Industrial Policies in Production Networks*

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Abstract

Many developing countries adopt industrial policies favoring selected sectors. Is there an economic logic to this type of industrial policy? I answer this question by characterizing industrial policy in production networks. Market imperfections compound through backward demand linkages, causing largest size distortions in upstream sectors. My key finding is that the distortion in sectoral size is a nonparametric 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, aggregate effects of sectoral interventions can be simply summarized by the cross-sector covariance between my sufficient statistic and policy spendings. My sufficient statistic predicts sectoral policies in South Korea in the 1970s and in modern-day China, suggesting that interventions might have generated positive aggregate effects in these economies.

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One of the oldest problems in economics is understanding how industrial policies can facilitate economic development. What is industrial policy? Broadly speaking, it is purposeful government intervention to selectively promote economic sectors. Industrial policies have been prominently adopted in many currently and formerly developing economies: Japan from the 1950s to 1970s, South Korea and Taiwan from the 1960s to 1980s, and modern-day China.

By their nature, these policies seek to affect the aggregate economy by targeting a few sectors; hence, cross-sector linkages are important considerations (Hirschman (1958)). Loose economic reasoning suggests that it may be advantageous to subsidize or promote the development of sectors thought to serve as backbones of the economy—natural resource production, iron and steel industries, etc. Indeed, this appears to be part of the strategy taken by countries implementing such policies, as public documents from these interventionist governments often explicitly state “network linkages” as a criterion for choosing sectors to promote.1

Despite their widespread use and loosely supporting intuition, economists have only a limited understanding of the forms these policies should take. Could there be an economic rationale behind these sectoral interventions? In this paper, I build on the production networks literature and provide the first formal analysis of industrial policy in the presence of cross-sector linkages and market imperfections. My key finding is that effects of market imperfections accumulate through what I call “backward demand linkages”, causing certain sectors to become the sink of distortions and thereby creating an incentive for well-meaning governments to subsidize them. The sectors in which distortions accumulate are typically designated in the networks literature as “upstream,” meaning they supply to many other sectors and use few inputs from other sectors. In the data, this notion corresponds with the same sectors policymakers seem to view as important targets for intervention.

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

Consider a government that selectively intervenes and subsidizes sectoral production. Which sector should be promoted first? The answer is nontrivial because distortionary effects of imperfections compound and accumulate over input-output linkages, and, therefore, subsidizing the most distorted sector might not improve efficiency.

My first result shows that interventions can be guided by a simple measure. I call this measure “distortion centrality”, and it is defined as the ratio between a sector’s influence and Domar weight; the former is an elasticity-based centrality measure of sectoral importance, and the latter is an expenditure-based measure of equilibrium sectoral size. Distortion centrality guides interventions because, starting from a decentralized, no-intervention economy, it is a nonparametric sufficient statistic for the marginal social value of public funds spent in each sector. The measure encapsulates general equilibrium effects of interventions and can be seen as a fiscal multiplier; a well-meaning government should prioritize funds towards sectors with high distortion centrality.

The intuition is as follows. Influence, the elasticity-based measure, captures the effect on output if resources in a sector proportionally expands; it can be seen as the value of sectoral resources under optimal production (Hulten (1978)). On the other hand, Domar weight, which captures the equilibrium value of sectoral resources, measures the proportional cost of expanding sectoral production. Their ratio—distortion centrality—therefore measures the distance between a sector’s optimal and equilibrium sizes and encapsulates the aggregate gains per unit of policy expenditure.

In an efficient economy, distortion centrality is identically one, and there is no role for intervention. With market imperfections, as I show, distortion centrality averages to one across sectors, thus uniformly promoting all sectors also generates no aggregate gains. Effective interventions have to disproportionately allocate public funds to sectors of 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 public spending per value-added. This formula enables nonparametric evaluation of aggregate policy effects using simple regressions.

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

In a general production network, distortion centrality depends on market imperfections in every sector of the economy, the estimation of which is a challenging task. Indeed, a leading criticism of industrial policies is that it is impossible for governments to identify market imperfections (Pack and
Yet, precisely because distortions backwardly accumulate, I show that if the network follows a “hierarchical” structure, then distortion centrality is insensitive to underlying imperfections. Loosely speaking, a hierarchical structure holds when *upstreamness* can be unambiguously defined, so that upstream sectors supply more strongly to other relatively upstream sectors. In such networks, distortion centrality tends to align with upstreamness, and, to first order, it is unnecessary to precisely estimate market imperfections in order to design welfare-improving interventions.

I apply my theoretical insights and empirically examine the input-output structures of South Korea during the 1970s and modern-day China, as these are two of the most salient economies with interventionist governments that actively implement industrial policies. I first show that, in these economies, productive sectors closely follow a hierarchical structure, and my theory suggests that distortion centrality should be insensitive to underlying market imperfections. To empirically verify this, I estimate market imperfections using a variety of strategies, based on which I then compute the corresponding distortion centrality. These strategies come with various pros and cons and require distinct assumptions; the goal here is to push against data constraints in as many directions as possible. To complement the estimated strategies, I also randomly simulate distortions from a wide range of distributions. My results show that distortion centrality is almost perfectly correlated across all specifications, thereby validating my theory that sectoral distortion centrality is largely driven by the network structure in these economies and are insensitive to underlying distortions.

Lastly, I examine sectoral interventions in these economies. I show that the sectors promoted by South Korea in the 1970s—the heavy and chemical manufacturing sectors—are upstream and have significantly higher distortion centrality than non-targeted sectors. In modern-day China, non-state-owned firms in sectors of higher distortion centrality have significantly better access to loans, face more favorable interest rates, and pay lower taxes; these sectors also tend to have more state-owned enterprises, to which the government directly extends substantial credit and subsidies. These patterns survive after controlling for a host of other potential, non-network motives for state intervention. My quantitative formula reveals that in China, differential sectoral interest rates, tax incentives, and funds given to state-owned firms altogether improve aggregate efficiency by between 2% and 6%.

To be clear, my findings by no means suggest that policies adopted by these economies were optimal, as my main results capture only first-order effects of interventions. Nor am I able to speculate about the decision process behind the adoption of these policies, as my model abstracts away from practical aspects of policy implementation as well as various political economy factors that affect policy choices in these economies. Nevertheless, the predominant view among economists is that industrial policies tend to generate resource misallocations and do harm to developing economies (e.g., see Krueger (1990), Lal (2000), Williamson (1990, 2000), and survey by Rodrik (2006)); yet, my findings show that there may be an *economic* rationale behind certain aspects of Korean and
Chinese industrial strategy, and these policies might have generated positive network effects.

Methodologically, my paper sits in the production networks literature, including Hulten (1978), Long and Plosser (1983), Horvath (1998), Basu and Fernald (2002), Horvath (2000), Dupor (1999), Shea (2002), Acemoglu et al. (2012), Petrin and Levinsohn (2012), Acemoglu et al. (2016, 2017), Atalay (2017), Oberfield (2018), Baqee and Farhi (2018a), among others. Particularly related to my theoretical results are papers that study theoretical properties of generic distortions in networks, including Jones (2011, 2013), Bigio and La’O (2016), and more recently, Baqee and Farhi (2018b); other papers in the fast-growing literature on distorted networks include Bartelme and Gorodnichenko (2015), Altinoglu (2017), Baqee (2016), Boehm (2017), Caliendo et al. (2017), Grassi (2017), Boehm and Oberfield (2018).\footnote{The presence of distortions implies that sectoral influence is decoupled from Domar weights in these papers. To the best of my knowledge, mine is the first paper to analyze policy interventions in distorted networks, and my theoretical contribution starts with the discovery that, by modeling distortions payments as deadweight losses, the ratio between influence and Domar weights—i.e. what I call “distortion centrality”—is a nonparametric and ex-ante sufficient statistic that guides intervention. How this technical result fits into the literature will be discussed in detail later. Building on the sufficient statistic result, I characterize how network structures shape distortion centrality and show that upstream sectors should be promoted first as they tend to have high distortion centrality. Furthermore, I provide formulas that summarize aggregate, general equilibrium effects of sectoral interventions into simple covariances and regression coefficients, providing handles for empirical applications.}

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The literature on industrial policies dates back to Rosenstein-Rodan (1943) and Hirschman (1958). In the modern literature, Itskholdi and Moll (2018) study optimal Ramsey policies in a multi-sector growth model with financial frictions; the paper does not consider input-output linkages, which is 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. Using the difference-in-difference approach, he finds that sectors downstream of promoted ones experienced positive spillovers. My empirical exercise on South Korea is complementary to Lane (2017)’s: rather than focusing on the spillovers from one sector to another, I analyze the aggregate, general equilibrium effects of interventions on the entire economy. The first-order nature of my nonparametric policy results relate to an older literature on marginal policy reforms, though in a different context of commodity taxation, including Hatta (1977), Ahmad and Stern (1984), Deaton (1987), Ahmad and Stern (1991), Dixit (1985). Other important references in the vast literature on industrial policies include Chenery et al. (1986), Amsden (1989), Murphy et al. (1989), Krueger (1990), Wade (1990), Westphal (1990),

\footnote{There is also a large urban and international trade literature that feature input-output linkages or production networks; see, for instance, di Giovanni and Levchenko (2010), Antras et al. (2012), Chaney (2014), Caliendo and Parro (2015), Carvalho et al. (2016), Antras and de Gortari (2017), Kikkawa et al. (2017), Redding and Rossi-Hansberg (2017), Auer et al. (2018).}

My empirical exercise on China relates to Song et al. (2011), who study, through the lens of a growth model with financial frictions, the reallocations between state-owned enterprises and private firms during China’s recent economic transition. Also related is Aghion et al. (2015), who show Chinese industrial policy increases productivity growth by fostering competition. My analysis is complementary to these other papers, as I show that, once input-output linkages are taken into consideration, sectoral interventions in modern-day China might have generated positive aggregate, general equilibrium effects. More broadly, my paper relates to a large literature on the aggregate implications of micro distortions, including the seminal work of Restuccia and Rogerson (2008), Hsieh and Klenow (2009), and other important work such as Hopenhayn and Rogerson (1993), Banerjee and Duflo (2005), Brandt and Rawski (2008), Banerjee and Moll (2010), Buera et al. (2011), Xiaodong (2012), Oberfield (2013), Song et al. (2014), Midrigan and Xu (2014), Storesletten and Zilibotti (2014), Li et al. (2015), Buera and Moll (2015), Buera et al. (2015), Edmond et al. (2015), Rotemberg (2017), Cheremukhin et al. (2017b,a), among many others.

1 Model

There is a composite production factor \( L \) in fixed supply and a numeraire consumption good that is endogenously produced. There are \( S \) 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

\[
Y^G = \mathcal{F}(Y_1, \cdots, Y_S),
\]

where \( Y_i \) is the intermediate good \( i \) used for consumption. Intermediate good \( i \) is produced by

\[
Q_i = z_i F_i \left( L_i, \{M_{ij}\}_{j=1}^S \right),
\]

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

Market Imperfections and Policy Interventions

The economy has two distinct deviations from a first-best environment: market imperfections and policy interventions. Market imperfections represent inefficient features of the economic environment. Relative to the first-best, these features distort intermediate production and generate deadweight losses. They can represent transaction costs such as financial and contracting frictions; they can also arise from production externalities and non-competitive conduct. Importantly, market imperfections
do not represent government taxes or subsidies. Policy interventions are separately modeled as production subsidies, and the goal of my theoretical analysis is to analyze how policy interventions affect aggregate efficiency, taking market imperfections as given.

Motivated by well-documented evidence of financial frictions in developing economies as well as the prominent role of credit market interventions in industrial policy episodes, I use financial frictions as my running narrative for market imperfections. The microfoundation induces a “wedge” representation that nests various other forms of imperfections.

Financial Frictions and Producer Problem  Financial frictions take the form of working capital requirements on intermediate transactions. Specifically, orders for intermediate inputs have to be placed before production and, to prevent hold-up, seller \( j \) requires buyer \( i \) to pay \( \delta_{ij} \geq 0 \) fraction of transactional value upfront, in the form of working capital. Producer \( i \) borrows working capital loans \( \Gamma_i \) from a lender at interest rate \( r_i \), solving the following profit maximization problem:

\[
\max_{\Gamma_i, L_i, \{M_{ij}\}_{j=1}^S} \quad P_i \left( L_i, \{M_{ij}\}_{j=1}^S \right) - \left( \sum_{j=1}^S \left( 1 - \tau_{ij} \right) P_j M_{ij} + (1 - \tau_{iL}) WL_i + r \Gamma_i \right) \quad \text{s.t.} \quad \sum_{j=1}^S \delta_{ij} P_j M_{ij} \leq \Gamma_i,
\]

where \( P_i \) is the market price of good \( i \) and \( W \) is the factor price. The producer receives government subsidies over production inputs, represented by \( \tau_{ij} \) and \( \tau_{iL} \). On the financial friction side, \( \delta_{ij} P_j M_{ij} \) is the working capital required for input \( j \), and \( r \Gamma_i \) is the total financial costs. Because the producer flexibly chooses how much to borrow, the working capital constraint always binds, and financial costs can be represented by reduced-form proportional wedges \( \chi_{ij} P_j \) to the lender; equilibrium prices solve the cost-minimization:

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

To focus on market imperfections in the network of intermediate goods, I assume the consumption good is produced without financial frictions. Price normalization implies

\[
1 \equiv \min_{\{y_j\}_{j=1}^S} \sum_{j=1}^S P_j y_j \quad \text{s.t.} \quad F \left( y_1, \ldots, y_S \right) = 1. \tag{4}
\]

Lender’s Problem  Issuing working capital is costly to the lender because producers cannot commit to repay and instead have an incentive to default that is increasing in loan size. In order to monitor and enforce repayment, the lender incurs a proportional disutility cost \( \lambda \geq 0 \) for every dollar of loans issued. The lender charges a competitive interest rate \( r = \lambda \) on loans, earning total income \( \Pi \equiv r \sum_{i=1}^S \Gamma_i \) as compensations. He spends the the income on consumption \( (Z = \Pi) \), but he earns zero utility net of monitoring costs.
Government, Consumer, and Markets

Policy interventions are modeled as sector-input-specific production subsidies ($\tau$’s) paid by the government. I later discuss how $\tau$’s can be used to represent other policy instruments, such as a uniform sectoral subsidy, or targeted sectoral credit. Let $B$ denote the total subsidy payments:

$$B \equiv \sum_{i=1}^{S} \left( \sum_{j=1}^{S} \tau_{ij}p_{j}m_{ij} + \tau_{il}w_{l} \right).$$

(5)

Besides policy interventions, the government also has real expenditures $G$, which represents public consumption. To balance its budget, the government charges lump-sum taxes $T$ from the consumer:

$$G + B = T.$$  
(Government Budget Constraint)

(6)

The representative consumer spends his post-tax factor income on private consumption $C$:

$$C = WL - T.$$  
(Consumer Budget Constraint)

(7)

Gross output of the consumption good equals the sum of private, public, and lender’s consumption:

$$Y^{G} = C + G + Z.$$

The market clearing condition for factor and intermediate goods are, respectively,

$$L = \sum_{i=1}^{S} L_{i}; \quad Q_{j} = Y_{j} + \sum_{i}^{S} M_{ij} \text{ for all } j = 1, \cdots, S.$$

(8)

Equilibrium Definition

Since the equilibrium interest rate is always equal to the monitoring cost ($r = \lambda$), I can redefine the reduced-form wedges as model primitives: $\delta_{i} \equiv \lambda \delta_{i} \geq 0$. Lender’s interest earnings can be written as

$$\Pi \equiv \sum_{i,j=1}^{S} \delta_{ij}p_{i}M_{ij}.$$

(9)

The lender spends his entire income to buy consumption ($Z = \Pi$), but he always earns zero utility net of monitoring costs. The interest earnings are therefore quasi-rents (as opposed to pure rents), and lender’s consumption can be equivalently interpreted as deadweight losses that leave the economy. For this reason, I refer to the sum of private and public consumption $Y \equiv C + G$ as “aggregate consumption” or “net output”, i.e. gross output net of financial costs. The market clearing condition for
the consumption good implies
\[ Y^G - \Pi = Y \equiv C + G. \]  
(10)

The national income accounting identity can be obtained by substituting government and consumer budget constraints (6 and 7) into (10):
\[ Y = WL - B. \]  
(11)

The identity states that net output—the sum of private and public consumption—can be written as the difference between factor income and total subsidies paid by the government.

I define equilibrium based on these conditions, treating reduced-form wedges \( \chi \) as primitives of the environment. I refer to \( \chi \)'s as “distortions”, \( \Pi \) as “distortion payments”, and \( \tau \)'s as “subsidies”.

**Definition 1.** Given productivities \( z_i \), distortions \( \chi_{ij} \), 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 \( T \), distortion payments \( \Pi \), and subsidy expenditure \( B \), such that prices solve the system of fixed point problem in (3) and (4); allocations satisfy the production functions in (1) and (2); government and consumer budget constraints (6) and (7) are satisfied; markets clear for the consumption good as in (10) and for the factor and intermediate goods as in (8).

I highlight two features of the distortion wedges \( \chi \): 1) they distort prices; 2) payments associated with these distortions are deadweight losses that leave the economy through the consumption good. In Appendix A.2, I show that distortion wedges with these features can be microfounded by a variety of other imperfections besides financial frictions, including contracting frictions, monopoly markups, and production externalities. Note, the second feature distinguishes distortions \( \chi \) from subsidies \( \tau \), as the latter only affect prices and do not directly bring resources into or out of the economy.\(^3\) Also, even though \( \chi \)'s generate deadweight losses, they behave distinctly from iceberg trade costs. The latter does not generate misallocations, whereas \( \chi \)'s create allocative inefficiency through pecuniary externalities, since the quantity loss of the consumption good depends on relative prices of intermediate goods. This distinction is explicitly characterized in section 2.4.3.

**Notations for the Rest of the Paper**

Throughout the paper, I refer to the economy with neither distortions nor subsidies as “efficient”. I refer to the economy with market imperfections but without any government interventions (\( \tau \equiv 0 \)) as “decentralized”. The decentralized economy serves as an important benchmark; my nonparametric policy results below are derived relative to this benchmark.

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\(^3\) Absent policy interventions, my model is a nonparametric production network with generic distortion wedges. The mathematical treatment of wedges is variegated in the literature. Jones (2013), Bigio and La’O (2016), and Baqae and Farhi (2018b) model wedges payments as pure economic rents that are rebated back to the consumer; distortion payments in Baqae (2016), Boehm and Oberfield (2018), and Caliendo et al. (2017) are deadweight losses that leave the economy. I adopt the deadweight-loss assumption, the mathematical role of which will be discussed later.
I introduce notations to capture several reduced-form objects in an equilibrium. Let $\Sigma = [\sigma_{ij}]$ be the $S \times S$ equilibrium elasticity matrix of the intermediate sectors, and let $\Omega = [\omega_{ij}] = [p_j M_{ij}/p_i Q_i]$ be the $S \times S$ matrix of sectoral expenditure shares. I similarly define $\sigma_L = [\sigma_{iL}]$ and $\omega_L = [\omega_{iL}]$ as the elasticity and expenditure share vector of the factor input. In equilibrium, $(1 + \chi_i - \tau_{ij}) \omega_{ij} = \sigma_{ij}$ for intermediate inputs and $(1 - \tau_{iL}) \omega_{iL} = \sigma_{iL}$ for the factor.

Let $\beta$ be the $S \times 1$ expenditure share for aggregating the consumption good, $\beta_j = p_j Y_j / \sum_i p_i Y_i$.

**Definition 2.** The influence $\mu_i$ of each sector follow $\mu' = \beta' (1 - \Sigma)^{-1}$.

**Definition 3.** The Domar weight of a sector is $\gamma_i = P_i Q_i / W L$.

Influence is an elasticity-based centrality measure of sectoral importance (the definition follows from Acemoglu et al. (2012)). Domar weight is an expenditure-share based centrality measure measure of equilibrium sectoral size, measuring the value of production resources in each sector relative to total factor payments in the economy; it can be expressed in vector form as $\gamma' = \beta' (I - \Omega)^{-1} \omega_L$. Both influence and Domar weights are reduced-form objects that describe the local equilibrium. The two measures coincide in an efficient economy ($\mu = \gamma$) but differ in distorted economies.

The ratio between influence and Domar weight is the key object of this paper.

**Definition 4.** Distortion centrality $\xi_i$ of sector $i$ is the ratio between its influence and Domar weight:

$$\xi_i = \mu_i / \gamma_i.$$

The rest of my paper illustrates the economic significance of distortion centrality. Section 2 shows why policymakers should subsidize sectors with higher $\xi$, and section 3 shows how $\xi$ depends on network structure and why it tends to be higher in upstream sectors. Section 4 are empirical applications, where I measure distortion centrality in the data, show it predicts sectoral interventions in South Korea and China, and quantify the aggregate impact of interventions. All proofs are in Appendix B.

## 2 Theory: Distortion Centrality and Industrial Policies

The decentralized economy is inefficient in the presence of market imperfections. How to design industrial policies and improve aggregate efficiency? This section provides several results that highlight the importance of distortion centrality for policy design. Proposition 1 shows that sectors with high distortion centrality should be promoted first, because the measure is a nonparametric sufficient statistic for the social value of policy expenditure and captures the “bang-for-the-buck” of government spendings. Propositions 2 and 3 present simple formulas for policy evaluations and counterfactuals, that the aggregate impact of interventions can be nonparametrically assessed by a simple regression of

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4The expression follows from the system of market clearing conditions; see derivations in Appendix B. The denominator $\beta' (I - \Omega)^{-1} \omega_L$ is equal to one in an efficient economy.
sectoral spendings on distortion centrality. Proposition 4 shows that under Cobb-Douglas assumption, distortion centrality is a sufficient statistic for constrained-optimal subsidies to the factor input.

My main propositions build on two simple lemmas. The first characterizes how factor income responds to economic shocks; it is a building block for understanding how policy affects allocations.

**Lemma 1.** 1. Influence is a sufficient statistic for the elasticity of factor income to productivity shocks:

\[
\left[ \frac{d \ln WL}{d \ln z_i} \right]_{i=1,\ldots,S} = \mu'.
\]

2. The elasticity of factor income with respect to distortions and subsidies in sector \(i\) is

\[
\frac{d \ln WL}{d \ln (1-\tau_{ij}+\chi_{ij})} = -\mu_i \cdot \sigma_{ij} \text{ for } j = 1, \ldots, S, L.
\]

Productivity shock \(z_i\) directly lowers the cost of good \(i\) and indirectly affects other prices through production linkages. The lemma shows that influence is a sufficient statistic for the impact of Hicks-neutral shocks \(z_i\) on factor income, as the measure summarizes general equilibrium price effects through the Leontief-inverse of the elasticity matrix, \((I-\Sigma)^{-1}\). The result also shows that subsidies and distortions affect factor income similarly to input-biased productivity shocks.

The property, that local elasticities are nonparametric sufficient statistics for the response of factor income, holds in both efficient and inefficient economies and applies to all equilibrium prices (see Appendix B). It is a manifestation of the envelope theorem: under cost-minimization, changes in elasticities \((d\Sigma)\) have only second-order impact on prices.

In contrast, the property does not extend to allocations, the response of which generically depends not only on elasticities \((\Sigma)\) but also on the changes in elasticities \((d\Sigma)\). This highlights precisely the difficulty with industrial policy design: the allocative impact of policy interventions cannot be ex-ante predicted based on reduced-form elasticities in the local equilibrium, but instead depends on structural features of the economy that govern how elasticities change in response to interventions. Hence, in order to evaluate policies in a production network, one generically has to impose parametric assumptions on production functions across all sectors of the economy.\(^5\)

\(^5\)Lemma 1 relates to the result of Hulten (1978), that, in efficient economies, elasticity of output can be summarized by Domar weights. Hulten’s theorem fails in inefficient economies for two distinct reasons: 1) output is different from factor payments; 2) influence differs from Domar weights. The second reason is well-known in the literature, but the first reason is less appreciated. For instance, Jones (2013) and Bigio and La’O (2016) analyze Cobb-Douglas networks, rebating distortion payments back to the consumer. The aggregate output in their papers is thus equivalent to the gross output in mine, \(Y^G = Y + \Pi\). These papers show \(\frac{d \ln Y^G}{d \ln z_i} = \mu_i \neq \gamma_i\). However, the equality sign depends on the Cobb-Douglas assumption and does not generically hold. Lemma 1 establishes, generically, the equality sign in the following:

\[
\frac{d \ln Y^G}{d \ln z_i} \neq \frac{d \ln Y}{d \ln z_i} \neq \frac{d \ln WL}{d \ln z_i} = \mu_i \neq \gamma_i.
\]
The next lemma partly circumvents this difficulty and demonstrates a way in which aggregate policy impact on \( Y \) can be nonparametrically characterized by local equilibrium objects. First, note the income accounting identity \( Y = WL - B \) (equation 11) links aggregate consumption to factor income and subsidy payments. Lemma 1 shows the policy response of \( WL \); the policy response of \( B \) follows

\[
\frac{dB}{d\tau_{ij}} = P_jM_{ij} + \sum_{k,n=1}^S \tau_{kn} \frac{d(P_nM_{kn})}{d\tau_{ij}} + \sum_{k=1}^S \tau_{kL} \frac{dWL_k}{d\tau_{ij}}.
\]

Subsidy \( \tau_{ij} \) expands targeted input and directly raises policy expenditure. The intervention also induces reallocations, causing firms in all sectors to adjust inputs. This leads to endogenous changes in the network structure, which then interact with existing subsidies and indirectly affect \( B \). Such indirect effects are the source of difficulty for policy design, as they cannot be nonparametrically characterized and depend on structural features of production technologies. In the decentralized economy, however, existing subsidies are zero, and the effects from endogenous network changes are second-order.

**Lemma 2.** In the decentralized economy, the effect of subsidies on aggregate consumption \( Y \) is

\[
\left. \frac{d\ln Y}{d\tau_{ij}} \right|_{\tau=0} = \omega_{ij} (\mu_i - \gamma_i) \quad \text{for } j = 1, \ldots, S, L.
\]

Lemma 2 nonparametrically summarizes the marginal impact of policy subsidies on aggregate consumption \( Y \), starting from the decentralized economy. On the one hand, subsidies raise factor income in ways similar to input-biased productivity shocks, the effect of which scales with the influence \( \mu_i \) of the targeted sector, as shown by Lemma 1. On the other hand, subsidies cost resources to the government, and in the decentralized economy, their first-order impact on government budget scales with sectoral Domar weight \( \gamma_i \). The distance between influence and Domar weight therefore scales with the efficiency gains of redirecting resources into the targeted sector.

Subsidies affect allocations by redistributing resources across sectors. Absent market imperfections, influence coincides with Domar weights \( \mu = \gamma \), and policy interventions have no first-order impact on net output—a manifestation of the First Welfare Theorem. In distorted economies, however, interventions can have first-order effects, as Lemma 2 attests. The main propositions of this paper, which I turn to now, highlight the economic implications of Lemma 2.\(^6\)

\(^6\)In recent work, Baqae and Farhi (2018b) study production networks with distortions \( \Pi \) rebated to consumers. The paper provides parametric, ex-ante formulas for how \( Y^\Pi = Y + \Pi \) responds to shocks under CES assumptions; it also provides nonparametric, ex-post accounting formulas, requiring elasticities to be observed from both before- and after-shock economies. In contrary, by modeling distortion payments as deadweight losses and focusing on \( Y \) as the aggregate outcome, Lemma 2—and my subsequent propositions—are nonparametric and ex-ante results, enabling one to compute policy counterfactuals using only reduced-form objects from the pre-intervention economy.
2.1 Social Value of Policy Expenditures and Nonparametric Counterfactuals

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

Aggregate consumption $Y$ is the sum of private and public consumption, $C$ and $G$, which respectively satisfy the consumer and government budget constraints (7 and 6, reproduced below):

$$C = WL - T.$$

consumer budget constraint

$$G + B = T.$$

government budget constraint

Now consider the trade-off between private and public consumption, as subsidies vary, while holding constant lump-sum tax $T$. In this case, subsidies raise factor income, thereby raising private consumption ($dC/d\tau_{ij} = dWL/d\tau_{ij}$). To finance the subsidy, the government cuts back public consumption in order to balance its budget ($dG/d\tau_{ij} = -dB/d\tau_{ij}$). The following definition captures the marginal rate of transformation between private and public consumption through policy subsidies.

**Definition 5.** In the decentralized economy, the social value of policy expenditure on $\tau_{ij}$ is

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

**Proposition 1.** Distortion centrality is a sufficient statistic for the social value of policy expenditure:

$$SV_{ij} = \xi_i \quad \text{for } j = 1, \cdots, S, L.$$

The social value of policy expenditure measures the gain in private consumption per unit reduction of public consumption, or “bang-for-the-buck” of government spendings, on subsidy $\tau_{ij}$. It is informative for policy design because it is a general equilibrium spending multiplier. Ceteris paribus, a benevolent government who trades off private and public consumption should prioritize subsidies to sectors with the highest social value. Proposition 1 shows that distortion centrality is a sufficient statistic for the social value of policy expenditure in the decentralized economy. This is intuitive in light of the preceding discussions: while influence captures the marginal benefits of subsidies accrued to the consumer through an increase in factor income, the marginal costs of subsidies—the impact on government’s budget and thus the reduction in public consumption—are captured by Domar weights. Their ratio, i.e. distortion centrality, therefore captures the bang-for-the-buck of policy spendings.

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

Consider multiple and simultaneously adopted subsidies. Let $s_i$ be the hypothetical policy spendings per value-added in sector $i$, evaluated using prices and quantities in the decentralized economy:

$$s_i \equiv \left( \sum_{j=1}^{S} \tau_{ij} P_j M_{ij} + \tau_{ii} W_L \right) \left( W_L i \right) \left[ P_j M_{ij}, W_L \right] \text{evaluated under } \tau \neq 0.$$

**Proposition 2.** Distortion centrality averages to one: $\mathbb{E} [\xi] = 1$. Furthermore, starting from the decentralized economy, the proportional gain in net output is, to first-order, the covariance between distortion centrality and sectoral policy spending per value-added:

$$\frac{\Delta Y}{Y} \approx Cov(\xi, s)$$

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

The result shows that distortion centrality averages to one; hence, promoting sectors uniformly—with constant sectoral policy expenditure per-value-added—does not affect aggregate consumption. This is because subsidies do not directly counteract deadweight losses but affect allocations only through redistributing resources. Uniform intervention does not redistribute resources and is equivalent to a lump-sum transfer from the government to the consumer, generating zero net effect on the sum of private and public consumption.

Even though distortion centrality always averages to one, its range and cross-sector variance depends on the magnitude of underlying distortions. Intuitively, when distortions are small in the economy, allocations are close to the first-best, and distortion centrality is close to one in all sectors. Conversely, severe imperfections lead to significant cross-sector dispersion in distortion centrality.

Proposition 2 further provides a succinct and quantitative formula for the first-order, general equilibrium impact of selective interventions. For a policy program to be effective in aggregate, subsidy expenditures have to positively selected towards sectors with high distortion centrality, and sectors with low distortion centrality should be taxed. The covariance formula is *nonparametric* and *ex-ante*: it predicts the impact of interventions entirely based on reduced-form, pre-intervention objects in the decentralized economy, without having to impose structural assumptions on production technologies.

Proposition 2 therefore enables econometricians and policymakers to compute nonparametric policy counterfactuals and 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 aggregate effect of interventions. That promoted industries utilize more resources and pay lower prices or interest rates is evidence of interventions at work—that funds are not entirely siphoned off into pockets of bureaucrats—and is not a telltale sign of policy failure; conversely, that promoted sectors expand production is not evidence for policy success. To evaluate policies, the important question to ask is the counterfactual, “what would have happened in aggregate, absent these interventions”. The answer inevitably hinges on general equilibrium, reallocative effects, which before-after studies are silent about.

In section 4, I apply these results to evaluate industrial policies in South Korea in the 1970s and in modern-day China. The following result is a simple corollary of Proposition 2, and it is especially relevant for my empirical applications later. Let \( sd(\xi) \) be the standard deviation of distortion centrality, where the \( sd(\cdot) \) operator uses relative sectoral value-added as the distribution.\(^7\) Let \( \bar{\xi}_i \equiv \xi_i / sd(\xi) \) be the standardized distortion centrality measure with unit variance.

**Proposition 3.** Consider the weighted bivariate regression of sectoral spending-per-value-added \( s_i \) on the standardized distortion centrality measure \( \bar{\xi}_i \):

\[
s_i = \alpha + \beta \cdot \bar{\xi}_i + \epsilon_i,
\]

where each observation is a sector and is weighted by its value-added, and \( \epsilon \perp \bar{\xi} \). The product, between the slope coefficient \( \beta \) and the standard deviation of distortion centrality \( \sigma \), captures, to first-order, the proportional gain in aggregate consumption due to cross-sector interventions \( \{s_i\} \):

\[
\frac{\Delta Y}{Y} \approx \beta \cdot sd(\xi).
\]

The result states the bivariate regression, of policy spendings on distortion centrality, is informative for aggregate effects of interventions. The formula is intuitive: higher \( \beta \) indicates better sectoral targeting and more policy expenditures in sectors with high distortion centrality; higher \( sd \) indicates more dispersion in distortion centrality (due to higher underlying distortions in the economy), thus greater scope for welfare-improving policies. Note, the residual term \( \epsilon_i \) captures the component of policy spendings that is orthogonal to distortion centrality; hence, conditioning on \( \beta \) and \( sd \), the variance of \( \epsilon_i \) and \( R^2 \) of the bivariate regression are not informative for first-order aggregate effects.

**Distortion Centrality and Other Measures**

Standard intuitions might suggest that, to improve efficiency, subsidies should be given to sectors that are most distorted. This intuition is incomplete because it ignores input-output linkages, along

\(^7\)That is, \( sd(\xi) = \sqrt{\text{Var}[\xi]} \) and \( \text{Var}[\xi] = E[\xi^2] - E[\xi]^2 = \sum \frac{\xi_i^2}{L} - (\sum \frac{\xi_i}{L})^2 \).
which sectoral distortions accumulate and compound into distortion centrality. Alternatively, one might also believe, based on Lemma 1 and the result of Hulten (1978), that the government should prioritize subsidies to influential or large sectors. My results show that these intuitions are also incomplete. While influence captures the effect of subsidies on factor income—similar to the effect of productivity shocks—it misses the fiscal costs of subsidies. Subsidies—unlike productivity shocks, which do not cost resources—affect allocations by redistributing resources; therefore, it is crucially important to include costs of subsidies into policy calculations. Targeting sectors by influence only considers benefits while targeting by size considers only costs, and neither intuition is complete. To better prioritize subsidies to influential or large sectors. My results show that these intuitions are also incomplete.

The distinctions between distortion centrality and these other measures are substantive, as promoting large, influential, or very distorted sectors can in fact lead to aggregate losses. To better understand why distortion centrality guides policy and how it relates to those other measures, I first turn to a simple example. Later in section 4, I also empirically demonstrate that distortion centrality differ substantially with these other measures in real-world networks.

2.2 Example: A Vertical Production Network

Three intermediate production sectors form a vertically connected network as shown in the figure below. Upstream good 1 is produced linearly from the factor input; midstream good 2 is produced from factor and good 1; downstream good 3 is produced from factor and good 2. The downstream good directly transforms into the consumption good (the final sector is omitted from the figure). Producers $i = 2, 3$ face financial distortions $\chi_i > 0$ when purchasing intermediate good $(i - 1)$.

\[
\begin{aligned}
&\text{Production Functions} \\
&Q_1 = L_1 \\
&Q_2 = L_2^{1-\sigma_2} M_2^{\sigma_2} \\
&Q_3 = L_3^{1-\sigma_3} M_3^{\sigma_3} \\
&Y^G = Y_3
\end{aligned}
\]

In the decentralized economy, sectoral influence, Domar weights, and distortion centrality follow\(^8\)

| (Influence)   | $\left(\mu_1, \mu_2, \mu_3\right)$ | $\propto \left(\begin{array}{ccc}
\sigma_2\sigma_3, & \sigma_3, & 1
\end{array}\right)$, |
| (Domar weights)| $\left(\gamma_1, \gamma_2, \gamma_3\right)$ | $\propto \left(\begin{array}{ccc}
\frac{\sigma_2}{(1+\chi_2)}, & \frac{\sigma_3}{(1+\chi_3)}, & 1
\end{array}\right)$, |
| (Distortion Centrality) | $\left(\xi_1, \xi_2, \xi_3\right)$ | $\propto \left(\begin{array}{ccc}
(1+\chi_2)(1+\chi_3), & (1+\chi_3), & 1
\end{array}\right)$, |

\(^8\)All derivations relating to this example are in Appendix A.7.
where $\sigma_i < 1$ is the production elasticity of intermediate input in sector $i$. For notational simplicity, these objects are expressed in proportional terms.

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

I highlight two observations. First, influence and sales are highest in downstream sector 3 and lowest in upstream sector 1. Influence is a measure of sectoral importance and sales is a measure of size; the two coincides absent distortions. Downstream is influential because its productivity shocks raise the value not only for factor inputs in the downstream sector, but, through production linkages, also for those in mid- and upstream sectors; likewise, downstream 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 shocks only benefit its own factor input and because its output constitutes only fractional value of mid- and downstream production.

Second, observe that the sectoral rankings by distortion centrality is unambiguously reversed to that 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 financial frictions in mid- and downstream sectors. This is because distortions accumulate into distortion centrality through *backward demand linkages*. Distortions in downstream sector 3 depress intermediate demand and lower the size of midstream sector relative to its influence; midstream distortions further depress demand for upstream goods, generating compounding effects and leaving upstream with high distortion centrality. In other words, what contribute to distortion centrality are not distortions within a sector itself but are instead distortions in sectors it supplies to, 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 is this sector’s distortion centrality.

**Promoting Upstream Mitigates Misallocations**

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

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

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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 little factor inputs to upstream and—conversely—to too much to downstream. Policy interventions improve efficiency only if they counteract misallocations, redirecting the factor input to the upstream sector.

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

### 2.3 Cobb-Douglas Case: Optimal Subsidies and Misallocations

Now consider constrained optimal (as opposed to marginal) interventions. Constrained optimality is always defined relative to the set of policy instruments $\mathcal{P}$ available to the planner. Given the policy set, optimal interventions to maximize net output is characterized by first-order conditions

$$\frac{dY}{d\tau_{ij}} = \frac{d(WL - B)}{d\tau_{ij}} = 0 \text{ for } \tau_{ij} \in \mathcal{P}.$$  

Away from the decentralized economy, $dY/d\tau_{ij}$ generically depends on parametric structures of production technologies because the network structure changes endogenous in response to policy. I now analyze a knife-edge parametric case: Cobb-Douglas production functions, with policy instruments constrained to be sector-specific subsidies to value-added factor inputs, $\mathcal{P} = \{\tau_{iL}\}_{i=1}^S$. The solution to this case is particularly simple, and it provides additional insights into the role of distortion centrality.

**Proposition 4.** Under Cobb-Douglas, the solution to the planning problem $\arg\max_{\tau_{iL}} \{Y\}$ satisfies

$$\left\{ \frac{1}{1-\tau_{iL}} = \xi_i \right\}_{i=1}^S.$$  

Moreover, $\{\tau_{iL}^*\}_{i=1}^S$ 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 ($\tau_{ij} \notin \{\tau_{iL}\}_{i=1}^S$), the levels of which are implicitly reflected in sectoral Domar weights and hence in distortion centrality.

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

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

Optimal subsidies therefore align distorted allocations to efficient ones ($\frac{\gamma_i}{1 - \tau_{iL}} = \mu_i$). Another interpretation is to consider a fictitious sector that buys the factor and sells to sector $i$, with $\mu_i \sigma_{iL}$ and $\frac{\gamma_i \sigma_{iL}}{1 - \tau_{iL}}$. 

18
respectively represent the influence and Domar weight of this fictitious sector. Proposition 3 states that subsidies should be chosen to align influence with Domar weight.

The intuition, that non-marginal interventions should align with distortion centrality, ignores the budgetary effects due to endogenous network changes. These indirect effects are zero in this particular case because a) elasticities are constant under Cobb-Douglas, and b) value-added subsidies do not affect expenditures shares on intermediate inputs; hence, they affect Domar weights only uniformly, without inducing relative changes across sectors.

As a technical note, the deadweight-loss nature of distortions is inconsequential in the case analyzed by Proposition 4, as constrained-optimal policies that maximize net and gross output \( (Y \text{ and } Y^G = Y + \Pi) \) coincide. To understand this, let \( Y^* \) denote output under first-best:

\[
Y^* > Y^G > Y.
\]

Market imperfections reduce net output \( (Y^* > Y) \) through two channels. The effect of misallocation is captured by \( Y^* - Y^G \); additionally, deadweight losses from distortion payments are reflected by \( Y^G - Y \). Subsidies do not directly counteract deadweight losses; they affect allocations only by re-distributing resources. In the case analyzed by Proposition 4, the network structure is policy-invariant, and \( Y \) is always proportional to \( Y^G \). In Appendix A.7, I analyze other constrained policy instruments under Cobb-Douglas, dealing with endogenous network changes.

2.4 Some Discussions and Extensions

In the next section 3, I analyze how network structure shapes distortion centrality. Before moving on, I pause and briefly discuss several issues and extensions to my results thus far, including how to incorporate within-sector heterogeneity, how my results apply to other policy instruments, as well as distinctions between market imperfections in my model and iceberg trade costs. Formal arguments are in Appendix A, where I also discuss other additional theoretical issues and extensions.

2.4.1 Within-Sector Heterogeneity

My theory concerns sectoral intervention, whereas real-world producers within a narrowly-defined industry classification can be subject to distinct levels of distortions and produce differentiated goods. Let “variety” (index by \( v \)) be the level at which heterogeneity is defined: productivities, distortions, policy instruments, and even production functions can differ across varieties. Ideally, to apply my theory, one would compute distortion centrality at the variety level; nevertheless, under some reasonable conditions, distortion centrality remains sector-specific—rather than variety-specific—and \( \xi_i \) captures the social value of government subsidies to any varieties in sector \( i \) \( (\xi_i(v) = \xi_i) \). I discuss the conditions below, with formal argument presented in Appendix A.1.
The first condition requires the production of each variety to feature constant-returns-to-scale, so that the unit cost of each variety does not depend on output quantities. The second condition is the existence of a constant-returns aggregator $G_i(q_i(\nu))$ which combines varieties within each sector into a homogeneous bundle, so that cross-industry transactions all take place using the same bundle of varieties. Under these conditions, it is without loss of generality to compute sectoral distortion centrality $\xi_i$ using sectoral production data and price indices (which are well-defined given the sectoral aggregators $G_i(\cdot)$), and $\xi_i$ would capture social value of interventions to any varieties within sector $i$.

Note, as a corollary, what matters for calculating aggregate effects of government interventions is the net—not gross—government spending within each sector, as subsidizing one variety by a dollar while taxing another in the same sector by one dollar generates exactly zero aggregate effect on net.

### 2.4.2 Policy Instruments

Propositions 1 through 3 are formulated using input-specific subsidies, but they also apply more broadly to other practical and real-world relevant policy instruments that affect the use of production inputs. For instance, a policy that promotes overall sectoral production is isomorphic to a uniform subsidy applied to all inputs; likewise, under financial frictions, credit market interventions can also be represented by input subsidies. To see the latter, suppose the government subsidizes sectoral interest rates to $(r - u_i)$, paying the difference $u_i$ to the lender out of government budget. The profit-maximization problem of producer $i$ becomes

$$\max_{t_i, Q_i, \{M_{ij}\}_{j=1}^S} P_i Q_i - \left( \sum_{j=1}^S P_j M_{ij} + WL_i + (r - u_i) \Gamma_i \right) \text{ s.t. (2) and } \sum_{j=1}^S \delta_{ij} P_j M_{ij} \leq \Gamma_i,$$

Credit subsidy $u_i$ generates production decisions and policy expenditures that are identical to those induced by the set of simultaneous input subsidies $\{\tau_{ij} = u_i \delta_{ij}\}$, thus Propositions 1 through 3 apply.

### 2.4.3 Market Imperfections ≠ Iceberg Costs

I assume distortion wedges generate deadweight losses ($\chi \geq 0$), consistent with microfoundations I provide in the main text and in Appendix A.2. Despite the deadweight-loss assumption, market imperfections are not isomorphic to iceberg trade costs. While both formulations cost resources and generate identical price effects, they have distinct efficiency implications. The distinction originates from the fact that, under market imperfections, the size of distortion payments is proportional to

---

9All Propositions 1 through 4 hold when distortion wedges take either signs, but non-negativity is important in understanding why distortionary effects accumulate to upstream sectors. The assumption is taken because market imperfections are meant to represent non-policy features of the economic environment that reduce productive efficiency, as positive wedges do. In contrast, negative wedges lower sectoral costs and raise net output; they run against the notion of “market imperfections” and therefore are not the focus of my analysis. Note that positive wedges can reflect both positive and negative production externalities (see Appendix A.2); the assumption does not impose restrictions on the direction of spillovers but simply requires that, holding input prices constant, sectoral unit cost of production is higher when market imperfections are present than when they are not.
transactional value; such dependency on relative prices in turn generates pecuniary externalities and allocative inefficiency. The two equations in (14) show that factor allocations under imperfections differ from those under the first-best; yet, as is well known (and I show in Appendix A.4), factor allocations under an iceberg economy coincides with those under the first-best. Furthermore, under Cobb-Douglas, as Proposition 4 shows, constrained-optimal value-added subsidies remain the same whether deadweight losses are incurred with imperfections or not, highlighting the re-allocative role of policy in economies with market imperfections. In Appendix A.4, I further demonstrate these distinctions by 1) comparing closed-form allocations under the two formulations through a simple example, and 2) showing that distortion centrality is always equal to one ($\mu_i = \gamma_i$) in iceberg economies, implying that policy interventions have no first-order effects.

3 Theory: Distortion Centrality and Network Structure

How does distortion centrality relate to the network structure? The vertical-network example in section 2.2 shows that market imperfections accumulate through backward demand linkages, and, consequently, sectors with high distortion centrality are upstream and supply, directly or indirectly, 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 with an unambiguous notion of upstreamness. Proposition 5 shows that in this type of hierarchical production networks, the ranking of distortion centrality is insensitive to underlying distortions, and that more upstream sectors tend to have higher distortion centrality. This last result paves the way for my empirical analysis in section 4.

To proceed, let $\theta_{ij} \equiv \frac{M_{ij}}{Q_j}$ be the fraction of good $j$ that is used by sector $i$. This object captures the importance of sector $i$'s as a buyer of good $j$. Likewise, let $\theta^F_j = \frac{Y_j}{Q_j}$ capture the importance of consumer demand for intermediate goods. The market clearing condition for good $j$ implies that $\theta^F_j + \sum_{i \in S} \theta_{ij} = 1$. Note that $\theta_{ij}$ is different from $\omega_{ij}$: the latter captures the importance of sector $j$ as a supplier to $i$. 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, the demand matrix $\Theta$ is the relevant representation for computing distortion centrality.

**Proposition 5.** The distortion centrality of sector $j$ can be written as

$$\xi_j = \left( \theta^F_j \cdot \delta + \sum_{i \in S} \xi_i \cdot (1 + \chi_{ij}) \cdot \theta_{ij} \right)$$

10Contracting frictions in *Boehm and Oberfield (2018)* features a similar type inefficiency.
for scalar \( \delta = \frac{WL}{\gamma \epsilon} \). In the decentralized economy, \( \xi \) can be expressed in matrix form as

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

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

The formula expresses distortion centrality in terms of network structure and underlying distortions; it formalizes the intuition that distortions accumulate through backward demand linkages. A sector has high distortion centrality not because itself is distorted but because its downstream, direct and indirect buyers are distorted. To see this, consider sector \( j \) which supplies to sectors indexed by \( i \). Distortions in input-using sectors \( \chi_{1} + \chi_{ij} \) depress demand for good \( j \) and contribute to sector \( j \)'s distortion centrality \( \xi_j \); the effect is magnified by \( \xi_i \) and weighted by the importance of the demand relationship \( \theta_{ij} \). The distortion centrality of sector \( j \) then travels through \( j \)'s input demand and contributes to the distortion centrality of \( j \)'s suppliers that are further upstream. The scalar \( \delta \) ensures distortion centrality averages to one across sectors; it captures total factor income relative to gross output and is inversely related to the total distortion payments in the economy.

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

In vertical production networks, distortion centrality is always unambiguously higher in more upstream sectors, as seen in section 2.2.\(^{11}\) Yet, the notion of upstreamness is not uniquely defined in a generic network because every sector potentially supplies to every other sector. I now define a class of hierarchical networks in which upstreamness is well-defined. I argue that the ranking of distortion centrality in this class of networks is insensitive to underlying distortions, and I later show that real-world production networks can be well-approximated by this class of networks.

**Definition 6.** (Hierarchical Networks) An \( S \times S \) matrix \( \Theta \) exhibits hierarchical property if its partial column sums are non-increasing:

\[
\sum_{k=1}^{K} \theta_{ik} \geq \sum_{k=1}^{K} \theta_{jk} \quad \text{for all } i < j \text{ and } K \leq S.
\]  

A production network is hierarchical if sectors can be ordered so that the input-output demand matrix satisfies the property. In a monotone network, sector \( i \) is said to be more upstream than \( j \) if \( i < j \).

Hierarchical networks are generalizations of vertical networks. Loosely speaking, a production network is hierarchical if there exists a sectoral ordering, interpreted as upstreamness, so that upstream sectors supply more strongly to other upstream sectors. That is, if \( i \) is upstream to \( j \), then for any \( K \), the fraction of \( i \)'s output supplied to sectors upstream to \( K \) is higher than the corresponding fraction of \( j \)'s output supplied to sectors upstream to \( K \).  

\(^{11}\)To gain further intuitions about how distortionary effects accumulate upstream, I provide another example network in Appendix A.9, which complements the vertical example in section 2.2.
Figure 1: An illustrative input-output demand matrix of a hierarchical network

output. Figure 1 visualizes the input-output demand matrix $\Theta$ of an example hierarchical network, with size of entries drawn in proportion to the strength of the demand linkages $\theta_{ij}$. The condition, that partial column sums are non-increasing, is evident from sparse entries in the bottom-left and dense entries just below the diagonal.

In hierarchical networks, distortion centrality tends to align monotonically with upstreamness because distortions backwardly accumulate. In order to break the alignment, producers throughout the economy have to face little distortions when purchasing upstream goods and enormous distortions—sufficiently strong to counteract the network effect—when purchasing downstream goods.

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 distortions $x$ when buying good 1 ($\chi_{31} = \chi_{21} = x$) and $y$ when buying good 2 ($\chi_{32} = y$). The economy can be summarized by

$$
\begin{bmatrix}
0 & 0 & 0 \\
0.9 & 0 & 0 \\
0.1 & 1 & 0
\end{bmatrix}, \quad
\begin{bmatrix}
0 & 0 & x \\
x & 0 & 0 \\
x & y & 0
\end{bmatrix};
$$

$$
\xi' \propto ((1+y) \times .9 + 0.1) \times (1+x), \quad (1+y), \quad 1.
$$

In this hierarchical (but non-vertical) network, downstream (sector 3) unambiguously has the least

---

12 A sufficient (but unnecessary) condition for an IO demand matrix $\Theta$ to satisfy the hierarchical property is for its entries $\theta_{im}$ to exhibit log-supermodular in $(i,m)$, i.e. $\theta_{im} \theta_{jm} \geq \theta_{in} \theta_{jn}$ for $i \leq j, m \leq n$. 

distortion centrality, but the $\xi$-ranking of sectors 1 and 2 depends on the size of distortions $x$ and $y$. To break the monotone ranking ($\xi_1 \geq \xi_2 \geq \xi_3$), a necessary condition is $y > \frac{10x}{1-0.9x}$, i.e. distortions over input 2 ($y$) has to be at least 10 times higher than those over input 1 ($x$); furthermore, the condition becomes disproportionally more stringent as $x$ 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.

I now provide two sufficient conditions under which distortion centrality aligns perfectly with upstreamness in a hierarchical network.

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

**Case 1.** (Fixed distortions) If $D \circ \Theta$ also satisfies the hierarchical property, then

$$\xi_i \geq \xi_j \text{ for all } i < j.$$ 

**Case 2.** (Random distortions) Suppose $\Theta$ is lower-triangular and there is no distortion with using one’s own output as a production input ($\chi_{ii} = 0$). If cross-sector distortions $\{\chi_{ij}\}$ are i.i.d. over finite and non-negative support, then

$$\mathbb{E}[\xi_i] \geq \mathbb{E}[\xi_j] \text{ for all } i < j.$$ 

Case 1 shows that distortion centrality aligns with upstreamness if $D \circ \Theta$ is hierarchical. This condition is satisfied, for instance, when upstream sectors are more financially constrained, and that more credit is required for sourcing upstream goods as inputs ($\chi_{im} > \chi_{jn}$ for all $i > j$ and $m > n$). This is not unreasonable because, as I show later, upstream sectors in real-world economies tend to be capital-intensive heavy manufacturing sectors and tend to produce capital goods such as industrial equipments and machineries. Case 2 of the proposition takes the equilibrium demand relationship $\Theta$ as fixed and imposes stochasticity on market imperfections. It shows that if cross-sectors distortions are i.i.d., then upstreamness and distortion centrality are aligned in expectation (taken over the distribution of $\chi_{ij}$’s) in lower-triangular hierarchical networks.

Note that these are sufficient but unnecessary conditions for the perfect alignment, across all sectors, of distortion centrality and upstreamness. As the earlier example shows, they still tend to align with each other even if these conditions are violated. It turns out that hierarchical networks approximate real-world IO tables extremely well. The stability of distortion centrality in these networks plays an important role in my empirical analysis, to which I now turn.
4 Application: Role of Linkages in Industrial Policy Episodes

My theory shows that distortion centrality is a sufficient statistic for the first-order impact of policy interventions to a decentralized economy, and the aggregate effect of interventions can be summarized by simple covariances and regression coefficients. In this section, I apply these 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 experienced a state-led industrial policy program that selectively promoted heavy and chemical industries (the program is known as the “HCI drive”); likewise, the interventionist government of modern-day China implements a variety of sectoral policies to influence its economy.

To measure distortion centrality, I apply the formula in Proposition 5, which expresses $\xi$ as a function of the network structure and underlying distortions. In my analysis, I use national input-output tables to measure network structures. A potential concern is that real-world production data is endogenous to policy interventions, and ignoring policy endogeneity might lead to inference errors. However, as my propositions have shown, policy-induced changes in network structure only have second-order effects on aggregate consumption. In what follows, I first suppress this issue. I discuss measurement in section 4.1 and conduct policy evaluations and counterfactuals in section 4.2, proceeding as if real-world production data is not contaminated by sectoral interventions. I address policy-endogeneity and other robustness issues in section 4.3, where I present extensive arguments and evidence that a) the direction of endogeneity goes against my empirical findings, thus correcting for it strengthens my results; b) the endogeneity is quantitatively unimportant, empirically verifying that its effect is indeed second-order.

4.1 Recovering Distortion Centrality

In this section, I discuss how to measure distortion centrality given network structures from national IO tables. The challenge is to recover underlying market imperfections. In principle, these distortions can be estimated from rich production data; in practice, credibly identifying all market imperfections in the entire economy, with sufficient degree of precision and certainty, is a demanding task. Ultimately, no strategy can recover all distortions perfectly, which is precisely why many scholars go so far as to argue that effective industrial policy is impossible (Pack and Saggi (2006), Rodrik (2008)). Indeed, one should be uncomfortable in applying my theory if policy evaluations turns out to be very sensitive to how distortions are specified.

This is where the discussion on hierarchical networks proves to be especially useful. I proceed in two steps to recover distortion centrality. First, I establish that IO tables of both South Korea and China are hierarchical: sectors in these economies exhibit a clear pecking order in their production networks, with unambiguously defined upstream and downstream sectors. Second, I empirically show
that not only is distortion centrality rank stable in these economies—as my theory suggests—but it
is also quantitatively stable with respect to underlying distortions. Specifically, I recover distortions
using a wide range of strategies, including standard ones from the literature and also ones specific to
my empirical setting. These strategies come with various pros and cons, require distinct assumptions,
and push against data constraints in different ways. I show that distortion centrality is almost perfectly
correlated across all specifications, indicating that it is the network structure—not underlying distor-
tions—that generates 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 trade into my
analysis towards the end of this subsection.

**Production Networks in South Korea and China Are Hierarchical**

The starting point of measurement is an national input-output table, whose entries capture the value
of cross-sector flow of intermediate goods \(P_jM_{ij}\) exclusive of distortion and subsidy payments.\(^13\)
I work with the IO tables of South Korea in 1970 and China in 2007, respectively disaggregated
at 148 and 135 three-digit sectors.\(^14\) For each country, I construct the input-output demand matrix
\(\Theta \equiv \left[ M_{ij}/Q_j \right]\) and vector \(\theta^F \equiv \left[ Y_j/Q_j \right]\) from the IO table by dividing appropriate entries with the total
output of input-supplying sectors.

To illustrate the hierarchical property, I first need to reorder sectors, as the property is defined based
on a sectoral ordering that maps into *upstreamness*, which does not align well with standard indus-
trial classification codes. To this end, I construct a simple benchmark distortion centrality measure,
\(\xi_i^{10\%}\), by assuming distortions to be 10% across all sectors and all inputs. This constant-distortion
assumption is intentionally simplistic: by construction, all variations in the measure originate from
the input-output structure. As I show later, this benchmark measure is almost perfectly correlated
with distortion centrality based on imperfections estimated from data.

Figure 2 visualizes the input-output demand matrices \(\Theta\) of South Korea and China, with sectors
arranged in decreasing order of the benchmark distortion centrality \(\xi_i^{10\%}\). For ease of visualization,
entries are drawn in proportion to the strength of demand linkages \(\theta_{ij}\) and are truncated below at 5%,
so that only important linkages are shown.

The figure uncovers 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

---

\(^13\)By construction, IO tables ensure market-clearing 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)).

\(^14\)I thank Nathaniel Lane for graciously sharing the input-output table of South Korea.
Figure 2: The IO demand matrices of South Korea (left) and China (right) are hierarchical depicted in Figure 1.\textsuperscript{15} 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 while the reverse is not true, as both matrices have dense entries below the diagonal and are sparse above. The lower-triangular entries are, on average, an order of magnitude larger than the upper-triangular ones.\textsuperscript{16} More importantly, both matrices exhibit the hierarchical property: the bottom-left area is sparse but gets denser towards the diagonal, indicating that upstream inputs are used more heavily by relatively upstream producers than by downstream producers.

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

<table>
<thead>
<tr>
<th>Relax inequalities by $\epsilon$ (\left(\sum_{k=1}^{K} \theta_{ik} \geq \sum_{k=1}^{K} \theta_{jk} - \epsilon\right))</th>
<th>South Korea</th>
<th>China</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>84.8%</td>
<td>86.0%</td>
</tr>
<tr>
<td>0.001</td>
<td>87.2%</td>
<td>87.4%</td>
</tr>
<tr>
<td>0.005</td>
<td>89.1%</td>
<td>88.9%</td>
</tr>
</tbody>
</table>

To formally assess the hierarchical property of these networks, I follow Definition 6 and exhaustively compare partial-column-sums of upstream sectors with those of downstream sectors. These comparisons correspondingly generate over one million inequalities to be tested for each economy,

\textsuperscript{15}The pattern is obfuscated when sectors are arranged by standard industrial codes; see Appendix Figure C.1.

\textsuperscript{16}The lower-triangular entries average to 0.81\% and 0.83\% for South Korea and China, respectively, and whereas entries above the diagonal average to 0.13\% and 0.33\%. 

27
84.8% of which hold true for South Korea and 86.0% hold true for China, as shown in Table 1. This is strong evidence that the production networks in these economies are hierarchical, as only 50% of the inequalities would have held true if demand linkages were randomly generated. Moreover, among the partial-sum comparisons that fail to hold, inequality violations are often minuscule and thus unlikely to have large effects on distortion centrality: close to 90% of partial-sum comparisons hold in both economies if violations smaller than 0.5% of supplying-sector’s output are tolerated.

**Recovering Market Imperfections**

The hierarchical network structure implies that sectoral ranking of distortion centrality is insensitive to underlying market imperfections, as my analysis in section 3 suggests. To verify this, I specify underlying distortions using a laundry list of strategies, including standard ones from the literatures as well as those specific to my setting. The strategies require distinct assumptions, and each has pros and cons. The goal here is not to argue that any particular estimates accurately represent all distortions in these economies; instead, the exercise is meant to push available data in as many directions as possible and to show that distortion centrality stays extremely stable across all specifications.

The production networks literature has adopted three broad approaches to specify distortions: (1) simulate random distortions (e.g. Jones (2013)); (2) use sectoral variables to proxy for distortions (e.g. Bigio and La’O (2016), Baqee and Farhi (2018b)); (3) use cross-country differences in input-output tables to proxy for distortions (e.g. Bartelme and Gorodnichenko (2015)). I adopt a variety of specifications based on the first two approaches. For every specification, I overlay the input-output demand matrix $\Theta$ with simulated or estimated distortions and compute distortion centrality based on Proposition 5. I show that distortion centrality is stable across all strategies. I do not adopt the last approach because doing so requires matching cross-country IO tables; since industrial codes differ significantly across countries, the approach unavoidably generates very coarse industrial partitions, eliminating much of the cross-sector variations required for my analysis.\(^\text{17}\)

Under the simulation approach, I draw imperfections $\chi_{ij}$ independently across $ij$ from a wide range of distributions, as listed in Tables 2 and C.1. I later show that non-i.i.d. distortions are unlikely to overturn my findings.

The second approach uses sectoral variables to proxy for distortions and is therefore more reliant on data. For modern-day China, I estimate distortions using five alternative strategies, exploiting sectoral data from national accounts as well as the Annual Survey of Manufacturers, a comprehensive survey of Chinese manufacturing firms. For South Korea, only two strategies ($\mathbf{B3}$ and $\mathbf{B5}$, described below) can be implemented due to the lack of firm-level data during the historical period. I briefly

\(^{17}\text{For instance, the finest common coarsening—based on careful hand-matching—of the 135 Chinese sectors and 389 U.S sectors contain only 52 sectors, among which only 25 belong to manufacturing.}\)
describe the strategies here, leaving execution details to Appendix C.2. The appendix also includes a long list of results based on variations of these strategies.

Strategies B1 and B2 use firm-level data to estimate production elasticities and recover wedges from expenditure shares. B1 non-parametrically estimates elasticities using the methodology of De Loecker and Warzynski (2012). B2 uses input shares by foreign-owned firms in China to proxy for elasticities, under the assumption that foreign firms face fewer distortions 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. B4 uses firms’ self-reported interest rates as proxy for financial wedge. Lastly, B5 assumes distortions arise from non-competitive conduct (see Appendix A.2 for microfoundation) and uses sectoral profit shares to proxy for distortion wedges.

For specifications that recover firm-level distortions, I compute sectoral averages according to my within-sector heterogeneity analysis in Appendix A.1, so that every specification results in one wedge per sector. In baseline analysis, I assume all intermediate inputs within each sector are equally distorted by the common sectoral wedge. Doing so does generate potential mis-specifications if distortions are input-specific; mis-specifications can also arise as some of these strategies recover “wedges” that represent market imperfections net of government interventions. I suppress these issues for now and come back to them later in the robustness section 4.3, where I address policy endogeneity and conduct extensive sensitivity analysis to systematic specification errors in distortions wedges.

**Distortion Centrality Are Highly Correlated Across Specifications**

For each specification described above, I compute the corresponding distortion centrality measure using Proposition 5. I then examine both Pearson’s correlation ($r$) and Spearman’s rank correlation ($\rho$) between these alternative measures and the benchmark measure $\xi_i^{10\%}$ (which sets distortion wedges to be 10% in all sectors). The results are reported in Table 2. Panel A shows simulated specifications, where the reported numbers are correlations averaged over 10,000 simulations. Panel B shows correlations based on estimation strategies.

Strikingly, for both South Korea and China, sectoral distortion centrality is close to being perfectly correlated across all specifications. This finding is especially notable, because the various estimation strategies are based on distinct assumptions and data moments, and they produce distortion estimates that only weakly correlate (see Appendix Table C.2); furthermore, the simulation strategies draw distortions independently by construction. Yet, the corresponding distortion centrality measures are not only rank-stable ($\rho \approx 1$) but also quantitatively stable, and the near-perfect Pearson correlations ($r \approx 1$) indicate that these various measures are almost affine transformation of one another. The

---

18The methodology of De Loecker and Warzynski (2012) recovers the ratio between elasticities and expenditure shares over inputs; the estimates are therefore consistent with my interpretation of $\chi$.

19For instance, B4 uses self-reported interest rates, which reflects financial frictions net of policy subsidies to credit.
Table 2: Distortion centrality is highly correlated across specifications

<table>
<thead>
<tr>
<th>Specifications</th>
<th>Average correlation with benchmark $\xi_{i}^{10%}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>South Korea in 1970</td>
</tr>
<tr>
<td></td>
<td>Pearson’s $r$ Spearman’s $\rho$</td>
</tr>
<tr>
<td></td>
<td>China in 2007</td>
</tr>
<tr>
<td></td>
<td>Pearson’s $r$ Spearman’s $\rho$</td>
</tr>
<tr>
<td>Panel A: Simulated $\chi_{ij}$’s</td>
<td></td>
</tr>
<tr>
<td>A1</td>
<td>constant $\chi_{ij} = 5%$</td>
</tr>
<tr>
<td>A2</td>
<td>log-$N(0.09,0.1)$</td>
</tr>
<tr>
<td>A3</td>
<td>$N(0.1,0.1)$</td>
</tr>
<tr>
<td>A4</td>
<td>$N(0.2,0.2)$</td>
</tr>
<tr>
<td>A5</td>
<td>max{$N(0.1,0.1),0$}</td>
</tr>
<tr>
<td>A6</td>
<td>$U[0,0.1]$</td>
</tr>
<tr>
<td>A7</td>
<td>$U[0,0.2]$</td>
</tr>
<tr>
<td>A8</td>
<td>$Exp(0.1)$</td>
</tr>
<tr>
<td>A9</td>
<td>$Exp(0.15)$</td>
</tr>
<tr>
<td>B1</td>
<td>De Loecker and Warzynski</td>
</tr>
<tr>
<td>B2</td>
<td>Foreign firms as controls</td>
</tr>
<tr>
<td>B3</td>
<td>Rajan and Zingales</td>
</tr>
<tr>
<td>B4</td>
<td>Self-reported financial costs from manufacturing census</td>
</tr>
<tr>
<td>B5</td>
<td>Sectoral profit share</td>
</tr>
</tbody>
</table>

(… more simulated specifications in Appendix Table C.1)

The reason for such stability is none other than the hierarchical network structure. In fact, correlations between simulated distortion centrality and the benchmark measure would have all been precisely zero, by construction, if intermediate sectors were perfectly symmetric in the network.

My finding 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, the various distortion centrality measures do differ in range and scale (see Appendix Table C.3), even though they are highly correlated and all average to one. This is because various specifications produce underlying distortion estimates of varying magnitudes. Intuitively, if market imperfections are small in the economy, distortion centrality is close to one in all sectors; conversely, severe imperfections lead to significant dispersion in cross-sector distortion centrality around one. Many of the policy exercises I do below are scale-invariant and are robust to using any of these measures, and I report those results using the benchmark measure $\xi_{i}^{10\%}$ for simplicity. For the scale-dependent exercises below, I report a range of specifications.
Open-Economy Adjustments

Both South Korea and China engage in international trade. How to think about trade in my framework? 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 it can in fact be very upstream if the country exchanges exports for imported inputs that are used heavily by 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 exogenous lump-sum transfers. It is easy to see that my theory applies to this economy.

Guided by this extension, I map the fictitious “intermediary” sector into IO tables and re-do my estimations. Table 3 reports correlations for the various distortion centrality measures before and after open-economy adjustments, showing that all specifications remain quantitatively stable. Interestingly, distortion centrality of the fictitious “trade intermediary” sector sits consistently above median in both economies and is approximately at the third quartile in modern-day China. This pattern indicates that imported inputs are quite upstream in these economies, and promoting export-intensive sectors—in exchange for more imports—can potentially generate aggregate gains.

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

Distortion Centrality Weakly Correlates with Other Sectoral Measures

Table 4 reports correlations between 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 β) will likely lead to aggregate losses. Row C2 shows that
the “upstreamness” measure by Antras et al. (2012) (“ACFH upstreamness” henceforth) correlates with distortion centrality only weakly in China ($r = 0.11, \rho = 0.15$) and negatively in South Korea ($r = -0.02, \rho = -0.08$). Across the various sectoral measures, only export intensity and expenditure share on intermediates correlate strongly with distortion centrality. I later compute welfare counterfactuals using these (and other) alternative measures as policy targets.

Table 4: Distortion centrality does not strongly correlate with other sectoral measures

<table>
<thead>
<tr>
<th>Specification</th>
<th>South Korea</th>
<th>China</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pearson’s $r$</td>
<td>Spearman’s $\rho$</td>
</tr>
<tr>
<td>C1</td>
<td>-0.20</td>
<td>-0.32</td>
</tr>
<tr>
<td>C2</td>
<td>-0.02</td>
<td>-0.08</td>
</tr>
<tr>
<td>C3</td>
<td>-0.42</td>
<td>-0.66</td>
</tr>
<tr>
<td>C4</td>
<td>0.31</td>
<td>0.22</td>
</tr>
<tr>
<td>C5</td>
<td>-0.25</td>
<td>-0.52</td>
</tr>
<tr>
<td>C6</td>
<td>0.45</td>
<td>0.23</td>
</tr>
</tbody>
</table>

**Which sectors have high distortion centrality?**

In both South Korea and China, sectors with high distortion centrality tend to be suppliers of intermediate inputs—those that produce metals, machines, chemicals, and transportation equipments. Conversely, light industries that supply more heavily to consumers—those that processed food products, textiles, and household appliances—tend to have low distortion centrality. Tables 5 and 6 list top-10 and bottom-10 manufacturing sectors ranked by the benchmark measure in these economies.

**4.2 Industrial Policies in South Korea and in China**

**4.2.1 South Korea in the 1970s**

Between 1973 and 1979, South Korea implemented a government-led industrialization program, officially termed the “Heavy-Chemical Industry” (HCI) drive. The program targeted six clusters of sectors, including those producing metal products, machineries, electronics, petrochemicals, automobiles, and shipbuilding. Firms that operated in the promoted sector received substantially favorable policy incentives (Woo (1991), Kim (1997), Lane (2017)), and some of the largest modern South Korean manufacturing conglomerates originated in this era. Appendix Table C.5 shows the full list of 38 targeted three-digit sectors.
Table 5: South Korean manufacturing sectors with high and low distortion centrality

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

Table 6: Chinese manufacturing sectors with high and low distortion centrality

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

**HCI Sectors are Upstream**

The upstreamness of HCI sectors can be transparently visualized. In Figure 3 below, I reproduce the IO demand matrix of South Korea with sectors ranked by the benchmark measure, as previously shown in Figure 2, but with one small change: cells are now darkened if their input-using sectors were promoted by the HCI drive. Note the $i$-th row and column in the figure correspond to the same sector.

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

**HCI Sectors Have High Distortion Centrality**

Table 7 compares the distortion centrality of targeted and non-targeted sectors. Because results are quantitatively similar across all measures of distortion centrality, I omit some of the simulated specifications to avoid redundancy. Results show that every HCI sector has distortion centrality consistently above one across all specifications, indicating that promoting HCI sectors likely leads to aggregate gains. Conversely, promoting non-HCI sectors tends to be ineffective and tends to create negative value on net. Take the benchmark measure, for instance: the HCI sectors have \(\xi_{10\%}\) averaging to 1.16, meaning that every dollar of public expenditures spent on subsidies to these sectors translate to 16 cents gains in aggregate consumption. Note that the average distortion centrality of non-HCI sectors is consistently very close to one; this is a reflection of the fact that total value-added from HCI sectors constitute only a small fraction (5.6\%) of the South Korean economy in 1970.

**Specification Errors?**

My evidence suggests that HCI sectors have higher distortion centrality than non-targeted ones. Can this finding be driven by specification errors in distortions? Intuitively, because distortions backwardly accumulate, it would require a particular type of mis-specifications for my finding to be spurious: distortions have to be under-specified for purchasing non-HCI goods as production inputs, and, conversely, over-specified for purchasing HCI goods. Such mis-specifications are a priori coun-
Table 7: HCI sectors have higher distortion centrality than non-targeted ones

<table>
<thead>
<tr>
<th>ξ Specification</th>
<th>sd(ξ)</th>
<th>Average ξ_i</th>
<th>Share of sectors with ξ_i &gt; 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark</td>
<td>0.09</td>
<td>1.16</td>
<td>100% 47.8%</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>0.06</td>
<td>1.12</td>
<td>100% 47.0%</td>
</tr>
<tr>
<td>B5 Sectoral profit share</td>
<td>0.16</td>
<td>1.28</td>
<td>100% 45.1%</td>
</tr>
<tr>
<td>A3 N(0.1,0.1)</td>
<td>0.09</td>
<td>1.17</td>
<td>100% 47.7%</td>
</tr>
<tr>
<td>A7 U[0,0.2]</td>
<td>0.09</td>
<td>1.16</td>
<td>100% 47.7%</td>
</tr>
<tr>
<td>A8 Exp(0.1)</td>
<td>0.10</td>
<td>1.17</td>
<td>100% 47.7%</td>
</tr>
</tbody>
</table>

Intuitive because, in contrast to capital goods produced by HCI sectors, non-HCI sectors tend to produce downstream, consumption goods that are more tradable, less durable, and generally less used as intermediate inputs. Most importantly, the scope of false-positives is severely limited in hierarchical networks, as distortions over downstream, non-HCI inputs eventually accumulate into distortion centrality for upstream, HCI sectors.

I demonstrate the intuition quantitatively. For each specification of distortions \( \chi_{ij} \), I assume true distortions \( \tilde{\chi}_{ij} \) follow

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

I correct for specification errors and correspondingly re-compute distortion centrality using \( \tilde{\chi} \). The parameter \( \kappa \in [0, 1] \) tunes the degree of mis-specification. The case \( \kappa = 1 \) is designed to minimize HCI distortion centrality, as it doubles distortions for non-HCI inputs and sets distortions over HCI inputs to zero. Under this case, HCI sectors can have high distortion centrality only through supplying to other high-ξ sectors. Table 8 shows that distortion centrality of HCI sectors remain consistently above one for the entire range of \( \kappa \in [0, 1] \), even at the extreme case of \( \kappa = 1 \) (conversely, \( \xi \) of non-HCI sectors all average below one). My finding is therefore unlikely to be driven by specification errors.

Table 8: The finding that \( \xi > 1 \) for HCI sectors is robust to specification errors

<table>
<thead>
<tr>
<th>Degree of mis-specification, ( \kappa )</th>
<th>0</th>
<th>0.1</th>
<th>0.2</th>
<th>0.3</th>
<th>0.4</th>
<th>0.5</th>
<th>0.6</th>
<th>0.7</th>
<th>0.8</th>
<th>0.9</th>
<th>1.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark</td>
<td>1.16</td>
<td>1.14</td>
<td>1.13</td>
<td>1.12</td>
<td>1.10</td>
<td>1.09</td>
<td>1.07</td>
<td>1.06</td>
<td>1.05</td>
<td>1.04</td>
<td>1.02</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>1.12</td>
<td>1.11</td>
<td>1.10</td>
<td>1.09</td>
<td>1.08</td>
<td>1.06</td>
<td>1.05</td>
<td>1.04</td>
<td>1.03</td>
<td>1.02</td>
<td>1.01</td>
</tr>
<tr>
<td>B5 Sectoral profit share</td>
<td>1.28</td>
<td>1.25</td>
<td>1.23</td>
<td>1.20</td>
<td>1.18</td>
<td>1.15</td>
<td>1.13</td>
<td>1.10</td>
<td>1.08</td>
<td>1.05</td>
<td>1.03</td>
</tr>
</tbody>
</table>

Counterfactuals

In Table 9, I compute counterfactuals in which different sectors are promoted. Across rows in the table, I separately select sectors that rank highly according to Domar weights, ACFH upstreamness
measure, sectoral share in the consumption bundle (β), export intensity, sectoral value-added, intermediate expenditure share, as well as by distortion centrality. For each scenario, I maintain the same number of promoted sectors (38) as in the HCI drive. 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. Net gains in aggregate consumption is equal to the reported numbers minus one. Columns (2) and (3) repeats the exercise using distortion centrality specifications B3 (Rajan-Zingales wedge) and B5 (profit share). On the right panel, I maintain the equal-spending assumption and 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 last row shows the scenario under which all sectors of the economy were equally promoted; by construction, this scenario 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, ACFH upstreamness, consumption share, as well as sectoral value-added will all result in aggregate losses, as sectors that rank highly according to these measures have distortion centrality less than one, on average. Promoting export-intensive sectors (row CF4) and those that rely significantly on intermediate inputs (row CF6) does result in aggregate gains, but these gains are lower than under the HCI drive. For instance, under the benchmark distortion centrality specification, counterfactuals CF4 and CF6 respectively generate net gains that are 46% and 41% relative to gains under the HCI drive. Row CF7 shows that promoting the 38 sectors with the highest distortion centrality only generates moderate gains (between 9% and 37%) over the HCI drive.

4.2.2 Modern-Day China

State intervention has a long tradition in China and remains alive and well today, as the government adopts a wide range of policy levers and instruments to exert influence over sectoral production. First, credit market is predominantly state-controlled: interest rates are heavily regulated, and banks often receive policy directives on lending priorities across sectors. Second, the corporate income tax law features a national standard tax rate with a menu of policy incentives that are “predominantly industry-oriented” (Ministry of Finance, P. R. China (2008)), providing various tax breaks to selected sectors. Third, the state directly engages in production through state-owned enterprises (SOEs), which receive not only subsidies from the government but also easy access to credit; Song et al. (2011) explicitly model Chinese SOEs as financially-unconstrained market participants. I refer interested readers to

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20Reliable data on by-sector government spending is unavailable for this historical period; see Lane (2017).
Table 9: Policy counterfactuals for South Korea

<table>
<thead>
<tr>
<th>Specification for $\xi_i$:</th>
<th>Average Distortion Centrality</th>
<th>Gains Relative to HCI Drive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>HCI Drive</td>
<td>1.16</td>
<td>1.12</td>
</tr>
</tbody>
</table>

Counterfactuals (select sector sorted by...)

| CF1  | Domar weight $\gamma$ | 0.98 | 0.99 | 0.96 | -11% | -9% | -13% |
| CF2  | ACFH upstreamness      | 0.99 | 0.99 | 0.98 | -6%  | -5% | -7%  |
| CF3  | Consumption share $\beta$ | 0.97 | 0.94 | 0.94 | -18% | -16% | -22% |
| CF4  | Export intensity       | 1.07 | 1.05 | 1.11 | 46%  | 44% | 40%  |
| CF5  | Sectoral value-added   | 0.98 | 0.99 | 0.98 | -10% | -9% | -8%  |
| CF6  | Interm. exp. share     | 1.07 | 1.04 | 1.08 | 41%  | 36% | 28%  |
| CF7  | Distortion centrality $\xi$ | 1.22 | 1.15 | 1.30 | 137% | 124% | 109% |
| CF8  | Uniform promotion      | 1    | 1    | 1    | 0%   | 0%  | 0%   |

Du et al. (2014) and Aghion et al. (2015) for detailed discussions of industrial policies in modern-day China, and to Boyreau-Debray and Wei (2005), Dollar and Wei (2007) and Riedel et al. (2007) for China’s credit market policies pertaining to SOEs.

I construct several quantitative measures of sectoral interventions in China based on private firms’ interest payments, debt obligations, corporate income taxes, and subsidies received from the government. I also measure the sectoral presence of SOEs. Information on corporate taxes is from the administrative enterprise income tax records for year 2008. The dataset contains detailed firm-level records of tax payments and tax incentives; it is collected by the State Administration of Taxation, which is China’s counterpart of 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 sheet and production data of manufacturing firms. Appendix C.1 provides detailed background of these datasets and description and of variable constructions.

I exploit cross-sector variations in policy interventions and examine how they covary with distortion centrality. Intervention measures are available for 79 three-digit manufacturing sectors, the finest partition that concords with both national IO table and firm-level datasets. Tables 10 and 11 provide some descriptive statistics, from which I highlight two features.

First, industrial policies in China vary substantially across sectors. Row 1 of Table 10 shows sectoral means for effective interest rates paid by private manufacturing firms. Producers in the median sector pay interests that are 4.12% of their debt obligations, whereas those in sectors with the highest

21“Private firms” refer to non-SOEs throughout the paper.
22That these two datasets are off by one year should not lead to systemic biases since I exploit cross-sector variations.
Table 10: Descriptive statistics: sectoral policies vary significantly across Chinese sectors

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

Table 11: Descriptive statistics: SOEs receive more favorable policies

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

and lowest interest rates pay as much as 12.33% and as little as 1.85% on average. Row 2 shows that the firms in the most indebted sector has an average debt-to-asset ratio that is over one-and-a-half times of those in the least indebted sector. Likewise, rows 3 through 6 show considerable variations in the fraction of firms receiving tax incentives (recorded by the tax authority), effective corporate income tax rates, fraction of firms that receive subsidies from the government (self-reported), and the average amount of subsidies (as a share of revenue) conditioning on having received any. All variables in rows 1 through 6 are based on the sample of domestic, privately-owned firms. Row 7 shows Chinese SOEs account for sectoral value-added that range from 0.66% to 74.5%, highlighting their heterogeneous presence across sectors.

Second, SOEs receive significantly more favorable policies relative to private firms, as shown in Table 11. On average, the effective interest rate paid by SOEs is half of that by private firms, despite debt ratios of the former being 9 percentage points (17 percent) higher than that of the latter. SOEs are also twice as likely to receive production subsidies from the government, and conditioning on having received any, SOEs receive more subsidies (as a share of revenue) relative to private firms.
Reduced-Form Evidence

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

\[
\text{Outcome}_i = \alpha_i + \beta \times \xi_i^{10\%} + \text{controls}_i + \epsilon_i.
\]

Each observation \(i\) is a sector, \(\text{Outcome}_i\) is the sectoral mean for the corresponding policy variable for non-SOEs, measured in percentage points. In accordance with my later application of Proposition 3, I weight each observation by sectoral 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, “one standard deviation higher in distortion centrality above the mean is associated with \(\beta\) percentage points higher in the policy outcome”. I control for several sectoral characteristics in order to partial out non-network reasons for state interventions, and I also standardize these control variables.

Regression results (Table 12) show that private firms in high distortion centrality sectors receive more favorable policies. Based on columns (2), (4), (6), and (8), one standard deviation higher in sectoral distortion centrality is associated with 0.99 percentage points lower in firms’ effective interest rate, 2.73 percentage points higher in debt-to-capital ratios, 2.91 percentage points higher likelihood to receive tax incentives, and 1.59 percentage points lower in effective corporate income tax rate. Such variations in these four policy variables are economically significant: one standard deviation in distortion centrality translates into policy differences of between 0.30 and 0.59 standard deviations in sectoral means of the respective policy variables (c.f. the last column of Table 10). These specifications control for a variety of sectoral characteristics, including capital intensity (fixed asset over output), Lerner index (operating profits over output), average log-fixed capital of firms during the first year of operation (a proxy for the minimum scale of operation), and export intensity (exports over output). Together, these variables serve to partial out other, non-network predictors for state interventions. Some of these control variables do have predictive power over certain intervention measures, although none is as consistently predictive as the distortion centrality measure. Also note that coefficients on distortion centrality remain almost unaffected after including the controls. Appendix Table C.4 shows that coefficients remains quantitatively robust after controlling for various estimates of sectoral wedges. The only policy variables for which distortion centrality lacks predictive power are direct subsidies that private firms receive from the government. As shown in Table 11, private firms tend to receive little subsidies to begin with, relative to SOEs.

Chinese manufacturing sectors used to be predominantly state-owned in the 1990s. Several waves of market reforms has taken place since then, during through small and unproductive SOEs were privatized or closed, and large and relatively successful SOEs were corporatized as market participants
Table 12: Private firms in Chinese manufacturing sectors with high distortion centrality receive more favorable policies

<table>
<thead>
<tr>
<th></th>
<th>Effective Interest Rate</th>
<th>Debt Ratio</th>
<th>Tax Break</th>
<th>Effective Tax Rate</th>
<th>Recipient of Subsidies</th>
<th>Subsidies Revenue</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \xi^{10%} )</td>
<td>(-0.895^{***})</td>
<td>(-0.987^{***})</td>
<td>(2.961^{***})</td>
<td>(2.726^{***})</td>
<td>(2.861^{**})</td>
<td>(2.911^{**})</td>
</tr>
<tr>
<td>Capital intensity</td>
<td>(-0.425^{**})</td>
<td>(-0.390)</td>
<td>(0.759)</td>
<td>(-0.253)</td>
<td>(1.403^{***})</td>
<td>(0.284^{**})</td>
</tr>
<tr>
<td>(0.199)</td>
<td>(0.556)</td>
<td>(1.263)</td>
<td>(0.385)</td>
<td>(0.517)</td>
<td>(0.113)</td>
<td></td>
</tr>
<tr>
<td>Lerner index</td>
<td>(-0.0247)</td>
<td>0.146</td>
<td>(-0.559)</td>
<td>0.0958</td>
<td>0.166</td>
<td>0.00943</td>
</tr>
<tr>
<td>(0.173)</td>
<td>(0.481)</td>
<td>(1.092)</td>
<td>(0.333)</td>
<td>(0.447)</td>
<td>(0.0975)</td>
<td></td>
</tr>
<tr>
<td>Log(fixed assets in starting year)</td>
<td>(-0.0273)</td>
<td>0.511</td>
<td>(-0.559)</td>
<td>(-0.643)</td>
<td>1.075^{**}</td>
<td>0.147</td>
</tr>
<tr>
<td>(0.204)</td>
<td>(0.568)</td>
<td>(1.290)</td>
<td>(0.394)</td>
<td>(0.528)</td>
<td>(0.115)</td>
<td></td>
</tr>
<tr>
<td>Export intensity</td>
<td>(-0.682^{***})</td>
<td>0.284</td>
<td>(2.824^{**})</td>
<td>(-0.375)</td>
<td>1.186^{**}</td>
<td>(-0.0977)</td>
</tr>
<tr>
<td>(0.172)</td>
<td>(0.487)</td>
<td>(1.105)</td>
<td>(0.337)</td>
<td>(0.452)</td>
<td>(0.0986)</td>
<td></td>
</tr>
<tr>
<td>adj. ( R^2 )</td>
<td>0.163</td>
<td>0.301</td>
<td>0.260</td>
<td>0.231</td>
<td>0.045</td>
<td>0.097</td>
</tr>
<tr>
<td># Obs.</td>
<td>79</td>
<td>79</td>
<td>79</td>
<td>79</td>
<td>79</td>
<td>79</td>
</tr>
</tbody>
</table>
Consequently, modern-day SOEs are large and perhaps overly profitable corporations (Bai et al. (2014), Li et al. (2015)). The predominant view in the literature is that they are overly capitalized, and their existence impedes the efficient allocation of resources within sectors (Song et al. (2011)). I do not dispute this view, but I highlight that, in a world with many policy constraints, SOEs might serve as a means to implementing sectoral policies, and strategically placing SOEs in selected sectors might play the role of expanding sectoral production. The 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).

As Figure 4 shows, distortion centrality predicts SOE share of sectoral value-added in year 2007. Each point represents a sector and is drawn in proportion to sectoral value-added. Table 13 translates the figure into regressions, showing that the correlation survives after the full set of sectoral controls. In 2007, a sector with distortion centrality one standard deviation above the mean is associated with 7.81 percentage points (0.46 standard deviations) higher in SOEs’ share of sectoral value-added. Moreover, the correlation is not driven by historical legacy: columns (3) through (6) examines sectoral value-added shares of SOEs that were established recently—after 2000s—and the correlations remain significant. These columns suggest that the placement of SOEs is being actively managed.

Figure 4: Sectors with high distortion centrality have more SOE presence

Policy Evaluations

I now apply Proposition 3 for welfare calculations. Recall the regression of sectoral policy spending per-value-added $s_i$ on standardized distortion centrality $\bar{\xi}_i$, weighting sectors by value-added:

$$s_i = \alpha + \beta \cdot \bar{\xi}_i + e_i.$$  (18)
Table 13: Sectors with high distortion centrality have more SOE presence

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>$s_i^{10%}$</td>
<td>7.577**</td>
<td>7.808***</td>
<td>2.960***</td>
<td>2.549***</td>
<td>2.123***</td>
</tr>
<tr>
<td></td>
<td>(2.963)</td>
<td>(2.834)</td>
<td>(1.059)</td>
<td>(0.886)</td>
<td>(0.725)</td>
</tr>
<tr>
<td>Capital intensity</td>
<td>0.914</td>
<td>0.774</td>
<td>0.717</td>
<td>0.602</td>
<td>0.199</td>
</tr>
<tr>
<td></td>
<td>(2.535)</td>
<td>(0.947)</td>
<td>(0.792)</td>
<td>(0.649)</td>
<td>(0.554)</td>
</tr>
<tr>
<td>Lerner index</td>
<td>-4.622**</td>
<td>-2.191***</td>
<td>-1.997***</td>
<td>-1.611***</td>
<td>-1.148**</td>
</tr>
<tr>
<td></td>
<td>(2.193)</td>
<td>(0.820)</td>
<td>(0.685)</td>
<td>(0.561)</td>
<td>(0.479)</td>
</tr>
<tr>
<td>Log(fixed assets in starting year)</td>
<td>6.974***</td>
<td>2.042**</td>
<td>1.632**</td>
<td>1.245*</td>
<td>1.028*</td>
</tr>
<tr>
<td></td>
<td>(2.590)</td>
<td>(0.968)</td>
<td>(0.809)</td>
<td>(0.663)</td>
<td>(0.565)</td>
</tr>
<tr>
<td>Export intensity</td>
<td>-5.660**</td>
<td>-2.013**</td>
<td>-1.810**</td>
<td>-1.484**</td>
<td>-1.145**</td>
</tr>
<tr>
<td></td>
<td>(2.218)</td>
<td>(0.829)</td>
<td>(0.693)</td>
<td>(0.568)</td>
<td>(0.484)</td>
</tr>
<tr>
<td>adj. $R^2$</td>
<td>0.066</td>
<td>0.290</td>
<td>0.269</td>
<td>0.284</td>
<td>0.276</td>
</tr>
<tr>
<td># Obs.</td>
<td>79</td>
<td>79</td>
<td>79</td>
<td>79</td>
<td>79</td>
</tr>
</tbody>
</table>

Proposition 3 states that the proportional gain in aggregate consumption ($\Delta Y / Y$) from $\{s_i\}$ is captured by $\beta \cdot sd(\xi)$, where $sd(\cdot)$ is the standard deviation operator. In what follows, I apply this bivariate regression to evaluate welfare gains of interventions.23

Based on the intervention measures used in previous tables, I compute policy spendings $\{s_i\}$ separately for 1) subsidized credit and 2) tax incentives based on the sample of private firms, as well as 3) policy incentives to SOEs. For subsidized credit, I assume the market interest rate is reflected by the highest sectoral mean effective interest rate ($r_{\text{max}} = \max_{i=1, \ldots, S} r_i$), 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 $\left( \frac{(r - r_i) \times \text{debt}}{VA_i} \right)$. Note, the choice of market rate $r$ is an unimportant normalization, since uniform cross-sector spending brings no welfare effects. I compute spendings on tax incentives using the difference between statutory corporate income tax rate and the effective tax rate $\left( \frac{\text{Profits}_i - \text{TaxesPaid}_i}{VA_i} \right)$. Lastly, I compute spendings on SOEs as the sum of credit subsidies, tax incentivecs, 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 spendings onto sectors outside of manufacturing, while maintaining the same covariances between distortion centrality and sectoral spendings. Alternatively, the

23I follow the bivariate specification as in Proposition 3 and do not include additional sectoral control variables because, as shown in Tables 12 and 13, these variables do not have consistent predictive power for sectoral interventions, and neither do they significantly impact the coefficients on distortion centrality.
reported numbers can be interpreted as the proportional gains in net manufacturing output.

As Table 14 shows, sectoral interventions by all three categories generate aggregate gains in China. The gains generated by these interventions are on the same order of magnitude, with subsidized credit playing a slightly stronger role than funding to SOEs, which in turn is slightly more effective than tax incentives. For instance, under specification B1 (De Loecker and Warzynski wedge), differential sectoral interest rates lead to 2.31% aggregate gains, while tax incentives and funds to SOEs respectively generate 1.59% and 1.84% gains. These gains are entirely due to the positive selection of policy expenditures in sectors with high distortion centrality. The pattern is qualitatively robust across various specifications of distortion centrality; quantitatively, the magnitude of these gains depends on the standard deviation of the corresponding distortion centrality measure. Gains are smaller under specification B4, for instance, because it features smaller sectoral wedges and, consequently, smaller misallocation and dispersion in distortion centrality across sectors. Altogether, these interventions generate total gains that range from 1.93% to 5.74% of aggregate consumption.

Table 14: Evaluating sectoral interventions in modern-day China

<table>
<thead>
<tr>
<th>Distortion centrality specification</th>
<th>sd(ξ)</th>
<th>Subsidized credit</th>
<th>Tax incentive</th>
<th>SOEs</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Benchmark (ξ^{10%})</td>
<td>0.22</td>
<td>1.69</td>
<td>1.23</td>
<td>1.40</td>
<td>4.32</td>
</tr>
<tr>
<td>B1 De Loecker and Warzynski</td>
<td>0.29</td>
<td>2.31</td>
<td>1.59</td>
<td>1.84</td>
<td>5.74</td>
</tr>
<tr>
<td>B2 Foreign firms as controls</td>
<td>0.16</td>
<td>1.20</td>
<td>0.81</td>
<td>0.78</td>
<td>2.79</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>0.11</td>
<td>1.01</td>
<td>0.70</td>
<td>0.72</td>
<td>2.43</td>
</tr>
<tr>
<td>B4 Self-reported financial costs</td>
<td>0.11</td>
<td>0.84</td>
<td>0.52</td>
<td>0.58</td>
<td>1.93</td>
</tr>
<tr>
<td>B5 Sectoral profit share</td>
<td>0.17</td>
<td>1.20</td>
<td>0.91</td>
<td>1.05</td>
<td>3.16</td>
</tr>
</tbody>
</table>

Policy Counterfactuals

Next, I conduct policy counterfactuals for modern-day China. Each counterfactual evaluates an entire vector of policy spendings across sectors; in order to keep the exercise tractable and transparent, I again rely on the structure entailed in equation (18) as follows.

Consider targeting sectors by an alternative measure—for instance, the Domar weight (standardized, $\bar{\gamma}_i \equiv \gamma_i / sd(\gamma)$). Rather than specifying an entire mapping from sectoral Domar weights to policies, I assume counterfactual policy expenditures follow the same stochastic structure as policies in the real world. Specifically, I assume that counterfactual spendings $\tilde{s}_i$ can be linearly projected onto Domar weights, with residuals $u_i$ independent to both Domar weights and distortion centrality:

$$\tilde{s}_i = \tilde{\alpha} + b \cdot \bar{\gamma}_i + u_i, \quad u \perp \tilde{\xi}, \bar{\gamma}. \quad (19)$$
In this case, I refer to Domar weights as the counterfactual policy target. The coefficient $b$ captures the alignment between policy expenditures and the policy target, and I refer to it as the “strength” of policy targeting. Let $\lambda$ be the slope coefficient from regressing $\bar{y}_i$ on $\bar{\xi}_i$: \[ \bar{y}_i = c + \lambda \cdot \bar{\xi}_i + \nu_i, \quad \nu \perp \bar{y}. \] (20)

Applying Proposition 3 and simple algebra, one can show that the proportional gains in aggregate consumption from counterfactual interventions $\{\tilde{s}_i\}$ is captured by $sd(\xi) \cdot b \cdot \lambda$. Intuitively, this is because to first-order, components of policy spendings that are orthogonal to distortion centrality (i.e., $u$ and $\nu$ in 19 and 20) do not generate aggregate effects, per Proposition 2.

Following the procedure, I compute counterfactuals in which various alternative measures become policy targets. Since the counterfactual gains is not scale-free and depends on cross-sector standard deviation of distortion centrality, I repeat each counterfactual over various specifications for $\xi$. For each specification and across counterfactual scenarios, I standardize policy targets to be unit-variance, and I normalize the strength of policy targeting to $b = \hat{b}$, where $\hat{b}$ is the estimated coefficient from regression (18) under the corresponding distortion centrality specification. Under this normalization, the slope coefficient $\lambda$ from (20) can be intuitively interpreted as the relative gains from counterfactual spendings $\{\tilde{s}_i\}$, as a fraction of the gains from real-world spendings $\{s_i\}$, evaluated using the corresponding $\xi$ specification.

Table 15: Policy counterfactuals for modern-day China

<table>
<thead>
<tr>
<th>Specification for $\xi$</th>
<th>Total gains across all interventions (percentage points)</th>
<th>Gains relative to real-world interventions ($\lambda$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\xi^{10%}$</td>
<td>B1</td>
</tr>
<tr>
<td>Real-world interventions</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Counterfactual policy target</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CF1 Domar weight $\gamma$</td>
<td>-1.71</td>
<td>-2.11</td>
</tr>
<tr>
<td>CF2 ACFH upstreamness</td>
<td>0.49</td>
<td>0.63</td>
</tr>
<tr>
<td>CF3 Consumption share $\beta$</td>
<td>-3.07</td>
<td>-3.82</td>
</tr>
<tr>
<td>CF4 Export intensity</td>
<td>1.36</td>
<td>1.75</td>
</tr>
<tr>
<td>CF5 Sectoral value-added</td>
<td>-1.56</td>
<td>-2.10</td>
</tr>
<tr>
<td>CF6 Interm. exp. share</td>
<td>1.61</td>
<td>2.04</td>
</tr>
</tbody>
</table>

Table 15 shows that using Domar weights, consumption share, or sectoral value-added as policy targets lead to aggregate losses. Targeting sectors by their ACFH upstreamness measure results in minor gains—between 6.9% and 19.0% as a fraction of the gains brought by real-world interventions. Among observable sectoral measures, only two could serve as good policy targets: export-intensity

---

24Both regressions (19) and (20) are weighted by sectoral value-added.
25Counterfactual gains under alternative targeting strength $b$ can be obtained by proportionally rescaling the numbers reported in Table 15.
(CF4) and intermediate expenditure shares (CF6). Interestingly, these are the same two measures that work well for South Korea. Promoting sectors with high intermediate shares, for instance, generate between 29% and 41% of the gains relative to real-world interventions, depending on the specification of distortion centrality. Putting it another way, for policy target CF6 to be as effective as real-world interventions, the strength of policy targeting \( b \) has to be twice or three-times as large as the coefficient \( \beta \) from the bivariate regression (18). This means higher cross-sector dispersions in policy spendings, as sectors with high intermediate shares need to receive 2-3 times more public funds under the counterfactual, relative to funds sent to high distortion centrality sectors under real-world interventions. 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 are quantitatively stable; the stability reflects high correlations across various distortion centrality measures.

### 4.3 Robustness: Data Aggregation and Systematic Measurement Errors

I now discuss two important robustness issues relating to my empirical exercises: data aggregation and systematic (non-i.i.d.) measurement errors, potentially induced by endogeneity of real-world data to policy interventions. I address these issues in turn. Note, the fact that distortion centrality is robust across i.i.d. simulated specifications (Table 2) suggest that my empirical analysis is robust to non-systematic errors.

#### 4.3.1 Data Aggregation

In section 2.4, I provide reasonable conditions 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 fails to exist, or because data is mismeasured due to firms operating across industries and conducting multi-stage production in-house.\(^{26}\)

While I cannot conclusively verify the empirical robustness of distortion centrality when underlying product differentiation is finer than the data available, I can indeed conduct the robustness check in reverse, testing the stability of distortion centrality when I use even coarser data than what is available. To this end, I merge sectors and progressively create coarser sectoral partitions over several iterations, and I re-compute distortion centrality using the collapsed IO tables at each iteration. For South Korea, the original, disaggregated table has 148 sectors, and I create collapsed tables with 54, 25, and 16 sectors. For modern-day China, the original table has 135 sectors and the collapsed tables have 57, 28, and 17 sectors.\(^{27}\)

\(^{26}\)Orr (2018) documents a high fraction of multi-product firms in Indian manufacturing sectors. Conceptually, multi-production could arise endogenously to minimize frictions associated with inter-firm trade (Oliver (1985)), but they could also generate new distortions—for instance, through low-powered incentives (Grossman and Hart (1986)).

\(^{27}\)When merging sectors, standardized codes are followed whenever possible. 54 and 57 sectors correspond respectively
Table 16: Distortion centrality based on coarse IO tables is highly correlated with benchmark measure

<table>
<thead>
<tr>
<th>Number of sectors ($S$)</th>
<th>South Korea in 1970</th>
<th>China in 2007</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_{SK}^{SK} = 54$, $S_{CN}^{CN} = 57$</td>
<td>Pearson’s $r$ = 0.97, Spearman’s $\rho$ = 0.96</td>
<td>Pearson’s $r$ = 0.97, Spearman’s $\rho$ = 0.99</td>
</tr>
<tr>
<td>$S_{SK}^{SK} = 25$, $S_{CN}^{CN} = 28$</td>
<td>Pearson’s $r$ = 0.94, Spearman’s $\rho$ = 0.91</td>
<td>Pearson’s $r$ = 0.97, Spearman’s $\rho$ = 0.94</td>
</tr>
<tr>
<td>$S_{SK}^{SK} = 16$, $S_{CN}^{CN} = 17$</td>
<td>Pearson’s $r$ = 0.94, Spearman’s $\rho$ = 0.88</td>
<td>Pearson’s $r$ = 0.98, Spearman’s $\rho$ = 0.95</td>
</tr>
</tbody>
</table>

Figure 5: Collapsed IO demand matrices are hierarchical in South Korea (left) and in China (right)

Table 16 shows that benchmark distortion centrality computed from the collapsed IO tables is almost perfectly correlated with the benchmark measure computed from the original, disaggregated tables. The correlations remain stable across iterations, even at the most aggregated level. The stability is once again due to the hierarchical property of the collapsed IO tables. Figure 5 visualizes the IO demand matrix for collapsed tables with 25 and 28 sectors respectively for South Korea and China. A comparison of figures 2 and 5 reveals an interesting, fractal-like property of these networks: linkages across broad sector categories seem to follow a hierarchical structure, and so do linkages within each broad category and across more narrowly defined sectoral definitions.

4.3.2 Policy Endogeneity and Systematic Specification Errors

While my theory requires distortion centrality to be measured from the decentralized economy, I have thus far used real-world data for my analysis, and my measures are therefore contaminated by

to two-digit sectors in these economies; 25 and 28 sectors correspond closely to sectoral definitions in the World Input-Output Data; the coarsest partition (16 and 17 sectors for the respective economies) only differentiates broad sectors (e.g. textiles, chemicals, metals, non-metals, machines). The number of sectors in collapsed IO tables differ slightly across the two economies due to initial differences in their disaggregated industrial codes.
existing policy interventions. In this section, I show that policy-induced endogeneity is second-order thus quantitatively unimportant, and, if anything, it creates biases against my findings. I also conduct a “stress test”, showing that my results survive even with significant specification errors.

Distortion centrality is constructed based on IO demand matrix $\Theta$ and sectoral distortions $\chi$. Policy-endogeneity in $\Theta$ could arise due to either 1) endogenous changes in production elasticities due to reallocations, or 2) failing to account for subsidies in observed input-output structure. Both sources of errors have only second-order effects on welfare ($Y$) around the decentralized economy, and since my empirical exercises aim to capture first-order effects, ignoring endogeneity in $\Theta$ does not quantitatively affect my inference.

Policy endogeneity of real-world data could also generate systematic errors in distortion wedges, as some of my estimated specifications (B1, B2, B4) might attribute imperfections net of subsidies ($\chi - \tau$) as true imperfections $\chi$. These errors bias $\xi$ against my findings in ways similar to under-specified distortions in promoted sectors. Intuitively, because distortions are multiplied by sectoral distortion centrality and then backwardly accumulate (c.f. equation 16), systematic under-specifications of $\chi$’s in high-$\xi$ sectors compress cross-sector $\xi$’s towards the mean, causing upstream distortion centrality to be biased downwards relative to other sectors. Consequently, policy-induced measurement errors in $\chi$ should also weaken any positive correlations between interventions and $\xi$, and correcting for such errors should strengthen my findings. Some of my other specifications are, in principle, not subject to this issue; nevertheless, my robustness checks can be seen as sensitivity analysis with respect to systematic errors in distortion wedges.

Indeed, it takes a particular type of systematic errors in $\chi$—policy-induced or otherwise—to generate spurious positive correlations between $\xi$ and interventions. Intuitively, false-positives arise when $\xi$ is biased negatively in downstream sectors, which happens only with under-specified distortions for using downstream goods as production inputs. In practice, the scope of type-I error is limited in hierarchical networks, because downstream goods are not intensively used as intermediate inputs.

I quantitatively verify all of these intuitions. The possibility of false-positives has already been explored in the case of South Korea (Table 8); I now conduct sensitivity analysis in the Chinese context. First, I illustrate that correcting for subsidies in $\Theta$ and $\chi$ have little quantitative impact, and, if anything, my findings are strengthened in the latter case. For simplicity, I measure sector-specific policy wedge $\tau_i$ as the total government spendings in each sector relative to sectoral revenue. I normalize $\tau_i$’s to mean zero, assume $\tau_i$ applies equally to all inputs in sector $i$, and I correct, separately and jointly, for errors in $\Theta$ and $\chi$. I correspondingly re-compute every specification of distortion

\footnote{Specifications B1 and B2 measures equilibirum differences between elasticities and expenditure shares, which should reflect distortions net of subsidies; likewise, B4 uses self-reported interest rates, which should capture financial distortions net of credit subsidies.}

\footnote{Because high-$\xi$ sectors tend to receive more subsidies, errors correction in $\chi$ effectively raises wedges in high-$\xi$ sectors}
centrality and replicate the welfare evaluation exercise using the corrected measure.

Table 17: Policy evaluations are robust to policy-induced endogeneity and specification errors

<table>
<thead>
<tr>
<th>Distortion centrality specification</th>
<th>Total gains ($\Delta Y/Y$) in percentage points</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Uncorrected</td>
</tr>
<tr>
<td></td>
<td>$\Theta$</td>
</tr>
<tr>
<td>Benchmark ($\xi^{10%}$)</td>
<td>4.32</td>
</tr>
<tr>
<td>B1 De Loecker and Warzynski</td>
<td>5.74</td>
</tr>
<tr>
<td>B2 Foreign firms as controls</td>
<td>2.79</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>2.43</td>
</tr>
<tr>
<td>B4 Self-reported financial costs</td>
<td>1.93</td>
</tr>
<tr>
<td>B5 Sectoral profit share</td>
<td>3.16</td>
</tr>
</tbody>
</table>

Table 17 re-calculates total gains in $Y$ from sectoral interventions using the corrected measures (the first column reports gains based on uncorrected measures, reproducing the last column of Table 14). Results show that welfare gains remain quantitatively unchanged, with magnitudes experiencing very slight increases when specification errors in $\chi$ are corrected. Appendix Table C.7 shows that endogeneity-corrected distortion centrality measures remain almost perfectly correlated with the respective uncorrected measures; first-order approximations work well in these exercises because sectoral government spendings account for only a small fraction of sectoral revenue (Appendix Table X).

Next, I conduct an exercise specifically designed to put stress on my empirical findings, in order to illustrate the limited scope for type-I errors. For each version of distortion centrality, I hypothetically assume that corresponding distortions are under-specified by 10 percentage points for purchasing downstream goods (i.e., those produced by sectors with below-median distortion centrality) and are symmetrically over-specified for purchasing upstream goods. These errors are assigned specifically to maximize the scope of false-positives, and the magnitude of errors is liberally chosen to be significantly higher than the full range of policy variations (see Table 10). Correcting for these hypothetical errors should quantitatively weaken welfare gains, but any positive gains should be seen as very conservative lower bounds and can be used to vindicate my findings from being type-I errors.

I re-do welfare evaluations using the corrected measures, reported in Table 18. Results show that, after corrections, the variance of $\xi$ significantly decreases across specifications; consequently, welfare gains are smaller. Yet, welfare gains remain consistently positive even after accounting for significant and lowers wedges in low-$\xi$ sectors. The correction formula for subsidies in $\Theta$ is more involved. I abuse notations and let $(1 + \chi - \tau)$ denote the matrix with entries $(1 + \chi_{ij} - \tau_{ij})$; likewise, let $\left(\frac{1 + \chi - \tau}{1 + \chi}ight)$ denote the matrix with entries $\left(\frac{1 + \chi_{ij} - \tau_{ij}}{1 + \chi_{ij}}\right)$. Assuming $\chi$ is appropriately specified, to compute distortion centrality with subsidies in $\Theta$ properly accounted for, one first computes the point-wise ratio between $\left(\theta^F\right)\left(I - \Theta \circ (1 + \chi - \tau)^{-1}\right)$ and $\left(\theta^F\right)\left(I - \Theta \circ \left(\frac{1 + \chi - \tau}{1 + \chi}\right)^{-1}\right)$, and then rescales the ratio so that it averages to one across sectors. The formula for correcting errors in both $\chi$ and $\Theta$ follows analogously. I provide derivations in Appendix B.
specification errors. This stress test lends credence to my earlier inference.

Table 18: Qualitative conclusion survives stress-testing

<table>
<thead>
<tr>
<th>Distortion centrality specification</th>
<th>Aggregate gains ($\Delta Y/Y$) by intervention (in percentage points)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$sd(\xi)$</td>
</tr>
<tr>
<td>Benchmark ($\xi^{10%}$)</td>
<td>0.13</td>
</tr>
<tr>
<td>B1 De Loecker and Warzynski</td>
<td>0.26</td>
</tr>
<tr>
<td>B2 Foreign firms as controls</td>
<td>0.12</td>
</tr>
<tr>
<td>B3 Rajan and Zingales</td>
<td>0.06</td>
</tr>
<tr>
<td>B4 Self-reported financial costs</td>
<td>0.08</td>
</tr>
<tr>
<td>B5 Sectoral profit share</td>
<td>0.13</td>
</tr>
</tbody>
</table>

5 Interpretation and Conclusion

Do my findings imply that South Korea and China adopted optimal policies? No. My nonparametric results capture welfare effects to the first order; they do not speak to optimality, and neither does my subsequent empirical application. This is not a shortcoming of my analysis so much as it reflects the inherent difficulty of evaluating industrial policies: to assess optimality, the econometrician has to be essentially omniscient. One has to acquire full knowledge about not only all market imperfections but also the entire—parametric and global—features of production functions across all sectors of the economy. Nor am I able to speculate about the why these policies were adopted, as my model abstracts away from practical aspects of policy implementation as well as various political economy factors that affect policy choices in these economies (Krueger (1990), Lane (2017), Rodrik (2008)).

What are the takeaways from my findings, then?

First, interventions should begin with sectors of 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 distortions accumulate through input-output linkages in a production network.

Second, propositions 2 and 3 provide simple formulas for nonparametric policy evaluations and counterfactuals. To first-order, economic gains are higher if more policy funds are allocated to high distortion centrality sectors, and the aggregate effect can be summarized by a simple regression of sectoral policy spendings on distortion centrality. It is usually difficult for empirical studies to shed light on aggregate effect of interventions, as the answer inevitably hinges on general equilibrium, reallocative effects. My results overcome this difficulty.
Third, misallocative effects of distortions accumulate through backward demand linkages, and, as a result, upstream sectors—those that supply directly or indirectly to many sectors—become sinks of distortions and tend to have higher distortion centrality. Moreover, in South Korea and China, sectors follow of a hierarchical structure of production, so that upstreamness can almost be unambiguously defined. In these economies, those with high distortion centrality tend to be the heavy- and chemical sectors; conversely, light manufacturing sectors tend to have low distortion centrality. This conclusion is insensitive to underlying distortions because of the hierarchical structure of sectoral production.

Fourth and finally, distortion centrality predicts sectoral interventions in these economies. According to my calculations, sectoral variations in credit availability, tax incentives, and policy funds to SOEs raise aggregate consumption in China by 2-6%; in South Korea, policy spendings in sectors targeted by the HCI drive also generated positive net effects.

There are several important caveats about my results: they concern marginal interventions and are silent on when subsidies become too high; they analyze economic effects of reallocation and omit political economy aspects of policy implementation; they focus on sectoral interventions and do not speak to differential, within-sector interventions; they assume market imperfections are policy invariant, yet the former could be directly influenced by the latter. I leave these considerations to future research.
References


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


Appendix

A Theory: Extensions, Microfoundations, and Discussions

In this appendix, I discuss a few additional extensions and issues relating to my theory. First, I show how within-sector distortions can be accommodated into the same framework. Second, I provide other microfoundations for distortions, including markups and Marshallian externalities. Third, I discuss the boundary of my results over the issue of multiple factors and distortions over factor inputs. Fourth, I further elaborate on distinctions between market imperfections and iceberg costs. Fifth, I discuss an extension in which policy instruments have an advantage over market transactions and can directly counteract deadweight losses. Sixth and lastly, I discuss the role of social welfare functions.

A.1 Within-Sector Heterogeneity

The model in the main text features constant-returns-to-scale (CRST) sectoral production and market imperfections $x_{ij}$ at the sector-pair level. I now incorporate within-sector firm heterogeneity into the model and show that, under certain conditions, distortion centrality remains sector-specific—rather than firm-specific—and $\xi_i$ captures the social value of government subsidies to any firms in sector $i$. In what follows, I use “good” when referring to output aggregated at the sector level and “variety” when referring to differentiated goods within each sector.

Consider modifying the model such that each good $i$ is combined from a continuum of varieties $\nu \in [0, 1]$ using a CRST aggregator

$$Q_i = G_i((q_i(\nu))).$$

Producers of variety $\nu$ in sector $i$ have a CRST production function $f_i^\nu$

$$q_i(\nu) = \bar{z}_i z_i (\nu) f_i^\nu \left( \frac{\ell_i (\nu)}{\sum_{j=1}^{S} m_{ij}(\nu)} \right),$$

where $\bar{z}_i$ represent a sector-specific productivity shifter that affects all varieties in sector $i$, $z_i (\nu)$ is a variety-specific productivity shifter, and $\ell(\nu)$ and $m_{ij}(\nu)$ represent variety-specific input quantities. Note, the fact that cross-sector demand has to go through an aggregator $G_i(\cdot)$ implies that different buyers of each good purchase the same bundle of underlying varieties; this is an important assumption.

Suppose market imperfections and subsidies are variety-specific, i.e. producer of variety $\nu$ in sector $i$ face distortion wedge $x_{ij}(\nu)$ and subsidy $\tau_{ij}(\nu)$. Given that each variety features CRST in production, one can relabel each variety as a sector and compute variety-specific distortion centrality $\xi_i(\nu)$. My theoretical results in section 2 trivially extends to this case, and $\xi_i(\nu)$ captures the social value of policy expenditures on subsidizing variety $\nu$ in sector $i$. More interestingly, distortion centrality remains
sector-specific in this environment: \( \xi_i(v) = \xi_i \) for all \( v \), where \( \xi_i \) is the distortion centrality computed by treating good \( i \) as a homogeneous sectoral good, with price index

\[
P_i \equiv \min_{q_i(v)} p_i(v) q_i(v) \text{ s.t. } G_i([q_i(v)]) \geq 1.
\]

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

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

\[
\xi_i(v) = \frac{d \ln W}{d \ln z_i(v)} \frac{d \ln W}{d \ln p_i(v)} = \frac{\partial \ln P_i}{\partial \ln p_i(v)} = \frac{p_i(v) q_i(v)}{\int p_i(v) q_i(v) dv},
\]

On the other hand, sector-specific distortion centrality equals

\[
\xi_i = \frac{d \ln W}{d \ln \bar{z}_i} = \frac{d \ln W}{d \ln \bar{p}_i(v) dv}.
\]

The existence of a sectoral aggregator \( G_i(\cdot) \) implies (the second equality follows from cost-minimization)

\[
\frac{d \ln W}{d \ln z_i(v)} = \frac{\partial \ln P_i}{\partial \ln p_i(v)} = \frac{p_i(v) q_i(v)}{\int p_i(v) q_i(v) dv},
\]

which in turn implies \( \xi_i(v) = \xi_i \), proving the claim.

Several comments are in order. First, this result depends crucially on the existence of a sectoral aggregator \( G_i \). This restriction ensures that buyers of good \( j \) are purchasing the same bundle of varieties within sector \( j \), a fact that in turn implies distortions are sector-specific on the supplier-side (i.e. buyer \( v \) in sector \( i \) faces the same distortion \( \chi_{ij}(v) \) when buying different varieties in sector \( j \)). Absent this restriction, distortions can be variety-pair specific, in which case the notion of variety indeed coincides with the notion of sector in the baseline model, and distortion centrality would become variety-specific.

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

Third, the fact that social value of policy expenditures is independent of within-sector heterogeneity is again a feature of the first-order effects that my theory concerns. Higher order effects, in the trade-off of which firms to target within each sector, do depend on parametric structures in production functions as well as the sectoral aggregator $G_i(\cdot)$.

### A.2 Other Microfoundations

First, note that the wedges can nest other frictions, e.g. contracting frictions. In what follows, I provide two additional microfoundations, respectively based on markups and Marshallian externality. Under both microfoundations, there are accounting profits (quasi-rents) but no economic profits (pure- rents), as accounting profits are competed away through entrepreneurial disutility cost of entry.

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

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

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

$$Q_i = N_i^{\frac{1}{1-\sigma_i}} \left( \int_0^{N_i} q_i(x)^{\frac{\sigma_i-1}{\sigma_i}} dx \right)^{\frac{\sigma_i}{\sigma_i-1}},$$

(A.1)

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

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

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

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

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

The baseline version of this microfoundation induces, for each seller $j$, a uniform price wedge over marginal cost of production, $P_j = \frac{\sigma_j}{\sigma_j - 1} C_j$. Conceptually, my theory extends to this environment, which is allocationally equivalent to one in which producers set prices equal to marginal costs but all buyer $i$’s of good $j$ have to incur proportional cost $\chi_{ij} = \frac{\sigma_j}{\sigma_j - 1}$ that are deadweight losses in terms of the numeraire good. Because sellers receive distortion payments as part of sectoral revenue when they charge markups, the notion for Domar weight has to be adjusted—the relevant definition is total sectoral production costs relative to factor payments, $\gamma_j \equiv \frac{C_j Q_j}{WL}$. Let $\tilde{\gamma}' = \beta' (I - \Omega)^{-1}$, then Domar weight in equilibrium can be written as $\gamma_j = \tilde{\gamma}' \frac{\sigma_j}{\sigma_j - 1}$.

Lastly, note that one can always microfound additional, buyer-seller specific distortions $\chi_{ij}$ using markups, by generalizing the aggregator in (A.1) to be buyer-specific aggregator functions. Specifically, suppose buyers from different sector $i$’s have distinct elasticity of substitutions across firm-level products, leading producers in sector $j$ to charge buyer-specific markups $\frac{\sigma_{ij}}{\sigma_{ij} - 1}$. Correspondingly, total deadweight losses induced by excess entry in that case would be $C_j \sum_i \frac{\sigma_{ij}}{\sigma_{ij} - 1} M_{ij}$.

**Marshallian Externality** Under the previous microfoundation, one firm’s entry imposes negative externalities upon other firms through the aggregator in (A.1). I now show that non-negative distortion wedges can also represent Marshallian externalities, under which firms impose positive spillovers to each other and under-produce relative to the first-best. Conceptually, the sign restriction $\chi_{ij} \geq 0$ does not assume the direction of spillovers but instead assumes that, holding input-prices constant, sectoral output prices are higher when imperfections are present than if they are not.

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

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

where $F_i(\cdot)$ features CRTS and $\alpha_i \in (0, 1)$. $N_i$ is again the measure of firms in sector $i$. The term $(Q_i/N_i)^{1-\alpha_i}$ represents Marshallian externalities; it captures the component of productivity that each firm takes as exogenous but is nevertheless dependent on the average firm output in the sector. The exponent $(1 - \alpha_i)$ controls the strength of Marshallian externality. In any equilibrium, firms within a sector make identical production decisions, and sectoral production emits a CRTS representation.
despite positive externalities. Firms under-produce relative to the first-best, and despite being price-takers, firm earn accounting profits because they take \( Q_i / N_i \) as exogenous while optimizing over a strictly concave production function. There is no pure, economic profits due to disutility entry cost. In equilibrium, firms in sector \( j \) set price \( p_j \) to be private marginal costs but is higher than the sectoral marginal costs \( C_j \), with a seller-specific sectoral wedge that is common to all buyers, \( \chi_{ij} = \frac{1 - \alpha_j}{\alpha_j} \).

### A.3 Interpreting Factors

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

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

**Distortions over Factors** An assumption in the main text is that producers do not directly make distortion payments over factor inputs, \( \chi_{jL} = 0 \). The main purpose of this specification is accounting, as the assumption implies that using factors does not directly generate deadweight losses. The case with \( \chi_{jL} > 0 \) can always be accomodated in the model by introducing additional, synthetic producers and relabeling. Because of input-output linkages, this specification does not rule out either cross-sector misallocation of factors or uniform wedges that depress all sectoral inputs, even without any relabeling. In the markup formulation above, for instance, misallocations due to a uniform wedge in sector \( j \) can be analyzed by a common wedge \( \chi_{ij} = \frac{\sigma_j}{\sigma_{j-1}} \) for all buyers \( i \).

### A.4 Imperfections ≠ Iceberg Costs

In this appendix section, I further demonstrate distinctions between market imperfections and iceberg costs. I first solve for closed-form allocations in a simple example, and I compare allocations
under market imperfections with those under iceberg cost. I then show that distortion centrality is always equal to one in iceberg economies, implying that policy interventions have no first-order effects.

**Compare Allocations Under Market Imperfections and Iceberg Costs**

Consider a simple example. Sectors 1 and 2 produce linearly from the factor and supply their entire output to sector 3, which faces distortion $\chi > 0$ for buying input 1 and no distortion over input 2. The consumption good is transformed directly from good 3. Following the notations in the paper,

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

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

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

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

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

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

\[ L_1^* = \alpha L, \quad L_2^* = (1-\alpha) L, \quad Y^* = \left(\frac{L_1^*}{l_1^*}\right)^\alpha \left(\frac{L_2^*}{l_2^*}\right)^{1-\alpha}. \]

I make two observations. First, imperfections cause factor inputs to be under-allocated to sector 1 and, conversely, over-allocated to sector 2 ($L_1 < L_1^*$, $L_2 > L_2^*$). Second, net output $Y$ is lower than the first-best output $Y^*$ for two reasons: $Y^* > Y^G$ due to misallocation, and $Y^G > Y$ due to deadweight losses associated with distortion payments. In this example, the Cobb-Douglas assumption implies that distortion payments is a constant share $\frac{\alpha \chi}{1+\chi}$ of gross output.

Now consider an iceberg economy, in which $\chi$ units of good 1 is lost for every unit delivered to sector 3 as production inputs. Market clearing condition for good 1 becomes

(market clearing condition for good 1 under iceberg economy) \[ Q_1 = (1+\chi) M_{31}. \]

Let $Y^{IB}$ be the output of consumption good; note there is no distinction between gross and net output in an iceberg economy. Allocations follow:

\[ L_1^{IB} = \alpha L, \quad L_2^{IB} = (1-\alpha) L, \quad Y^{IB} = \left(\frac{L_1^{IB}}{l_1^{IB}}\right)^\alpha \left(\frac{L_2^{IB}}{l_2^{IB}}\right)^{1-\alpha}. \]

I make three observations, all of which apply more broadly, to arbitrary networks with CRTS produc-
tion functions, and are not specific to this example. First, factor allocation is efficient in the iceberg economy, \( L^I_t = L^*_t \). This is a manifestation of the well-known fact that iceberg costs do not induce misallocations. Second, iceberg costs do lower output in ways similar to negative technology shocks. In this example, the iceberg cost \( \chi \) is equivalent to a proportional productivity shock \( \left( \frac{1}{1+\chi} \right) \) to sector 1. Third, simple algebra shows that

\[
Y^* > Y^G > Y = Y^I_t,
\]

i.e., absent policy interventions, net output in my economy with imperfections is always equal to the output level in an iceberg economy with wedges of the same size. This follows from the fact that 1) absent interventions, \( Y = WL \) in a distortion economy, and \( Y^I_t = W^I_t L \) in an iceberg economy; 2) iceberg costs and my distortions wedges have identical effects on prices.

**Distortion Centrality Is Always One In Iceberg Economies** Note that sectoral influence in iceberg economies can be defined using elasticities of cost functions, \( \mu^t \equiv \beta^t (I - \Sigma)^{-1} \), in the same way as it is defined in my distortion economy. Moreover, Lemma 1 holds, and influence captures the elasticity of factor price with respect to sectoral TFP shocks.

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

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

where \( \chi_{ij} \) represents the proportional loss in good \( j \) during transportation to sector \( i \). Multiplying both sides by \( P_j \frac{Q_j}{WL} \) and noting that \( P_j M_{ij} \left( 1 + \chi_{ij} \right) = \sigma_{ij} P_i Q_i \) under iceberg economy, one derives

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

or, in matrix notation,

\[
\gamma' = \beta' + \gamma' \Sigma
\]

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

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

**A.5 Extension: Subsidies Counteract Deadweight Losses**

In my model, subsidies redistribute resources but do not counteract deadweight losses. Specifically, given subsidy \( \tau_{ij} \), distortion payments \( \chi_{ij} P_j M_{ij} \) scale with the market value of transaction
$P_j M_{ij}$, not the subsidized value $\left(1 - \tau_{ij}\right) P_j M_{ij}$. I adopt the first formulation as the baseline because it subjects government spendings to the same imperfections as faced by market-based transactions, thereby isolating only the reallocate effects of policy interventions. Under the latter formulation, interventions have advantages over private transactions and can directly counteract deadweight losses by manipulating transaction prices. It is easy to show that, in this latter case, the social value of policy expenditures consists of two parts: a) the reallocate effect captured by sectoral distortion centrali-

ty, and b) the efficiency gain by directly canceling out deadweight losses: $SV_{ij} = \xi_i \times (1 + \chi_{ij})$. My baseline model isolates the first effect.

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

The normative interpretation of my positive characterizations in Propositions 1 through 3 implicitly assumes a social welfare function $U(C, G)$ that places equal marginal value over private and public consumption (for instance, $U(C, G) = C + G$). This is without loss of generality when the government has unrestricted access to lump-sum taxes, which enables one-for-one transfers between private and public consumption. That said, my results are still useful when lump-sum taxes are restricted: the generic welfare impact of a subsidy $\tau_{ik}$ financed by marginally cutting back $G$ is

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

The social value of policy expenditures, as characterized in Proposition 1, directly translate into a preference ordering over policy instruments under $U(\cdot)$. 
Additional appendices to be added.