	100%	47.0%
B4	Sectoral profit share	0.16	1.28	100%	45.1%
A3	$N(0.1, 0.1)$	0.09	1.17	100%	47.7%
A7	$U[0, 0.2]$	0.09	1.16	100%	47.7%
A8	$Exp(0.1)$	0.10	1.17	100%	47.7%

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

Table V were promoted by the HCI program, and none of the bottom 10 sectors were targeted.

HCI sectors' upstreamness translates into high distortion centrality, as shown in Table VII. Because results are quantitatively similar across all specifications, I omit some simulated specifications to avoid redundancy. Results show that every HCI sector has distortion centrality consistently above 1 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 $\xi_i^{10\%}$ 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 1, 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 V.C and Online Appendix D.

3. Counterfactuals. In Table VIII, 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 (β), export intensity, sectoral value added, and intermediate expenditure shares. For each scenario, I maintain the HCI drive's number (38) of promoted

TABLE VIII
POLICY COUNTERFACTUALS FOR SOUTH KOREA

	Specification for ξ_i:	Average distortion centrality			Gains relative to HCI drive		
		Benchmark (1)	B3 (2)	B4 (3)	Benchmark (4)	B3 (5)	B4 (6)
HCI Drive		1.16	1.12	1.28	100%	100%	100%
Counterfactuals (select sector sorted by...)							
CF1	Domar weight γ	0.98	0.99	0.96	−11%	−9%	−13%
CF2	Consumption share β	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	Interm. exp. share	1.07	1.04	1.08	41%	36%	28%
CF6	Distortion centrality ξ	1.22	1.15	1.30	137%	124%	109%
CF7	Uniform promotion	1	1	1	0%	0%	0%

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 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 1. 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 ξ—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 1, 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. Modern-Day China. State intervention has a long tradition in China and remains alive and well today, as the government

14. Reliable data on sectoral policy spending are unavailable for this historical period; see Lane (2017).

employs a wide range of policy levers and instruments to exert influence over sectoral production. 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 subsidies from the government and easy access to credit; Song, Storesletten, and Zilibotti (2011) explicitly model modern-day Chinese SOEs as financially unconstrained market participants. I refer interested readers to Du, Harrison, and Jefferson (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, Jin, and Gao (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.[15] I also measure SOEs' sectoral presence. Information on corporate taxes comes from the administrative enterprise income tax records for 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.[16] Online Appendix C.1 provides details on these data sets and variable construction.

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

15. "Private firms" refers to non-SOEs.

16. That these two data sets are misaligned by one year should not lead to systemic biases because I exploit cross-sector variations.

and firm-level data sets.[17] Tables IX and X provide some descriptive statistics, from which I highlight two features.

First, industrial policies in China vary substantially across sectors. The first row of Table IX 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. The second row shows that firms in the most-indebted sector have an average debt-to-asset ratio that is over 1.5 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. The seventh row 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 X. On average, the effective interest rate paid by SOEs is half that paid by private firms, despite the 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 conditional on having received any, SOEs receive more subsidies (as a share of revenue) than private firms.

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

$$Outcome_i = a + b \times \xi_i^{10\%} + \text{controls}_i + \varepsilon_i.$$

Each observation i is a sector, and $Outcome_i$ 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

17. I exclude the tobacco sector from the policy analysis because it is heavily regulated and entirely state-owned in China.

TABLE IX

DESCRIPTIVE STATISTICS: SECTORAL POLICIES VARY SIGNIFICANTLY ACROSS CHINESE SECTORS

Sectoral means (in percentage points)	Min	1st quartile	Median	3rd quartile	Max	Average	Std. dev.
Effective interest rate	1.85	3.39	4.12	5.00	12.33	4.45	1.67
Debt ratio	40.91	51.54	54.78	57.04	65.39	54.45	4.82
Fraction of firms with tax incentives	8.70	24.88	30.81	36.55	61.33	31.23	9.84
Effective corporate income tax rate	9.08	15.13	17.48	19.45	24.78	17.29	2.94
Fraction of firms receiving subsidies	6.65	9.62	11.77	13.93	28.83	12.42	3.83
Subsidies/revenue	0.60	0.98	1.36	1.79	4.74	1.57	0.83
SOE share of sectoral value-added	0.66	4.76	10.67	24.40	74.50	17.32	17.04

TABLE X
DESCRIPTIVE STATISTICS: SOES RECEIVE MORE FAVORABLE POLICIES

Variable means by ownership	Private firms	SOEs
Effective interest rate	4.63	2.23
Debt ratio	54.38	63.49
Fraction of firms with tax incentives	31.93	31.48
Effective corporate income tax rate	17.29	14.98
Fraction of firms receiving subsidies	11.46	22.41
Subsidies/revenue	1.56	2.78

value-added. $\bar{\xi}_i^{10\%}$ 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, "1 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 to partial out nonnetwork reasons for state interventions, and I also standardize these control variables.

Regression results (Table XI) show that private firms in high distortion centrality sectors receive more-favorable policies. Based on columns (2), (4), (6), and (8), a 1 standard deviation higher sectoral distortion centrality is associated with having a 0.99 percentage point 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: 1 standard deviation in distortion centrality translates into policy differences of between 0.30 and 0.59 standard deviations of the respective policy variables (see the last column in Table IX). 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, nonnetwork 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

TABLE XI

PRIVATE FIRMS IN CHINESE MANUFACTURING SECTORS WITH HIGH DISTORTION CENTRALITY RECEIVE MORE-FAVORABLE POLICIES

	Effective interest rate		Debt ratio		Tax break		Effective tax rate		Recipient of subsidies		$\frac{\text{Subsidies}}{\text{Revenue}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\xi_i^{10\%}$	−0.895***	−0.987***	2.961***	2.726***	2.861**	2.911**	−1.595***	−1.589***	−0.556	−0.236	−0.210	−0.102
	(0.222)	(0.223)	(0.556)	(0.622)	(1.323)	(1.412)	(0.396)	(0.431)	(0.593)	(0.578)	(0.127)	(0.126)
Capital intensity		−0.425**		−0.390		0.759		−0.253		1.403***		0.284**
		(0.199)		(0.556)		(1.263)		(0.385)		(0.517)		(0.113)
Lerner index		−0.0247		0.146		−0.559		0.0958		0.166		0.00943
		(0.173)		(0.481)		(1.092)		(0.333)		(0.447)		(0.0975)
Log(fixed assets in starting year)		−0.0273		0.511		−0.559		−0.643		1.075**		0.147
		(0.204)		(0.568)		(1.290)		(0.394)		(0.528)		(0.115)
Export intensity		−0.682***		0.284		2.824**		−0.375		1.186**		−0.0977
		(0.172)		(0.487)		(1.105)		(0.337)		(0.452)		(0.0986)
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
# Obs.	79	79	79	79	79	79	79	79	79	79	79	79

Notes. The table examines correlations between standardized benchmark distortion centrality $\xi_i^{10\%}$ and measures of government interventions. The benchmark distortion centrality is constructed by assuming imperfections $\chi_{ij} \equiv 0.1$ for all i, j. Industry averages of firm-level variables are computed after dropping outliers at 1%. Standard errors are in parentheses. *** and ** indicate significance at the 1% and 5% level, respectively.

unaffected after including the controls. Online 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 X, private firms tend to receive few subsidies to begin with, compared with SOEs.

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 (Li, Liu, and Wang 2015; Bai, Hsieh, and Song 2019). The predominant view in the literature is that these SOEs are overcapitalized, and their existence impedes the efficient allocation of resources within sectors (Song, Storesletten, and Zilibotti 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 XII shows that distortion centrality predicts the sectoral presence of SOEs. In 2007, in sectors with distortion centrality 1 standard deviation above the mean, SOEs had a 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 2000, and the correlations remain significant.

6. Policy Evaluations. The reduced-form evidence suggests that Chinese sectors with high distortion centrality—that is, 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 ξ_i to quantitatively evaluate these sectoral policies' aggregate impact. Note the covariance can be calculated using a bivariate regression: let $\bar{\xi}_i \equiv \frac{\xi_i}{sd(\xi)}$ denote distortion centrality standardized to unit variance; then

TABLE XII

SECTORS WITH HIGH DISTORTION CENTRALITY HAVE LARGER SOE PRESENCE

	All SOEs in 2007		SOEs established after year T			
			$T = 2000$	$T = 2001$	$T = 2002$	$T = 2003$
	(1)	(2)	(3)	(4)	(5)	(6)
$\xi_i^{10\%}$	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. R^2	0.066	0.290	0.269	0.284	0.276	0.220
# Obs.	79	79	79	79	79	79

Notes. Outcome variable: SOEs' Share of Sectoral Value Added in 2007. The table examines correlations between standardized benchmark distortion centrality $\xi_i^{10\%}$ and SOEs' share of sectoral value added. SOEs are identified following Hsieh and Song (2015). The benchmark distortion centrality is constructed by assuming imperfections $\chi_{ij} \equiv 0.1$ for all i, j. Standard errors are in parentheses. *** and ** indicate significance at the 1% and 5% level, respectively.

$Cov(s_i, \xi_i) = b \cdot sd(\xi)$, 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 partialing out $\bar{\xi}_i$, has no first-order impact on output Y.

To proceed, I compute policy spending $\{s_i\}$ separately for (i) subsidized credit, (ii) tax incentives based on the sample of private firms, and (iii) 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 ($(r - r_i) \times \text{debt}_i$). 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 XIII 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

TABLE XIII

EVALUATING SECTORAL INTERVENTIONS IN MODERN-DAY CHINA

			Aggregate gains ($\Delta \ln Y$) by intervention (in percentage points)			
Distortion centrality specification		$sd(\xi)$	Subsidized credit	Tax incentive	SOEs	Total
	Benchmark ($\xi^{10\%}$)	0.22	1.69	0.64	1.27	3.60
B1	De Loecker and Warzynski	0.42	3.07	1.19	2.39	6.65
B2	Foreign firms as controls	0.25	1.69	0.67	1.16	3.51
B3	Rajan and Zingales	0.11	1.01	0.36	0.65	2.02
B4	Sectoral profit share	0.17	1.20	0.47	0.95	2.62

estimates 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 (see Online Appendix 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 0 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 (see Online Appendix 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 noncompetitive 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. Online Appendix Table 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.

7. Policy Counterfactuals. I now conduct policy counterfactuals for China. Each policy experiment evaluates the aggregate impact of a hypothetical vector of sectoral subsidies. 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, $\bar{\gamma}_i \equiv \frac{\gamma_i}{sd(\gamma)}$) 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., $\tilde{s}_i = \tilde{\alpha} + \tilde{b} \cdot \bar{\gamma}_i + u_i$ 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

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

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

Table XIV 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 measures also 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 $\bar{\xi}_i$. This means higher cross-sector dispersions in policy spending: sectors with high intermediate shares need to receive two or

TABLE XIV

POLICY COUNTERFACTUALS FOR MODERN-DAY CHINA

		Total output gains across all interventions (in percentage points)					Output gains relative to real-world interventions (correlation between ξ and the counterfactual policy target)				
Specification for ξ		$\xi^{10\%}$	B1	B2	B3	B4	$\xi^{10\%}$	B1	B2	B3	B4
Real-world interventions		3.60	6.65	3.51	2.02	2.62	100%	100%	100%	100%	100%
Counterfactual policy target											
CF1	Domar weight γ	−1.42	−2.57	−1.18	−0.83	−1.14	−39.5%	−38.6%	−33.5%	−41.3%	−43.6%
CF2	Consumption share β	−2.56	−4.62	−2.43	−1.44	−1.90	−71.1%	−69.5%	−69.3%	−71.3%	−72.6%
CF3	Export intensity	1.13	1.98	0.99	0.79	0.80	31.4%	29.8%	28.3%	38.9%	30.5%
CF4	Sectoral value-added	−1.30	−2.41	−1.11	−0.75	−0.95	−36.2%	−36.3%	−31.7%	−37.3%	−36.4%
CF5	Interm. exp. share	1.34	2.39	1.11	0.83	0.87	37.2%	35.9%	31.6%	41.2%	33.3%
CFO	Optimal assignment	5.33	10.18	5.85	2.97	3.97	148.1%	153.4%	166.8%	147.0%	151.5%

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 XIV (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.

V.C. Robustness of Empirical Findings

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

1. Data Aggregation. In Section III.D, 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 multistage production in-house. Although 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 Online 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. Online Appendix Table D.1 shows that at all levels of aggregation for both

18. Specifically, row (CFO) of Table XIV shows the covariance between $s_{(i)}$, the ith highest sectoral policy spending per value added, and $\xi_{(i)}$, the ith highest distortion centrality.

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 Online Appendix Figure D.1.

2. Policy Endogeneity and Systematic Specification Errors. In the main text, I construct distortion centrality using real-world data, yet both the IO demand matrix Θ and market imperfections χ could 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 (i) endogenous changes in production elasticities or (ii) 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 Online 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 ($\chi - \tau$) as true imperfections χ. These errors are also second order; more important, 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 downward (upward). These errors in χ therefore weaken any positive correlations between subsidies and ξ, and correcting for the errors should strengthen my findings. Online 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, because imperfections over buying shoes eventually also accumulate into upstream sectors' distortion centrality. Online Appendix D.3 verifies these intuitions by showing that my findings are robust even with substantial specification errors of the most perverse kind.

Online 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 XI and XII, using the upstreamness measure from Antràs et al. (2012) as an instrumental variable for the benchmark distortion centrality measure. The instrumental variable should purge specification errors in distortions insofar as upstreamness captures nonpolicy features of the input-output relationship; results show that coefficients remain quantitatively unchanged. Table D.8 shows that my reduced-form findings are also robust after including estimated market imperfections as control variables.

VI. 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. Furthermore, 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 reallocative 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.

PRINCETON UNIVERSITY

Supplementary Material

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online. Data and code replicating tables and figures in this article can be found in Liu (2019), in the Harvard Dataverse, doi: 10.7910/DVN/MIWUVM.

References

Acemoglu, Daron, Ufuk Akcigit, and William Kerr, "Networks and the Macroeconomy: An Empirical Exploration," *NBER Macroeconomics Annual*, 30 (2016), 273–335.

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "The Network Origins of Aggregate Fluctuations," *Econometrica*, 80 (2012), 1977–2016.

Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "Microeconomic Origins of Macroeconomic Tail Risks," *American Economic Review*, 107 (2017), 54–108.

Aghion, Philippe, Jing Cai, Mathias Dewatripont, Luosha Du, Ann Harrison, and Patrick Legros, "Industrial Policy and Competition," *American Economic Journal: Macroeconomics*, 7 (2015), 1–32.

Ahmad, Ehtisham, and Nicholas Stern, "The Theory of Reform and Indian Indirect Taxes," *Journal of Public Economics*, 25 (1984), 259–298.

———, *The Theory and Practice of Tax Reform in Developing Countries* (Cambridge: Cambridge University Press, 1991).

Altinoglu, Levent, "The Origins of Aggregate Fluctuations in a Credit Network Economy," Technical Report, 2018.

Antràs, Pol, Davin Chor, Thibault Fally, and Russell Hillberry, "Measuring the Upstreamness of Production and Trade Flows," *American Economic Review*, 102 (2012), 412–416.

Antràs, Pol, and Alonso de Gortari, "On the Geography of Global Value Chains," NBER Working Paper no. 23456, 2017.

Atalay, Enghin, "How Important Are Sectoral Shocks?," *American Economic Journal: Macroeconomics*, 9 (2017), 254–280.

Auer, Raphael A., Andrei A. Levchenko, and Philip Sauré, "International Inflation Spillovers through Input Linkages," *Review of Economics and Statistics*, 101 (2019), 507–521.

Bai, Chong-En, Chang-Tai Hsieh, and Zheng Michael Song, "Special Deals with Chinese Characteristics," NBER Working Paper no. 25839, 2019.

Banerjee, Abhijit V., and Esther Duflo, "Growth Theory through the Lens of Development Economics," in *Handbook of Economic Growth*, Philippe Aghion and Steven Durlauf, eds. (Amsterdam: Elsevier, 2005), 1: 473–552.

Banerjee, Abhijit V., and Benjamin Moll, "Why Does Misallocation Persist?," *American Economic Journal: Macroeconomics*, 2 (2010), 189–206.

Banerjee, Abhijit, and Kaivan Munshi, "How Efficiently Is Capital Allocated? Evidence from the Knitted Garment Industry in Tirupur," *Review of Economic Studies*, 71 (2004), 19–42.

Baqaee, David Rezza, "Cascading Failures in Production Networks," *Econometrica*, 86 (2018), 1819–1838.

Baqaee, David, and Emmanuel Farhi, "The Macroeconomic Impact of Microeconomic Shocks: Beyond Hulten's Theorem," *Econometrica*, 87 (2019), 1155–1203.

———, "Productivity and Misallocation in General Equilibrium," Quarterly Journal of Economics, forthcoming.

Bartelme, Dominick, and Yuriy Gorodnichenko, "Linkages and Economic Development," NBER Working Paper no. 21251, 2015.

Bigio, Saki, and Jennifer La'O, "Distortions in Production Networks," NBER Working Paper no. 22212, 2019.
Boehm, Johannes, "The Impact of Contract Enforcement Costs on Value Chains and Aggregate Productivity," Working Paper, 2018.
Boehm, Johannes, and Ezra Oberfield, "Misallocation in the Market for Inputs: Enforcement and the Organization of Production," NBER Working Paper no. 24937, 2019.
Boyreau-Debray, Genevieve, and Shang-Jin Wei, "Pitfalls of a State-Dominated Financial System: The Case of China," NBER Working Paper no. 11214, 2005.
Buera, Francisco J., Joseph P. Kaboski, and Yongseok Shin, "Finance and Development: A Tale of Two Sectors," *American Economic Review*, 101 (2011), 1964–2002.
———, "Entrepreneurship and Financial Frictions: A Macrodevelopment Perspective," *Annual Review of Economics*, 7 (2015), 409–436.
Caliendo, Lorenzo, and Fernando Parro, "Estimates of the Trade and Welfare Effects of NAFTA," *Review of Economic Studies*, 82 (2014), 1–44.
Caliendo, Lorenzo, Fernando Parro, and Aleh Tsyvinski, "Distortions and the Structure of the World Economy," NBER Working Paper no. 23332, 2017.
Carvalho, Vasco, Makoto Nirei, Yukiko Saito, and Alireza Tahbaz-Salehi, "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," BFI Working Paper Series 2017-01, 2016.
Chaney, Thomas, "The Network Structure of International Trade," *American Economic Review*, 104 (2014), 3600–3634.
Chang, Ha-Joon, "State-Owned Enterprise Reform," *United Nations DESA Policy Notes* (2007).
———, "Industrial Policy: Can We Go Beyond an Unproductive Confrontation?," Plenary paper for Annual World Bank Conference on Development Economics, 2009.
Cheremukhin, Anton, Mikhail Golosov, Sergei Guriev, and Aleh Tsyvinski, "The Economy of People's Republic of China from 1953," NBER Working Paper no. 21397, 2015.
———, "The Industrialization and Economic Development of Russia through the Lens of a Neoclassical Growth Model," *Review of Economic Studies*, 84 (2016), 613–649.
Deaton, A., *Econometric Issues for Tax Design in Developing Countries* (Washington, DC: World Bank, 1987).
De Loecker, Jan, and Frederic Warzynski, "Markups and Firm-Level Export Status," *American Economic Review*, 102 (2012), 2437–2471.
di Giovanni, Julian, and Andrei A. Levchenko, "Putting the Parts Together: Trade, Vertical Linkages, and Business Cycle Comovement," *American Economic Journal: Macroeconomics*, 2 (2010), 95–124.
Dixit, Avinash, "Tax Policy in Open Economies," in *Handbook of Public Economics* (Amsterdam: Elsevier, 1985), 313–374.
Dollar, David, and Shang-Jin Wei, "Das (Wasted) Kapital: Firm Ownership and Investment Efficiency in China," NBER Working Paper no. 13103, 2007.
Domar, Evsey D., "On the Measurement of Technological Change," *Economic Journal*, 71 (1961), 709–729.
Du, Luosha, Ann Harrison, and Gary Jefferson, "FDI Spillovers and Industrial Policy: The Role of Tariffs and Tax Holidays," *World Development*, 64 (2014), 366–383.
Dupor, Bill, "Aggregation and Irrelevance in Multi-Sector Models," *Journal of Monetary Economics*, 43 (1999), 391–409.
Gandhi, Amit, Salvador Navarro, and David Rivers, "On the Identification of Gross Output Production Functions," University of Western Ontario working paper, 2017.
Grassi, Basile, "IO in I-O: Competition and Volatility in Input-Output Networks," Meeting Papers 1637, 2017.

Greenwald, Bruce C., and Joseph E. Stiglitz, "Externalities in Economies with Imperfect Information and Incomplete Markets," *Quarterly Journal of Economics*, 101 (1986), 229–264.

Hatta, Tatsuo, "A Theory of Piecemeal Policy Recommendations," *Review of Economic Studies*, 44 (1977), 1–21.

Hernandez, Zenaida, "Industrial Policy in East Asia: In Search for Lessons," Technical Report 31350, 2004.

Hirschman, Albert O., *The Strategy of Economic Development* (New Haven, CT: Yale University Press, 1958).

Horvath, Michael, "Cyclicality and Sectoral Linkages: Aggregate Fluctuations from Independent Sectoral Shocks," *Review of Economic Dynamics*, 1 (1998), 781–808.

———, "Sectoral Shocks and Aggregate Fluctuations," *Journal of Monetary Economics*, 45 (2000), 69–106.

Hsieh, Chang-Tai, and Peter J. Klenow, "Misallocation and Manufacturing TFP in China and India," *Quarterly Journal of Economics*, 124 (2009), 1403–1448.

Hsieh, Chang-Tai, and Zheng M. Song, "Grasp the Large, Let Go of the Small: The Transformation of the State Sector in China," NBER Working Paper no. 21006, 2015.

Hulten, Charles R., "Growth Accounting with Intermediate Inputs," *Review of Economic Studies*, 45 (1978), 511–518.

Itskhoki, Oleg, and Benjamin Moll, "Optimal Development Policies with Financial Frictions," *Econometrica*, 87 (2019), 139–173.

Jones, Charles I., "Intermediate Goods and Weak Links in the Theory of Economic Development," *American Economic Journal: Macroeconomics*, 3 (2011), 1–28.

———, "Misallocation, Economic Growth, and Input-Output Economics," in *Advances in Economics and Econometrics, Tenth World Congress Society Monographs* (Cambridge: Cambridge University Press, 2013), 419–456.

Jones, Leroy P., "The Measurement of Hirschmanian Linkages," *Quarterly Journal of Economics*, 90 (1976), 323–333.

Kikkawa, Ayumu Ken, Glenn Magerman, and Emmanuel Dhyne, "Imperfect Competition and the Transmission of Shocks: The Network Matters," Technical Report, 2017.

Kim, Eun Mee, *Big Business, Strong State: Collusion and Conflict in South Korean Development, 1960–1990* (Albany: State University of New York Press, 1997).

Krueger, Anne O., "Government Failures in Development," *Journal of Economic Perspectives*, 4 (1990), 9–23.

Kuo, Shirley W. Y., *The Taiwan Economy in Transition* (Boulder, CO: Westview, 1983).

Lal, Deepak, *The Poverty of "Development Economics"* (Cambridge, MA: MIT Press, 2000).

Lane, Nathaniel, "Manufacturing Revolutions: Industrial Policy and Networks in South Korea," Technical Report, 2017.

Li, Kwoh-ting, and Tzong-Shian Yu, "*Experiences and Lessons of Economic Development in Taiwan*" (Taipei: Academic Sinica, 1982).

Li, Xi, Xuewen Liu, and Yong Wang, "A Model of China's State Capitalism," HKUST IEMS Working Paper, 2015.

Liu, Ernest, "Replication Data for: 'Industrial Policies in Production Networks'," (2019), Harvard Dataverse, doi:10.7910/DVN/MIWUVM.

Long, John B., and Charles I. Plosser, "Real Business Cycles," *Journal of Political Economy*, 91 (1983), 39–69.

Midrigan, Virgiliu, and Daniel Yi Xu, "Finance and Misallocation: Evidence from Plant-Level Data," *American Economic Review*, 104 (2014), 422–458.

Ministry of Finance, P. R. China, "*P.R.China Corporate Income Tax Law: Public Notice*" (2008).

Oberfield, Ezra, "A Theory of Input-Output Architecture," *Econometrica*, 86 (2018), 559–589.

Pack, Howard, and Kamal Saggi, "The Case for Industrial Policy: A Critical Survey (English)," World Bank Policy, Research Working Paper no. 3839, 2006.
Rajan, Raghuram G., and Luigi Zingales, "Financial Dependence and Growth," *American Economic Review*, 88 (1998), 559–586.
Redding, Stephen J., and Esteban Rossi-Hansberg, "Quantitative Spatial Economics," *Annual Review of Economics*, 9 (2017), 21–58.
Restuccia, Diego, and Richard Rogerson, "Policy Distortions and Aggregate Productivity with Heterogeneous Establishments," *Review of Economic Dynamics*, 11 (2008), 707–720.
Riedel, James, Jing Jin, and Jian Gao, *How China Grows: Investment, Finance, and Reform* (Princeton, NJ: Princeton University Press, 2007).
Rodrik, Dani, "Normalizing Industrial Policy," Commission on Growth and Development Working Paper no. 3, 2008.
Rodrik, Dani, and World Bank, "Goodbye Washington Consensus, Hello Washington Confusion? A Review of the World Bank's 'Economic Growth in the 1990s: Learning from a Decade of Reform'," *Journal of Economic Literature*, 44 (2006), 973–987.
Rosenstein-Rodan, P. N., "Problems of Industrialisation of Eastern and South-Eastern Europe," *Economic Journal*, 53 (1943), 202–211.
Rotemberg, Martin, "Equilibrium Effects of Firm Subsidies," Technical Report, 2018.
Shea, John, "Complementarities and Comovements," *Journal of Money, Credit and Banking*, 34 (2002), 412–433.
Song, Zheng, Kjetil Storesletten, and Fabrizio Zilibotti, "Growing Like China," *American Economic Review*, 101 (2011), 196–233.
State Development Planning Commission of China, *Strategy for Chinese Pillar Industries* (1995).
United Nations Department of Economic and Social Affairs, *Handbook of Input-Output Table Compilation and Analysis* (1999).
Williamson, John, "*Latin American Adjustment: How Much Has It Happened?*" (Washington, DC: Peterson Institute for International Economics, 1990).
———, "What Should the World Bank Think about the Washington Consensus?," *World Bank Research Observer*, 15 (2000), 251–264.
Yang, Ya-Hwei, "Government Policy and Strategic Industries: The Case of Taiwan," in *Trade and Protectionism*, Takatoshi Ito and Anne O. Krueger, eds. (Chicago: University of Chicago Press, 1993), 387–411.