Misallocation in the Market for Inputs: Enforcement and the Organization of Production*

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June 21, 2018

Abstract

The strength of contract enforcement determines how firms source inputs and organize production. Using microdata on Indian manufacturing plants, we show that production and sourcing decisions appear systematically distorted in states with weaker enforcement. Specifically, we document that in industries that tend to rely more heavily on relationship-specific intermediate inputs, plants in states with more congested courts shift their expenditures away from intermediate inputs and appear to be more vertically integrated. To quantify the impact of these distortions on aggregate productivity, we construct a model in which plants have several ways of producing, each with different bundles of inputs. Weak enforcement exacerbates a holdup problem that arises when using inputs that require customization, distorting both the intensive and extensive margins of input use. The equilibrium organization of production and the network structure of input-output linkages arise endogenously from the producers' simultaneous cost minimization decisions. We identify the structural parameters that govern enforcement frictions from cross-state variation in the first moments of producers' cost shares. A set of counterfactuals show that enforcement frictions lower aggregate productivity to an extent that is relevant on the macro scale.

KEYWORDS: Production Networks, Intermediate Inputs, Misallocation, Productivity, Contract Enforcement, Value Chains
JEL: E23, O11, F12

*We are grateful to David Baqaee, Hugo Hopenhayn, Eduardo Morales, Steve Redding, Matt Rognlie, Meredith Startz, Gustavo Ventura, and various seminar participants for helpful suggestions. Anusha Guha, Hélène Maghin, and Juan Manuel Castro provided excellent research assistance. We are grateful to Daksh India for sharing data, and to CEPR/PEDL and the Sciences Po/Princeton partnership for financial support. Boehm thanks the International Economics Section at Princeton for hospitality during the later stages of the project. This document is an output from the research initiative "Private Enterprise Development in Low-Income Countries" (PEDL), a programme funded jointly by the by the Centre for Economic Policy Research (CEPR) and the Department for International Development (DFID), contract reference PEDL_LOA_4006_Boehm. The views expressed are not necessarily those of CEPR or DFID. All mistakes are our own.

1 Introduction

Weak contract enforcement hinders firm-to-firm trade and distorts production decisions. For example, a manager who cannot rely on courts for timely and cheap enforcement may need to purchase low-quality substitutes from her cousin, vertically integrate the production process, or altogether switch to a different technique that avoids the bottleneck input. Regardless of the chosen alternative she will find herself producing at a higher cost. Collectively, the micro distortions induced by weak enforcement alter the equilibrium network structure of production and reduce aggregate productivity.

This paper studies theoretically and empirically how weak legal institutions—more precisely, slow contract enforcement due to congestion of the courts—shapes technology choices and the organization of production. We develop a framework that allows us to use detailed micro production data to quantify the impact of these frictions on aggregate productivity.

We study contract enforcement frictions in the context of the Indian manufacturing sector. India is a country with infamously slow and congested courts: the World Bank (2016) currently ranks India 172nd (out of 190) when it comes to the enforcement of contracts, behind countries such as the Democratic Republic of Congo (171st) and Zimbabwe (165th). Around 6m of the 22m pending cases are older than five years, and while India's Law Commission has been advocating vast reforms for several decades, these reforms have not been implemented, and pendency ratios have not decreased. At the same time, India's liberalization and growth has spurred demand for timely enforcement of contracts.

Using plant-level data from India's Annual Survey of Industries, we document several facts about how court congestion alters plants' input choices. While there is an enormous amount of heterogeneity in the input bundles plants use even within narrowly defined (5-digit) industries,[1] the bundles differ in systematic ways related to the quality of courts. To focus on these differences, we differentiate between inputs that are relatively homogeneous and standardized from those that require customization or are relationship specific, using the classification from Rauch (1999). Users (or potential users) of relationship-specific inputs are most likely to benefit from better formal enforcement of supplier contracts.

Our first fact is that in states where courts are more congested, plants in industries that typically rely on relationship-specific intermediate inputs systematically shift production away from intermediate inputs, whereas plants in industries that typically rely on homogeneous intermediate inputs systematically shift their expenditures toward intermediate inputs. The former is consistent with slow courts raising the effective cost of relationship-specific inputs while the latter is consistent with slow courts raising the effective cost of primary inputs. Second, we show that, where courts are slower, plants in all industries shift the composition of their intermediate input bundles toward

[1] Some of this heterogeneity reflects different organizational and technological choices. As an example, a plant that produces frozen chicken may purchase live chicken and slaughter and freeze them; or it may purchase chicken feed, and raise, slaughter, and freeze the chicken on the same vertically integrated plant. Other examples indicate horizontal technological choices, e.g., the chicken producer could use a sophisticated machine that mechanically packages the chicken or use more basic implements.

homogenous inputs. Third, we construct a new measure of vertical integration and show that, where courts are more congested, plants in industries that typically rely on relationship-specific inputs tend to be more vertically integrated. To alleviate concerns that higher court quality might arise endogenously from higher demand for formal contract enforcement, we use an instrumental variable strategy that exploits the historical origins and structure of the Indian judiciary.

To interpret these facts and to quantitatively evaluate their ramifications for aggregate productivity and for the organization of production, we construct a multi-industry general-equilibrium model of heterogeneous firms and intermediate input linkages that form between them. Firms face a menu of technology/organizational choices ("recipes") and draw suppliers along with match-specific productivities. Both primary inputs and relationship-specific inputs are subject to wedges that reflect weak contract enforcement. Each firm chooses the production technique and suppliers that minimize cost. The effective cost of an input depends on the match-specific productivity, the supplier's marginal cost, and the wedge. We model the enforcement wedge as randomly drawn to reflect the idea that formal enforcement may only sometimes be relevant at the margin. For example, formal enforcement may not be necessary if the buyer and supplier are engaged in a long-term relationship, are related, or share other social ties.

In our model, wedges distort choices and build up along entire supply chains. Weak enforcement has a direct impact on producers that use inputs that require contract enforcement, but may also lead firms to switch to suppliers with a higher cost or to an entirely different production technique with a different set of inputs. We think of vertical integration as one such option.

To make quantitative statements, we structurally estimate technological parameters and distributions of wedges that distort the use of relationship-specific intermediate inputs and of primary inputs that are specific to each state. Our identification strategy exploits the idea that the quality of courts should have no impact on the effective cost of homogeneous inputs (which, if anything, is conservative). The identified wedges on relationship-specific intermediate inputs are correlated with the observed speed of the regional courts, in line with the motivating reduced-form regressions.

Our results suggest that courts may be important in shaping aggregate productivity. For each state we ask how much aggregate productivity of the manufacturing sector would rise if congestion were reduced to be in line with the least congested state. On average across states, the boost to productivity is roughly 5%, and the gains for the states with the most congested courts are roughly 11%.

Our model builds on recent models of firm linkages in general equilibrium that include Oberfield (2018), Eaton, Kortum and Kramarz (2015), Lim (2017), Lu, Mariscal and Mejia (2013), Chaney (2014), Acemoglu and Azar (2017), Taschereau-Dumouchel (2017), and Tintelnot et al. (2017)[2], and uses aggregation techniques pioneered by Houthakker (1955) and Jones (2005). We model the technology choice and choice of organization concurrently with the sourcing decision, motivated by evidence that increased access to intermediate inputs has a productivity-enhancing effect (e.g.

[2]These are also closely related to models of global value chains and global sourcing such as Costinot, Vogel and Wang (2012), Fally and Hillberry (2015), Antràs and de Gortari (2017), Antras, Fort and Tintelnot (2017).

Pavcnik (2002), Khandelwal and Topalova (2011), Goldberg et al. (2010), Bas and Strauss-Kahn (2015)). As in Grossman and Helpman (2002), one producer's choice of organization depends on the industry environment and the choices of other producers.

Our paper is also closely related to the literature on misallocation in developing countries (see Hopenhayn (2014) for a survey). Several papers have extended the work of Hsieh and Klenow (2009) to settings in which distortions affect the use of intermediate inputs, e.g., Jones (2013), Bartelme and Gorodnichenko (2014), Fadinger, Ghiglino and Teteryatnikova (2016), Bigio and La'O (2016), Caprettini and Ciccone (2015), Liu (2017), Caliendo, Parro and Tsyvinski (2017), Baqaee and Farhi (2017). These papers typically posit industry-level production functions and use industry-level data. Our approach of identifying wedges from factor shares (in our case, intermediate input expenditure shares) extends the work of Hsieh and Klenow (2009) along three key dimensions. First, we relate the estimated wedges to the quality of Indian state-level institutions, which allows us draw policy conclusions from our exercise. Second, we confront the fact that firms produce in very different ways even in narrowly defined industries by explicitly modeling this heterogeneity; we allow firms to choose among several types of technologies (recipes) in the theory and identify these recipes in the data through the application of techniques from statistics/data mining. Third, we identify wedges from systematic differences in first moments, which helps to alleviate concerns about mismeasurement being interpreted as misallocation.[3] In fact, our model predicts that, even in the absence of distortions, firms that use the same broad technology would use inputs with varying intensities.

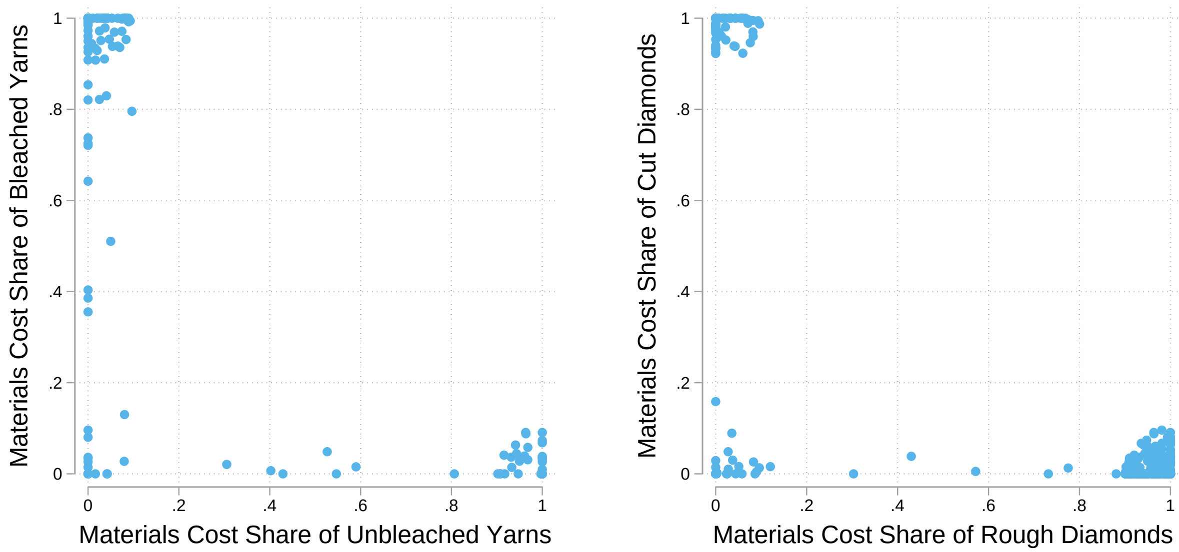
The paper is related to the literatures on legal institutions and economic development La Porta et al. (1997), Djankov et al. (2003), Acemoglu and Johnson (2005), Nunn (2007), Levchenko (2007), Acemoglu, Antràs and Helpman (2007), Laeven and Woodruff (2007) among many others). Ponticelli and Alencar (2016) and Chemin (2012) argue that better courts reduce financial frictions. Amirapu (2017) shows that where district courts in India are more congested, firms in industries that relied on relationship-specific inputs grew faster. Johnson, McMillan and Woodruff (2002) provide survey evidence that reduced trust in courts makes firms that rely on relationship-specific inputs less likely to switch suppliers. By embedding a contracting friction into a general equilibrium model, we explore its quantitative importance for aggregate outcomes. Boehm (2016) characterizes the impact of weak enforcement on aggregate productivity, using cross-country differences in input-output tables to show that weak legal institutions have a larger impact on industry pairs that are more vulnerable to holdup problems.

2 Input Use among Indian Manufacturing Plants

2.1 Intermediate Input Use

We use data from the 2000/01 to 2012/13 rounds of the Annual Survey of Industry (ASI), the official annual survey of India's formal manufacturing sector. The ASI is a panel that covers all

[3]See Bils, Klenow and Ruane (2017) and Rotemberg and White (2017).



(a) Input mixes for Bleached Cotton Cloth (63303)

(b) Input mixes for Polished Diamonds (92104)

Figure 1 Heterogeneity in input mixes within narrow industries

In the left panel, "bleached yarns" refer to yarns that have been bleached or dyed. Observations on the bottom left mostly produce their output from unbleached cloth (left panel) or industrial diamonds (right panel). Points have been jittered to improve readability.

establishments with more than 100 employees, and, every year, a fifth of all establishments with more than 20 employees (or more than 10 if they use power). The ASI's unique feature is that it contains detailed product-level information on each plant's intermediate inputs and outputs. Products codes are at the 5-digit level, of which there are around 5,200 codes in their classification. The product classification remains largely unchanged during the years 2000/01 to 2009/10. The rounds 2010/11 to 2012/13 use a different (albeit similar) product classification, and we bring product-level data to the classification of the earlier years using the official concordance table published by the Ministry of Statistics. Appendix A contains more details on the data and a description of our sample.

One striking feature of the data is that even in narrowly defined industries, plants produce using very different input bundles. Figure 1 shows two examples that are particularly clear. Among respective producers of bleached cotton cloth and polished diamonds, output is made using different sets of inputs. While we believe that much of the heterogeneity in organization and input bundles is not associated with inefficiencies and would arise naturally, Section 2.3 below shows that some of the differences are systematically related to court congestion.

Intermediate inputs vary in their degree to which buyers and sellers are subject to hold-up problems. Producers of goods that are tailored to a particular buyer ("relationship-specific") may find that buyers refuse to pay for the supplied good, knowing that they are useless to anyone but themselves (Iyer and Schoar (2008)). We use the Rauch (1999) classification that divides goods into homogeneous goods (those that are traded on organized exchanges or for which a reference price exists), and relationship-specific goods (the remainder). Holdup problems are more likely to arise with relationship-specific inputs. Firms may rely more heavily on judicial institutions to enforce supplier contracts when trading goods belonging to the latter category (Johnson, McMillan and Woodruff (2002)).

2.2 Court Congestion in India

Among all ills of the Indian judicial system, its slowness is perhaps the most apparent one. As of 2017, about nine percent of pending cases in district courts and six percent of pending cases in High Courts are older than ten years.[4] Some cases make international headlines, such as in 2010, when the Bhopal District Court convicted eight executives for death by negligence during the 1984 Bhopal gas leak which killed thousands of people. The conviction took place some 25 years after the disaster; one of the eight executives had already passed away, and the remaining seven appealed the conviction.[5]

The slowness of the Indian courts is at least partly due to the uneven distribution of workload across its three tiers.[6] The lowest tier are the Subordinate (District) Courts, which have courthouses in district capitals and major cities.[7] The next tier are the High Courts, of which there generally exists one for each state, and which have both appellate and original jurisdiction over cases originating from their state (and sometimes an adjacent union territory). High Courts also administer subordinate courts in their jurisdiction. The highest tier is the Supreme Court of India. All three tiers are heavily congested, with district courts facing the additional problems that judges are often inexperienced and make erroneous decisions. While contract cases between firms should, in principle, be filed at the district level, litigants typically bypass this step by claiming an infringement of their fundamental rights or appealing to the constitution of India, in which case they are permitted to file the claim directly at a high court.[8] High Court judges, often taking a dim view of the subordinate judiciary, tend to accommodate this practice. The result is that the Indian judiciary is relatively heavy in its upper levels, with only the simplest cases being dealt with in the subordinate courts.[9] For the better or worse, it is the quality of the higher judiciary that determines whether and how contracts can be enforced.

We construct a measure of court quality from microdata on pending civil cases in High Courts,

[4] Figures for district courts are from the National Judicial Data Grid (2017). Figures for High Courts are based on authors' calculations from the Daksh data (see below).

[5] "Painfully slow justice over Bhopal", Financial Times, June 7, 2010.

[6] See Robinson (2016)) for an overview of the Indian judiciary. Hazra and Debroy (2007) discuss its problems in relation to economic development.

[7] Districts are the administrative divisions below states. Between 2001 and 2010 there were around 620 districts and 28 states in India. Union territories are small administrative divisions (typically cities or islands) that are under the rule of the federal government, as opposed to states, which have their own government.

[8] Some High Courts, such as the High Courts of Bombay, Calcutta, Madras, and Delhi, even allow civil cases to be filed directly whenever the claim exceeds a certain value.

[9] Between 2010 and 2012, about 40% of all disposed cases in subordinate courts were related to traffic tickets, another seven percent related to bounced cheques (Law Commission of India (2014)).

which the Indian NGO Daksh collects from causelists and other court records (Narasappa and Vidyasagar (2016)). These records show the status and age of pending and recently disposed cases, along with characteristics of the case, such as the act under which the claim was filed or a case type categorization. Our measure of high court quality is the average age of pending civil cases in each court, at the end of the calendar year 2016. Whenever a high court has jurisdiction over two states and a separate bench in each of them (such as the Bombay High Court, which has jurisdiction over Maharashtra and Goa), we construct the statistic by state. We prefer this measure over existing measures of the speed of enforcement, such as pendency ratios published by the High Courts, which suffer from the problem that different high courts measure pendencies in vastly different ways (as recently emphasized by the Law Commission of India (2014)).

The average age of pending civil cases varies substantially across high courts – from less than one year in Goa and Sikkim, to about four and a half years in Uttar Pradesh and West Bengal. The cross-state average is two and a half years.

The problems of the Indian judiciary are not a recent phenomenon, and have not gone unnoticed. Throughout the modern history of India as an independent nation, the Law Commission of India has pointed out the enormous backlogs and arrears of cases (14th report, 1958, 79th report, 1979, 120th report, 1987, and 245th report, 2014), and suggested a plethora of policies to alleviate the situation. The vast majority of these proposals have not been adopted, and the few exceptions seem to have had little impact. Overall, the backlogs have slowly but continually accumulated.

The main explanation for why court speed varies so much across states lies in the history of India's political subdivisions. The first high courts (Madras, Bombay, and Calcutta) were set up by the British in the 1861 Indian High Courts Act, and served as the precursor for India's post-independence high courts. Upon independence, India was divided into a number of federated states, with the Constitution of India (1947) mandating a high court for each state. Throughout the twentieth century and beyond, India has frequently subdivided its states, often because of ethno-nationalist movements. These subdivisions were often accompanied with new high courts being set up, which then start without any existing backlog of cases.[10] The age of the high court is hence a strong determinant of its speed of enforcement (see Figure 2). We will later use the age of high courts as an instrument for its quality.

2.3 Motivating Facts

We first turn to documenting the correlation between court quality and plants' intermediate input use. For the sake of preciseness we restrict our attention here to single-product plants.[11]

Fact 1 *In states with worse formal contract enforcement, cost shares of intermediate inputs are relatively lower in industries that tend to rely more on relationship-specific intermediate inputs.*

[10] Table VII in the data appendix summarizes the reasons for the high court being set up, or the state being formed.

[11] One difficulty that arises when studying multi-product plants is that we do not observe which inputs are used to produce each product. Nevertheless, the results in this section are quantitatively similar when we include multi-product plants and assign the plant to the category of its highest-revenue product.

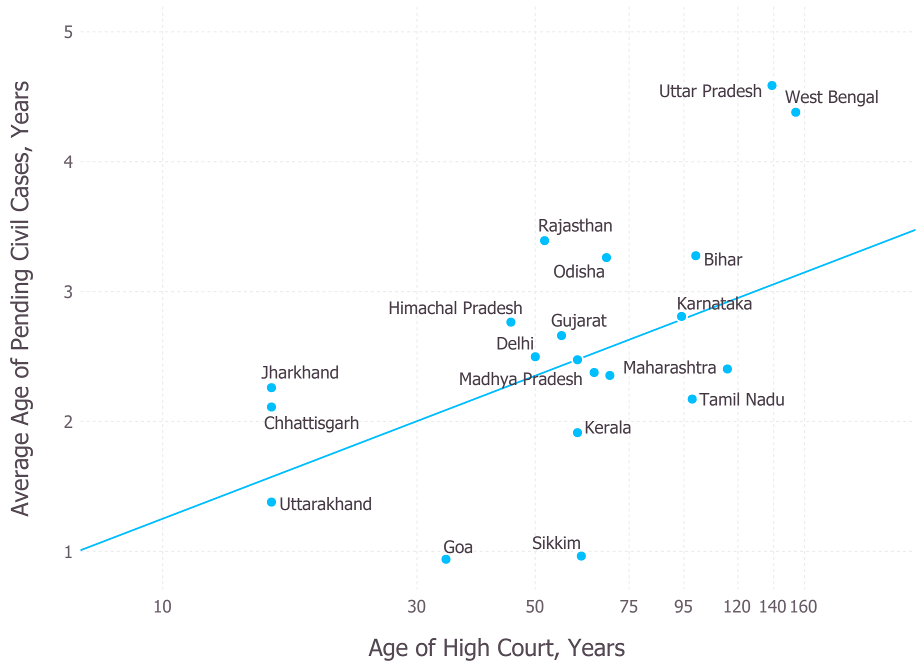


Figure 2 Age of the High Court and Speed of Enforcement

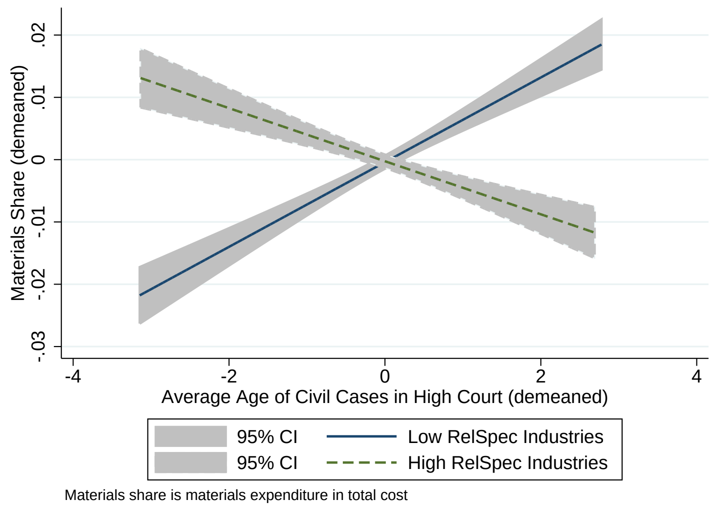
Figure 3 shows the relationship between plants' intermediate input shares and court quality as measured by the average age of pending cases in the state's high court, separately for industries with above-median expenditure shares on relationship-specific intermediate inputs (dashed line) and for industries with below-median expenditure shares on relationship-specific intermediate inputs (solid line).[12] All variables are centered around zero within each industry. In low-relationship-specific-intense industries, plants in states with better courts have on average lower materials shares, while in industries that rely heavily on relationship-specific inputs, plants have lower materials shares when they are located in states with bad courts. One interpretation of these patterns is that weak contract enforcements deters the use of relationship-specific inputs and primary inputs more than the use homogeneous inputs.

Table I shows this result formally using linear regression with a continuous interaction rather than separating industries into above and below median. A primary concern is that court congestion is standing in for the level of development, or that the level of development is correlated with the relative productivity of industries that rely on relationship-specific inputs. Column (1) shows that the difference remains statistically significant when we use district fixed effects to control for district characteristics such as income per capita and population density. Column (2) controls for the interaction of relationship specificity with income per capita and column (3) adds controls for

[12] We measure an industry's reliance on relationship-specific inputs at the national level by computing the fraction of intermediate input expenditures spent on relationship-specific inputs across all plants in the industry. See Appendix A.1 for details.

the interaction of relationship specificity with a variety of state characteristics including measures of trust, corruption, linguistic fragmentation, and fragmentation by caste. While the coefficients (reported in Appendix C) suggest that ethnic homogeneity facilitates the use of relationship-specific inputs, this appears to be orthogonal to court congestion. Finally, columns (4) to (6) employ an instrumental variables strategy that we discuss below in Section 2.4.

Figure 3 Court quality and materials shares



The figure shows the relationship between plant's materials shares and the speed of the high court in the state where the plant is located. All variables are deviations from industry means.

Table I Materials Shares and Court Quality (Fact 1)

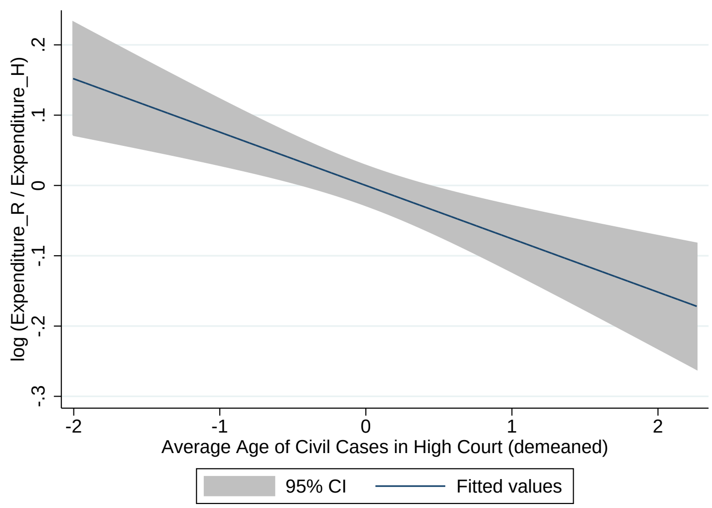
	Dependent variable: Materials Expenditure in Total Cost					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Age Of Civil Cases * Rel. Spec.	-0.0167**	-0.0155*	-0.0165*	-0.0156+	-0.0206*	-0.0237*
	(0.0046)	(0.0066)	(0.0069)	(0.0085)	(0.0098)	(0.0094)
LogGDPC * Rel. Spec.		-0.00159	-0.0130		-0.00836	-0.0230
		(0.012)	(0.015)		(0.016)	(0.018)
Rel. Spec. × State Controls			Yes			Yes
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	IV	IV	IV
R^2	0.480	0.482	0.484	0.480	0.482	0.484
Observations	208527	199544	196748	208527	199544	196748

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
"Rel. Spec. × State Controls" are interactions of trust, language herfindahl, caste herfindahl, and corruption with relationship-specificity.

Fact 2 *In states with worse formal contract enforcement, intermediate input bundles are tilted towards less relationship-specific intermediate inputs.*

Our first fact related court quality to how plants divided their expenditures between intermediate and primary inputs. We next study how the composition of plants' intermediate input baskets covaries with court quality. Figure 4 shows the fitted line from a regression of the log of the ratio of a state-industry's expenditure on relationship-specific intermediate inputs to expenditure on homogenous intermediate inputs on court quality. In states where courts are faster, plant's intermediate input baskets are tilted towards relationship-specific intermediate inputs. Table II shows that this correlation remains statistically significant when controlling for district income per capita and other state characteristics.

Figure 4 Court quality and the input mix



The figure shows the relationship between plant's log share of expenditure on relationship-specific vs homogeneous intermediate inputs and the speed of the high court in the state where the plant is located. All variables are deviations from industry means.

Table II Input Mix and Court Quality (Fact 2)

	Dependent variable: $X_j^R/(X_j^R + X_j^H)$					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg age of Civil HC cases	-0.00547*	-0.00621**	-0.00530*	-0.0144**	-0.0146**	-0.0167**
	(0.0022)	(0.0023)	(0.0024)	(0.0044)	(0.0044)	(0.0045)
Log district GDP/capita		-0.00389	-0.00384		-0.00912^{+}	-0.00980^{+}
		(0.0045)	(0.0046)		(0.0051)	(0.0051)
State Controls			Yes			Yes
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	IV	IV	IV
R^2	0.441	0.446	0.449	0.441	0.446	0.449
Observations	225590	204031	199339	225590	204031	199339

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
"State Controls" are trust, language herfindahl, caste herfindahl, and corruption.

Fact 3 *In states with worse formal contract enforcement, plants in industries that tend to rely more on relationship-specific intermediate inputs are more vertically integrated.*

A low materials share suggests that a plant may be doing more of production in-house, i.e., be more vertically integrated. For example, a car producer that assembles components may also manufacture those components in the same facility. The regressions in Table III show how court quality is related to a measure vertical integration. We first construct a measure of the "vertical distance" between an output good ω to an input ω'. This is intended to capture the typical number of "steps" between the use of ω' and the production of ω, where we define a step to be the activity performed by a single plant.[13] Finally, for each plant, our measure of vertical integration is the expenditure weighted average of the distance to its intermediate inputs. A higher number indicates that the plant uses inputs that are typically more distant, and suggests that the plant is performing more "steps" in-house. Table III shows that, in industries that rely more heavily on relationship-specific inputs, plants tend to be more vertically integrated in states with worse courts.

Table III Vertical Integration of Plants and Court Quality (Fact 1)

	Dependent variable: Vertical Distance of Inputs from Output					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Age Of Civil Cases * Rel. Spec.	0.0195^{+}	0.0341^{*}	0.0320^{*}	0.0292	0.0414^{+}	0.0437^{*}
	(0.011)	(0.014)	(0.014)	(0.019)	(0.022)	(0.021)
LogGDPC * Rel. Spec.		0.0517^{+}	0.0309		0.0613^{+}	0.0471
		(0.029)	(0.034)		(0.037)	(0.040)
Rel. Spec. × State Controls			Yes			Yes
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	IV	IV	IV
R^2	0.443	0.451	0.453	0.443	0.451	0.453
Observations	163334	156191	154021	163334	156191	154021

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
"Rel. Spec. × State controls" are interactions of trust, language herfindahl, caste herfindahl, and corruption with relationship-specificity.

2.4 Endogeneity, and the Historical Determinants of Indian Court Efficiency

The main caveat in the above regressions is the concern that there are unobserved covariates of court quality that may also affect the cost of firms' inputs, and thereby their input shares. The simplest version is reverse causality. In principle, the bias from reverse causality could be positive or negative. Suppose that a state had, for exogenous reasons, many firms that produced using relationship-specific inputs. The disputes that arise may cause the courts to be congested. Or alternatively, the

[13] We construct national input-output tables using our plant-level data. For each output good ω and input good ω', we take a weighted average of the number of steps along any path from ω' to ω, weighted by the product of the input-output shares along that path, excluding any path which cycles. This measure is similar to $Upstreamness_{ij}$ of Alfaro et al. (2015). Appendix B gives the precise mathematical definition of vertical distance.

state may respond to the disputes that arise and spend resources to reduce congestion. Either of these would be problematic for interpreting the regressions as a causal relationship.

While we believe reverse causality is unlikely to arise—the fraction of cases related to firm-to-firm trade is relatively low[14]—it is difficult to rule out other factors that may influence both court congestion and usage of relationship-specific inputs.

We therefore employ an instrumental variables strategy that uses the historical determinants of congestion. As discussed in Section 2.2, courts have been continually accumulating backlogs throughout the 20th century. At certain points in time, however, states were split or reorganized, mostly in response to ethno-nationalist movements. In the course of these reorganizations, new high courts were set up, which initially started with a clean slate but were, like existing courts, understaffed and started accumulating backlogs. The time since their founding—the court's age—is therefore a strong predictor for the current backlog, which in turn determines the present-day speed of enforcement. Our instrumental variable for the speed of enforcement is hence the (log) age of the high court, and the instrument for an interaction of an industry-level variable with court speed is the interaction of the industry-level variable with the log age of the court. Figure 2 in Section 2.2 shows the strong correlation between court age and speed of enforcement.

Columns (4) to (6) of Tables I, II, and III repeat the regressions while instrumenting for the speed of enforcement. The point estimates of the coefficient of the interaction term is usually slightly larger than the OLS estimates.

There are a few reasons that the exclusion restriction may be violated. We argue that two candidates would lead us to conclude that the true relationships are *stronger* than reported in the IV regressions. First, new states tend to be relatively poor and have low state capacity. Thus the usual concern that a high level of development causes firms to use more sophisticated technologies that use relationship-specific inputs would cause the newer states to have higher use of homogeneous inputs. Alternatively, it may be that when a state splits, many firms lose their suppliers and must switch. It may be easy to find a new supplier of homogeneous inputs, whereas it might be harder to find a supplier of relationship-specific inputs. This channel would also cause newer states to be more intensive in homogeneous inputs. In either case, the true relationship would be stronger than reported. A third reason that the exclusion restriction might be violated is that newly formed states might be more ethnically homogenous, so that newer courts might be correlated with better informal enforcement. This is a particular concern here because ethno-nationalist conflicts are a primary reason that states split. Nevertheless, we can control for states' ethnic fragmentation—or more specifically the interaction of relationship-specificity with various measures of ethnic-fragmentation—as we do in columns (3) and (6) of tables I, II, and III. Controlling for these has little impact on the main coefficients of interest.

A final concern is that an industry's reliance on relationship-specific inputs is correlated with other industry characteristics such as capital intensity, skill intensity, or upstreamness. In Appendix

[14]The fraction of cases that is related to the enforcement of supplier contracts is hard to pinpoint exactly because courts classify cases very broadly, and in different ways across states. We know, however, that they account for less than 5%, 14%, and 7% of the pending cases in the High Courts of Allahabad, Mumbai, and Kolkata, respectively.

C.6 we show that the estimates are robust to controlling for the respective interactions of court congestion with each of these industry characteristics.

3 Model

The previous section showed that imperfect contract enforcement alters the production decisions of manufacturing firms in India in systematic ways. We next aim to quantify the impact of weak enforcement on the productivity of the manufacturing sector. Our main identifying assumption is that imperfect contract enforcement distorts the use of relationship-specific inputs and of labor, but not the use of homogeneous inputs. Motivated by the reduced form evidence, we will ultimately identify the impact of the distortions by studying how patterns of firms' expenditure shares differ across states.

However, several factors complicate the tasks of measuring distortions and assessing their impact. First, there are many ways to avoid contracting frictions. Suppose a firm needed to use an input that required customization and gave rise to a holdup problem. In the face of weak formal contract enforcement, the firm might buy the intermediate input from a cousin or rely on the repeated interactions of a long-term relationship. Such decisions, however, may come at a cost. A family member may not be the optimal supplier of an intermediate input, and if a firm is in a long term relationship, it may pass up using new, more cost-effective inputs in order to remain in that long term relationship.[15] Such a firm's production cost is higher than it would be with better contract enforcement. Nevertheless, since the firm avoids the holdup problem, its expenditure shares will not be distorted. The higher production cost is an *indirect* consequence of weak formal enforcement. We can infer this indirect cost by incorporating such decisions in the model, albeit in a reduced form way.

Second, as discussed in Section 2.1, even in narrowly defined industries, firms produce in qualitatively different ways. As a simple example, consider two plants that both produce tires, one that buys rubber and another that harvests rubber itself. It may well be the case that the latter's decision to vertically integrate was a consequence of a distortion. But simply comparing the two plants' expenditure shares won't give a direct measure of the size of the distortion. Similarly, some shoe producers make the shoes by hand and others using sophisticated technologies. Fortunately the ASI provides an extremely detailed characterization of plants' input bundles. As such, one goal is to use an analytical framework that incorporates decisions of producing using alternative modes of production and to use this feature of the data to inform the model and our measurement of distortions.

In the model, firms may produce using many inputs. Using some inputs gives rise to a holdup problem that can be alleviated with good contract enforcement. The model incorporates two

[15] Lim (2017) documents that in each year, firms switch roughly 40% of suppliers, and Lu, Mariscal and Mejia (2013) document that ubiquitous switching of imported inputs among importers, suggesting gains from taking advantage of new opportunities that arise. Johnson, McMillan and Woodruff (2002) show that those who distrust courts are less likely to switch suppliers, suggesting that weak enforcement inhibits this.

ways that weak enforcement might cause firms to alter their production decisions. A firm might change the intensities with which it uses specific inputs, or it might switch methods of production altogether. There is a tremendous amount of heterogeneity across firms in the number, types, and cost shares of inputs used, even within extremely narrowly defined industries. Our model takes the stand that much of this heterogeneity is natural and would arise even in the absence of distortions, due to realizations of match-specific productivity differences. The natural heterogeneity gives rise to a structural error term in our estimating equations that we can interpret as stemming from non-neutral productivity differences rather than distortions.

3.1 The Environment

There is a set of industries Ω. For industry $\omega \in \Omega$, there is a mass of firms with measure J_ω that produce differentiated varieties. There is a representative household that inelastically provides a mass of labor with measure L and has nested CES preferences over all varieties in each industry, maximizing consumption of the bundle C defined as

$$C = \left[\sum_{\omega \in \Omega} \upsilon_\omega^{\frac{1}{\eta}} C_\omega^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}$$

$$C_\omega = \left[\int_0^{J_\omega} c_{\omega j}^{\frac{\varepsilon_\omega - 1}{\varepsilon_\omega}} dj \right]^{\frac{\varepsilon_\omega}{\varepsilon_\omega - 1}}$$

where $\{\upsilon_\omega\}$ reflect the household's taste for different industry aggregates, η is the elasticity of substitution across industries, and ε_ω is the elasticity of substitution across varieties in industry ω.

Each firm randomly draws many different ways of producing its good and suppliers from whom it may source inputs. In equilibrium, the firm produces using the combination of production function and suppliers that is most cost-effective.

There are many *recipes* that may be used to produce a good of type ω. A recipe, denoted by $\rho \in \varrho_\omega$, is a production function $G_{\omega\rho}(\cdot)$ that can be used by a firm in industry ω to produce its good using labor and a particular bundle of inputs $\hat{\Omega}^\rho$.[16] The only restrictions we place on the production function $G_{\omega\rho}$ are that it exhibits constant returns to scale and that all inputs are complements. Note that the specification of the production function allows, e.g., for the first intermediate input to be more important than the second.

Assumption 1 *For any recipe $\rho \in \varrho_\omega$, the production function $G_{\omega\rho}$ exhibits constant returns and all inputs are complements.*

Firm j in industry ω has, for each recipe $\rho \in \varrho_\omega$, a random set of *techniques* $\Phi_{j\rho}$ to produce using that recipe. A technique $\phi \in \Phi_{j\rho}$ is a variation on recipe ρ consisting of input-augmenting productivities for each input and a set of potential suppliers for each intermediate input. If a recipe

[16] For example, some electricity producers use coal as an intermediate input while others use natural gas. Some producers of frozen chicken use chickens as an intermediate input while others use chicken feed.

uses the intermediate input bundle $\hat{\Omega} = \{\hat{\omega}_1, ..., \hat{\omega}_n\}$, then a technique would be characterized by (i) its input augmenting productivities $(b_l, b_{\hat{\omega}_1}, ..., b_{\hat{\omega}_n})$, (ii) the set of potential suppliers for each input $S_{\hat{\omega}_1}, ..., S_{\hat{\omega}_n}$, (iii) for each supplier $s \in S_{\hat{\omega}_i}$, a match-specific productivity z_s and, if $\hat{\omega}_i$ is a relationship-specific input, a wedge $t_{xs} \in [0,1]$. If j used that technique and chose to employ l units of labor and purchase $\{\hat{x}_{s_1}, ..., \hat{x}_{s_n}\}$ units of intermediate inputs from respective suppliers $s_1 \in S_{\hat{\omega}_1}, ..., s_n \in S_{\hat{\omega}_n}$, its output would be

$$y_j = G_{\omega\rho}\left(b_l l, b_{\hat{\omega}_1} x_{\hat{\omega}_1}, ..., b_{\hat{\omega}_n} x_{\hat{\omega}_n}\right)$$

where $x_{\hat{\omega}_i} \equiv z_{s_i} t_{xs_i} \hat{x}_{s_i}$ is effective units of good $\hat{\omega}_i$.

Each technique is specific to the firm producing the output (the "buyer") and the potential suppliers that might provide the intermediate inputs. Techniques within a particular recipe may differ in how intensively the particular inputs are used, as this depends on the input-augmenting productivities and the prices charged by the suppliers. The probability distribution governing the set of techniques with which firm j can produce $(\{\Phi_{j\rho}\}_{\rho \in \varrho_\omega})$ will be described below.

Each supplier in the set $S_{\hat{\omega}}$ is uniformly drawn from all firms that produce $\hat{\omega}$.

3.2 Market Structure and Timing

Terms of trade among firms determine their choices of inputs, productions decisions, and productivity. Firms engage in monopolistic competition when selling to the representative household. We also assume that sales of goods for intermediate use are priced at the supplier's marginal cost.[17] Firms remit all profit to the household.

First, nature chooses the sets of techniques available to all firms $\{\{\Phi_{j\rho}\}_{\rho \in \varrho_\omega}\}_{j \in J_\omega, \omega \in \Omega}$. Then each all firms simultaneously set prices and make their production decisions to minimize cost taking into account the decisions of others. All firms have perfect information about the economy's production possibilities and about other firms' choices.

3.3 Contracting Enforcement

Enforcement of contracts facilitates the use of inputs that require customization and the use of labor. Imperfect enforcement introduces wedges between the effective cost to the buyer and the payment to the supplier and between the effective cost of labor and the wage received by workers. The wedges takes the form of tax paid using the buyer's output that is a fixed fraction of the value

[17] One interpretation of this assumption is that in firm-to-firm trade, buyers have all of the bargaining power. For example, in a simpler environment, Oberfield (2018) characterizes an alternative market structure in which firm-to-firm trade is governed by bilateral trading contracts specifying a buyer, a supplier, a quantity of the supplier's good to be sold to the buyer and a payment. Given a contracting arrangement, each entrepreneur makes her remaining production decisions to maximize profit. The economy is in equilibrium when the arrangement is such that no countable coalition of entrepreneurs would find it mutually beneficial to deviate by altering terms of trade among members of the coalition and/or dropping contracts with those not in the coalition. The terms of trade described here are one particular equilibrium in which buyers have all of the bargaining power.

of the transaction and is thrown away.[18] Appendix E.3 provides one microfoundation for modeling imperfect enforcement in this way, although there are other microfoundations that are equally plausible. We briefly describe the microfoundation here and refer the reader to Appendix E.3 for details.

If an input requires customization, the supplier can shirk and provide a good that is imperfectly customized to the buyer. If this happens, the buyer uses up output correcting the defect. This is wasteful because the supplier has a comparative advantage in performing the customization. Similarly, workers can steal output, but the effort required to steal is wasteful. Buyers, suppliers, and workers can write contracts that require perfect customization or prohibit stealing, but imperfect enforcement of these contracts implies that some of this misbehavior will occur in equilibrium. While all parties anticipate equilibrium behavior and build this into prices, the behavior leads to a wedge that wastes resources.

For each potential supplier of a relationship-specific intermediate input, there is a random input wedge $t_x \in [0, 1]$ that distorts the use of that input, drawn from a distribution with CDF $T(t_x)$. If the supplier's price is p_s and match-specific productivity is z_s, the effective cost to the buyer is $\frac{p_s}{z_s t_x}$.

The distribution $T(t_x)$ summarizes the quality of enforcement. Perfect enforcement of contracts would imply that $t_x = 1$ for all suppliers. We interpret worse enforcement as a stochastically dominated distribution of wedges.

Similarly, if production is subject to the labor wedge t_l, then if a worker receives the wage w, the effective cost to the firm is w/t_l. For simplicity we assume that t_l is the same across all techniques.

3.4 Discussion of Assumptions

Before analyzing the equilibrium outcomes, we pause to discuss some of the modeling choices we have made and how we interpret some of the assumptions. First, as discussed earlier, courts are not the only way to enforce contracts; contracts could be enforced informally through social punishments or reputation. t_x and t_l should be interpreted as the wedges that prevail after all forms of enforcement are exhausted. For example, if formal enforcement would leave the wedge t_x^{formal} while informal enforcement would leave the wedge t_x^{informal}, then the parties would use whichever form of enforcement is better, i.e., $t_x = \max\{t_x^{\text{formal}}, t_x^{\text{informal}}\}$ (and similarly for t_l).[19] Improving the quality of courts would reduce the wedges t_x^{formal} but would not change t_x^{informal}.

Second, we model the wedges as random and specific to a supplier. First, as discussed earlier, for some suppliers (i.e., family members, those with whom the buyer is in a long term relationship) the possibility of informal enforcement may mitigate any hold-up problem. For others, the holdup problem may be more severe.

[18]This wedge is, in some ways, similar to an iceberg cost. However, since the tax is paid in units of the buyer's output and is proportional to the value of the transaction, there is scope for industrial policy to increase output by manipulating relative prices. In contrast, if the distortion took the form of an iceberg cost, there would be no such possibility. See Liu (2017) for a good discussion of these issues.

[19]Of course, the argument extends in the obvious way if there are multiple ways of enforcing contracts informally.

Third, we model the wedges as wasting resources rather than an implicit tax or subsidy as in Hsieh and Klenow (2009) which does not waste resources. An implicit tax may stand in for rationing or a Lagrange multiplier on a collateral constraint, and would raise the buyer's shadow cost of an input relative to the supplier's price without using up resources.

The facts presented in Section 2 provide no information about whether the wedges use up resources. However, there is at least one observable dimension that we can use to distinguish between the two types of frictions. With implicit taxes, those subject to larger wedges should have higher ratios of revenue to cost. If wedges use up resources they should lead to weakly lower ratios of revenue to cost.[20] In Appendix C.2 we ask whether those firms that we believe are subject to larger wedges—those in industries that tend to use relationship-specific inputs in states with congested courts—have higher or lower revenue-cost ratios. Our findings are consistent with wedges wasting resources: larger distortions are associated with lower revenue-cost ratios.

3.5 Production Decisions

For each technique, firm j draws a set of potential suppliers to provide each input. For each potential supplier, there is a match-specific productivity draw and a wedge, so that the effective cost of using that supplier would be $\frac{p_s}{z_s t_{xs}}$. j's effective cost of input $\hat{\omega}$ for technique ϕ is the minimum across all potential suppliers:

$$\lambda_{\hat{\omega}}(\phi) = \min_{s \in S_{\hat{\omega}}(\phi)} \frac{p_s}{z_s t_{xs}}.$$

The unit cost delivered by a technique depends on the input-augmenting productivities and the effective cost of each input. Let $\mathcal{C}_{\omega\rho}$ be the unit cost function that is the dual of the production function $G_{\omega\rho}$, so that j's cost of producing one unit of output using technique ϕ would be $\mathcal{C}_{\omega\rho}\left(\frac{w}{t_l b_l(\phi)}, \left\{\frac{\lambda_{\hat{\omega}}(\phi)}{b_{\hat{\omega}}(\phi)}\right\}_{\hat{\omega}\in\hat{\Omega}}\right)$. Minimizing cost across all techniques, j's unit cost is

$$\min_{\rho \in \varrho_\omega} \min_{\phi \in \Phi_{j\rho}} \mathcal{C}_{\omega\rho}\left(\frac{w}{t_l b_l(\phi)}, \left\{\frac{\lambda_{\hat{\omega}}(\phi)}{b_{\hat{\omega}}(\phi)}\right\}_{\hat{\omega}\in\hat{\Omega}}\right)$$

In words, firm j's unit cost equals that of the technique that delivers the lowest cost across all techniques of all recipes.

In this section, we specialize to particular functional form assumptions that prove tractable. The set of techniques available to each firm is random and governed by the following assumptions about the distributions of input-augmenting and match-specific productivities. Assumption 2 describes the frequency of matches.

Assumption 2 *For a each technique of recipe ρ, the number of suppliers of input $\hat{\omega}$ with match-*

[20] Whether the wedges would lead to no change or lower ratios of revenue to cost depends on the demand system. With Dixit-Stiglitz demand, the ratio of revenue to cost would be invariant with respect to wedge, whereas if the demand system features imperfect pass-through, a larger wedges would lower the ratio of revenue to cost.

specific productivity greater than z follows a Poisson distribution with mean

$$\begin{array}{ll} Zz^{-\zeta_R} & \hat{\omega} \in \hat{\Omega}^{\rho}_R \\ Zz^{-\zeta_H} & \hat{\omega} \in \hat{\Omega}^{\rho}_H \end{array}$$

where Z is a constant.

Assumption 2 implies above any threshold, match-specific productivities follow a power law.[21] Z summarizes the level of these match-specific productivity draws.[22] We will show later that the industry-level elasticity of substitution across groups of suppliers of the same inputs is $\zeta + 1$.

The next two assumptions describe the input-augmenting productivities of a technique.

Assumption 3 *For a firm in industry ω, the number of techniques of recipe $\rho \in \varrho_\omega$ (which uses inputs $\hat{\Omega}^\rho = (\hat{\omega}_1, ..., \hat{\omega}_n)$) with input-augmenting productivities that strictly dominate[23] b_l, $b_{\hat{\omega}_1}$, $b_{\hat{\omega}_2}$,...,$b_{\hat{\omega}_n}$ follows a Poisson distribution with mean*

$$B_{\omega\rho} b_l^{-\beta_l^\rho} b_{\hat{\omega}_1}^{-\beta_{\hat{\omega}_1}^\rho} ... b_{\hat{\omega}_n}^{-\beta_{\hat{\omega}_n}^\rho}.$$

Assumption 4 *There is a γ such that for each ω and each $\rho \in \varrho_\omega$, such that for every recipe $\rho \in \varrho_\omega$, $\beta_l^\rho + \beta_{\hat{\omega}_1}^\rho + ... + \beta_{\hat{\omega}_n}^\rho = \gamma$ and $\gamma > \varepsilon_\omega - 1$.*

Assumption 3 says that the input-augmenting productivities of a technique follow independent power laws. $B_{\omega\rho}$ summarizes the level of these productivity draws. We take these to be primitives, although a deeper model might model them as resulting endogenously from directed search or from the diffusion of technologies across entrepreneurs that know each other.

Assumption 4 says that for each recipe, the sum of the power law exponents is the same, equal to γ. This restriction could be relaxed, but for reasons we will discuss later, we do not believe it is quantitatively important. We will show later that the industry-level elasticity of substitution across recipes is $\gamma + 1$. The restriction that $\gamma > \varepsilon_\omega - 1$ is necessary to keep utility finite.

[21] This type of functional form assumption goes back to at least Houthakker (1955), and versions of it are also used by Kortum (1997), Jones (2005), Oberfield (2018), and Buera and Oberfield (2016). Note that the expected number of matches for a technique is unbounded. Formally, an economy satisfying Assumption 2 can be thought of as the limit of a sequence of economies that satisfy more standard assumptions. Consider an economy in which firms were restricted to use only suppliers with a match-specific productivity greater than $\underline{z}$. Then the number of potential suppliers for each input of a technique would be given by a Poisson distribution with mean $Z\underline{z}^{-\zeta}$ and the match-specific productivity for each supplier would be drawn from a Pareto distribution with CDF $1 - (z/\underline{z})^{-\zeta}$. An economy satisfying Assumption 2 can be thought of as the limit of such an economy as $\underline{z} \to 0$. In this limit, the number of suppliers for each input of a technique grows arbitrarily large, but the match-specific productivity associated with any single supplier is drawn from an arbitrarily poor distribution. The limit is well behaved because the probability of drawing a supplier with match-specific productivity greater than z does not change as $\underline{z} \to 0$.

[22] We could allow Z to vary by input-output pair and recipe, reflecting the idea that industries are often concentrated geographically or ethnically, which may imply that a given output industry may face an unusually high number of good suppliers in the input industry relative to other output industries. However, it turns out that Assumptions 2 and 3 imply that any variation in $\{Z_{\omega\rho\hat{\omega}}\}$ would be absorbed into the constant $B_{\omega\rho}$ that is defined below in Assumption 3.

[23] We say that a vector $(x_0, x_1, ..., x_n)$ strictly dominates the vector $(y_0, y_1, ..., y_n)$ if $x_0 > y_0$, $x_1 > y_1$,...,$x_n > y_n$.

It will be useful to decompose the power law exponents into two parts. For recipe ρ, define

$$\alpha_L^\rho = \frac{\beta_l^\rho}{\gamma}, \qquad \alpha_{\hat{\omega}}^\rho \equiv \frac{\beta_{\hat{\omega}}^\rho}{\gamma}, \qquad \hat{\omega} \in \hat{\Omega}^\rho$$

Note that this implies that $\alpha_L^\rho + \sum_{\hat{\omega}\in\hat{\Omega}} \alpha_{\hat{\omega}}^\rho = 1$. Further, for some results, it will be useful to define $\alpha_R^\rho = \sum_{\hat{\omega}\in\hat{\Omega}_R^\rho} \alpha_{\hat{\omega}}^\rho$ and $\alpha_H^\rho = \sum_{\hat{\omega}\in\hat{\Omega}_H^\rho} \alpha_{\hat{\omega}}^\rho$.

Second, it will be useful to define, for each firm j, the variable q_j to the inverse of j's unit cost in units of labor, i.e., the ratio of the wage to j's unit cost. We call q_j firm j's *efficiency*. This satisfies

$$\frac{\lambda_{\hat{\omega}}(\phi)}{w} = \min_{s\in S_{\hat{\omega}}(\phi)} \frac{1}{q_s z_s t_{xs}}.$$

$$q_j = \max_{\rho\in\varrho_\omega} \max_{\phi\in\Phi_{j\rho}} \mathcal{C}_{\omega\rho}\left(\frac{1}{t_l b_l(\phi)}, \left\{\frac{\lambda_{\hat{\omega}}(\phi)}{w}\frac{1}{b_{\hat{\omega}}(\phi)}\right\}_{\hat{\omega}\in\hat{\Omega}}\right)^{-1} \tag{1}$$

Finally, let $F_\omega(q)$ be the fraction of firms in industry ω with efficiency no greater than q.

With these assumptions in hand, we now characterize the equilibrium. All proofs are contained in Appendix E

Proposition 1 *Under Assumptions 1, 2, 3, and 4, the fraction of firms with efficiency no greater than q among those that produce good ω is*

$$F_\omega(q) = e^{-(q/Q_\omega)^{-\gamma}}$$

where

$$\begin{aligned} Q_\omega &= \left\{\sum_{\rho\in\varrho_\omega} \kappa_{\omega\rho}\left((t_x^*)^{\alpha_R^\rho}(t_l)^{\alpha_L^\rho}\prod_{\hat{\omega}\in\hat{\Omega}^\rho} Q_{\hat{\omega}}^{\alpha_{\hat{\omega}}^\rho}\right)^\gamma\right\}^{\frac{1}{\gamma}} \\ t_x^* &= \left(\int_0^1 t_x^{\zeta^R} dT(t_x)\right)^{1/\zeta_R} \end{aligned} \tag{2}$$

and $\kappa_{\omega\rho}$ is a constant that depends on $B_{\omega\rho}$ and technological parameters.

Proposition 1 shows that the distribution of efficiencies takes the simple form of a Frechet distribution with shape parameter γ and scale determined by Q_ω. Q_ω summarizes the level of efficiency in the industry; a higher Q_ω improves the distribution in the first-order stochastic dominant sense. (2) relates industry ω's efficiency to that of the industries that provide the inputs for each recipe and to t_x^* and t_l, which summarize the impact of imperfect enforcement on those that produce the inputs used in recipe ρ. t_x^* accounts for both the direct impact of the wedges—the wasted resources from holdup problems—and the indirect impact: wedges might cause firms to switch to a supplier with higher cost or lower productivity, or to a different technique altogether.

(2) is a system of equations that implicitly determines each industry's efficiency, $\{Q_\omega\}_{\omega\in\Omega}$. Proposition 2 shows that these are sufficient to characterize aggregate productivity.

Proposition 2 *Under Assumptions 1, 2, 3, and 4, the household's utility is*

$$C = \left\{ \sum_{\omega \in \Omega} \upsilon_\omega J_\omega^{\frac{\eta-1}{\varepsilon_\omega - 1}} \Gamma \left(1 - \frac{\varepsilon_\omega - 1}{\gamma} \right)^{\frac{\eta-1}{\varepsilon_\omega - 1}} Q_\omega^{\eta-1} \right\}^{\frac{1}{\eta-1}} L$$

We next turn to industry-level expenditure shares. The next proposition characterizes the aggregate share of total expenditures (on both intermediate inputs and labor) that is spent on each input among all firms that use a particular recipe.

Proposition 3 *Suppose that assumptions 1, 2, 3, and 4 hold. Among firms that, in equilibrium, produce using recipe ρ, the share of total expenditures that is spent on inputs from $\hat{\omega} \in \hat{\Omega}_R^\rho$ is*

$$\frac{\alpha_{\hat{\omega}}^\rho \bar{t}_x}{\alpha_L^\rho t_l + \alpha_R^\rho \bar{t}_x + \alpha_H^\rho},$$

the share of total expenditures that is spent on inputs from $\hat{\omega} \in \hat{\Omega}_H^\rho$ is

$$\frac{\alpha_{\hat{\omega}}^\rho}{\alpha_L^\rho t_l + \alpha_R^\rho \bar{t}_x + \alpha_H^\rho},$$

and the share of expenditures spent on labor is

$$\frac{\alpha_L^\rho t_l}{\alpha_L^\rho t_l + \alpha_R^\rho \bar{t}_x + \alpha_H^\rho}$$

where $\bar{t}_x \equiv \int_0^1 t d\tilde{T}(t_x)$ and $\tilde{T}(t_x) \equiv \frac{\int_0^{t_x} t^{\zeta_R} dT(t)}{\int_0^1 t^{\zeta_R} dT(t)}$.

Proposition 3 provides a relatively simple expression for the industry-level cost shares of each input among those using a particular recipe. In the absence of distortions, these factor share would depend only on technological parameters, not on the relative prices of the inputs. Thus at industry level, there would be a Cobb-Douglas production function. This extends the celebrated aggregation result of Houthakker (1955) who derived a similar result under the assumption that individual production functions are Leontief.[24] We require only that the production function exhibits constant returns to scale and that all inputs are complements.[25]

[24] Jones (2005) builds on Houthakker (1955) but derives a different type of result. Jones first shows that if a single plant draws many Leontief production functions where factor augmenting productivities are drawn from independent Pareto distributions, then the envelope of those production functions is Cobb-Douglas. He then shows numerically that the result extends beyond Leontief to CES production functions when the factors are complements. Note that these are not aggregation results; these results apply at the level of a single firm.

[25] Why complements? When inputs are complements, when the price of an input is higher, there are two offsetting effects on the industry cost share. The higher price raises that cost share on that input for any firm that uses the input. At the same time, firms that use that input more intensively are likely to shrink or switch to a technique that uses the input less intensively. When factor-augmenting productivities are drawn from independent Pareto distributions, these offset exactly and factor shares are unchanged. If inputs were substitutes, the two effects would push in the same direction, so that if the price of an input rose, its industry cost share would fall.

Imperfect enforcement, on the other hand, reduces the expenditure share of inputs that require enforcement. Recall that imperfect enforcement drives a wedge between the effective cost to the buyer and payment to the supplier. The buyer's production decisions depend each input's effective cost, whereas the expenditures reflect the actual payment to each supplier.

3.6 Counterfactuals

The quality of contract enforcement can be summarized by the distribution of wedges T. Suppose that the quality of enforcement changed in such a way that the distribution of wedges changed from T to T'. How would this impact aggregate productivity? Taking J_ω and $B_{\omega\rho}$ as primitives[26], the following proposition shows how one can compute the impact of such a change.

Let HH_ω be the share of the household's expenditure on goods from industry ω in the current equilibrium. Among those of type ω, let $R_{\omega\rho}$ be the share of total revenue of those that use recipe ρ in the current equilibrium.

Proposition 4 *If the quality of enforcement changed so that the distribution of wedges changes from T to T', the change in household utility would be*

$$\frac{C'}{C} = \left(\sum_\omega HH_\omega \left(\frac{Q'_\omega}{Q_\omega} \right)^{\eta-1} \right)^{\frac{1}{\eta-1}}$$

and the change in industry efficiencies would satisfy the following system of equations

$$\left(\frac{Q'_\omega}{Q_\omega} \right)^\gamma = \sum_{\rho \in \varrho_\omega} R_{\omega\rho} \left[\left(\frac{t_x^{*\prime}}{t_x^*} \right)^{\alpha_R^\rho} \prod_{\hat{\omega} \in \hat{\Omega}^\rho} \left(\frac{Q'_{\hat{\omega}}}{Q_{\hat{\omega}}} \right)^{\alpha_{\hat{\omega}}^\rho} \right]^\gamma \tag{3}$$

The first part of the proposition states that to know how a change in court quality affects aggregate productivity, it is sufficient to know only the change industry efficiencies, $\frac{Q'_\omega}{Q_\omega}$. In turn, the change in each industry's efficiency depends on the weighted average over each recipe of the change in the efficiency of the industries that supply inputs to the recipe along with the change in the wedges that distort production in that recipe (again, taking into account the direct and indirect impact of these wedges). (3) describes a system of equations that implicitly characterize these changes in industry efficiencies.

While Proposition 4 describes exactly how a change in enforcement would alter welfare, it is instructive to study a perturbation of the distribution of wedges to show which features of the economy are important for determining the first order impact of a change in the quality of enforcement.

[26] An interesting alternative exercise is asking what would happen if J and $\{B_{\omega\rho}\}$ also responded to the change in T.

Corollary 1 *The marginal welfare impact of a change in court quality is*

$$d\log U = \sum_{\omega\in\Omega} HH_{\omega} d\log Q_{\omega}$$

and the change in industry efficiencies can be summarized by the following system of equations

$$d\log Q_{\omega} = \sum_{\rho\in\varrho_{\omega}} R_{\omega\rho}\left[\alpha_R^{\rho} d\log t_x^* + \sum_{\hat{\omega}\in\hat{\Omega}^{\rho}} \alpha_{\hat{\omega}}^{\rho} d\log Q_{\hat{\omega}}\right]$$

One implication is that, to a first order, the change in utility resulting from a change in the quality of enforcement does not depend on γ or η.

4 Identification and Estimation

Our main counterfactual of interest is how aggregate productivity and the organization of production would change if the quality of enforcement improved. We do this in several steps. We first parameterize the model using information from the ASI under the assumption that the quality of enforcement varies by state. We then project the implied quality of enforcement for each state on our measures of court congestion. Finally, we compute the gains from reducing congestion to the level prevailing in the least congested state.

Our most important identifying assumption is that weak enforcement may introduce a wedge in the use of inputs that require customization and in the use of labor, but not in the use of standardized inputs. Given our scheme for identification, we view this as a conservative assumption. If the use of standardized inputs were also distorted by weak contract enforcement, then all of the wedges would be larger than the ones we infer.

The following proposition shows a set of moments that we can use in a GMM procedure to estimate the model parameters

Proposition 5 *Let s_{Rj}, s_{Hj}, s_{Lj} be firm j's spending on relationship-specific inputs, homogeneous inputs, and labor respectively as shares of its revenue. Under assumptions 1-4, the first moments of revenue shares among firms that produce ω that, in equilibrium, use recipe ρ satisfy:*

$$\begin{aligned} \mathbb{E}\left[\frac{1}{\bar{t}_x}\frac{s_{Rj}}{\alpha_R^{\rho}} - \frac{s_{Hj}}{\alpha_H^{\rho}}\right] &= 0 \\ \mathbb{E}\left[\frac{1}{t_l}\frac{s_{Lj}}{\alpha_L^{\rho}} - \frac{s_{Hj}}{\alpha_H^{\rho}}\right] &= 0 \end{aligned}$$

Assumption 5 *We impose that the following objects are the same across states: (i) the form of the production function for each recipe $\{G_{\omega\rho}\}$; (ii) the power law exponents for the input-augmenting productivity draws for techniques of each recipe $\{\beta_l^{\rho}, \beta_{\hat{\omega}_1}^{\rho}, ..., \beta_{\hat{\omega}_n}^{\rho}\}$, and (iii) the power law exponent for the match-specific productivity draws, ζ_R and ζ_H.*

We allow all other features of preferences and technology to vary freely across states. This includes absolute and comparative advantages in recipes, $\{B_{\omega\rho}\}$, (ii) the measure of firms of each type $\{J_\omega\}$, (iii) the households tastes, $\{\upsilon_\omega\}$, and most importantly, (iv) the quality of contract enforcement, T, and t_l.

We also impose a parametric form for the stochastic wedges that a firm draws for each supplier of a relationship-specific input. In particular, the reciprocal of the wedge is drawn from a Pareto distribution, where the shape parameter is specific to a state.

Assumption 6 *The distribution of wedges in state d is $T_d(t_x) = t_x^{\tau_d}$.*

Using a Pareto distributions has several attractive properties. First, following the discussion in Section 3.3, contracts might be enforced formally or informally. If the probability that the formal wedge is no greater than t_x is $t_x^{\tau_d^{\text{formal}}}$ and the probability that the informal wedge is no greater than t_x is $t_x^{\tau_d^{\text{informal}}}$, then the probability that the effective wedge is no greater than t_x is $t_x^{\tau_d}$, where $\tau_d = \tau_d^{\text{formal}} + \tau_d^{\text{informal}}$.[27] This will lead to a clean interpretation of the counterfactual of interest.

Our algorithm for identification is thus as follows:

1. Start with an initial guess of $\bar{t}_x^d$ for each state d.

2. Identify recipes from plant's cost shares (see next section for details), taking out the distortion to the cost shares of relationship-specific inputs $\bar{t}_x^d$.

3. Use Proposition 5 to estimate the production parameters that are common across locations $\left\{\alpha_L^\rho, \alpha_H^\rho, \alpha_R^\rho\right\}_{\rho\in\varrho_\omega}, \omega \in \Omega$ and a new set of the state specific variables, $\{\bar{t}_x^d, t_l^d\}$. Go back to step 2 until the $\bar{t}_x^d$ have converged.

4. Compute t_x^* for each state. Assumption 6 implies that $\bar{t}_x = \frac{\zeta_R+\tau_d}{1+\zeta_R+\tau_d}$ and $t_x^* = \left(\frac{\tau_d}{\tau_d+\zeta_R}\right)^{1/\zeta_R}$. We estimate ζ_R externally, and then use this along with our estimates of $\bar{t}_x$ to compute t_x^*.

5. For the counterfactual, we also need values of the industry-level output elasticities of each input for each recipe, $\{\alpha_{\hat{\omega}}^\rho\}$. To do this, we pool data across states to estimate the remaining production function parameters, $\alpha_{\hat{\omega}}$, by using the aggregate expenditures. For example, if the sourcing industry $\hat{\omega}$ is relationship specific, then $\alpha_{\hat{\omega}}^\rho$ is equal α_R^ρ multiplied by the ratio of total expenditure on input $\hat{\omega}$ by those that use recipe ρ to total expenditure on relationship-specific inputs.

6. For each state-recipe, directly measure the share of revenue among firms $\{R_{\omega\rho}\}$, and for each state, directly measure $\{HH_\omega\}$.

7. Calibrate η and γ externally.

[27] This follows from the fact that the Pareto family is closed under the minimum operation.

In implementing this algorithm, we make several auxiliary assumptions that, in principle, could be relaxed. First, we assume that there is no trade across state borders. While it would be fairly straightforward to incorporate interstate trade, we lack the relevant data.[28] A second assumption is that the recipes used by multi-product firms and the distribution of wedges facing them are the same as those of single-product firms. This type of assumption, while strong, is standard in the literature, as we lack the data that indicates which inputs are used in the production of which products. It allows us to to estimate wedge distribution parameters and the α's using single-product plants only, while still being able to make statements about the whole formal manufacturing sector by including multi-product plants when we calculate revenue and expenditure shares $R_{\omega\rho}$ and HH_{ω}. Third, we treat service inputs and energy inputs as primary inputs.

4.1 Defining recipes

One of the salient facts of the Indian manufacturing data is that even within narrow industries, plants are using vastly different combinations of intermediate inputs to produce the same output. Our model provides a natural way to think of these input-output combinations as different recipes $\rho \in \rho(\omega)$ that could be used to produce the same output ω. In order to estimate the model from the microdata, we need a procedure that classifies each plant-year observation into which recipe the plant is using.

The idea that guides our classification is that, for a given output good, similar input mixes should belong to the same recipe. We describe each plant j's input mix by the vector of its input expenditure shares, $(m_{j\omega})_{\omega\in\Omega} = (X_{j\omega}/\sum_{\omega'} X_{j\omega'})_{\omega\in\Omega}$. Graphically, each vector corresponds to a point in the $|\Omega|$-dimensional hypercube that is lying on the hyperplane where the sum of all coordinates equals to one. Our task is to find plants with similar input mixes, i.e. clouds of points that are close to each other (according to some metric). In statistics, this task is known as *cluster analysis*, and there is a large number of algorithms that classify clusters based on distance, density, shape, and other criteria. Looking at the input mixes of plants in many different industries (see the examples of bleached cotton cloth and polished diamonds in Figure 1) convinced us that these clusters do exist and have a meaningful economic interpretation.

Our preferred method is due to Ward (1963), and constructs clusters recursively, starting with the partition where every cluster is a singleton. In each step, two clusters are merged to minimize the sum squared errors:

$$\min_{\rho_n \geq \rho_{n-1}} \sum_{\rho\in\rho_n} \sum_{j\in\rho} \sum_{\omega} \left(m_{j\omega} - \overline{m}_{\rho\omega}\right)^2$$

where the ρ_n are partitions of J_ω, and in each step ρ_n runs over all partitions that are coarser than ρ_{n-1}. This method constructs a hierarchical set of partitions of J_ω: one for each desired number of clusters.

[28] To this point there is no publicly available data about cross-state trade in goods. The conventional wisdom has been that interstate trade is minimal, although the 2016-17 Economic Survey of India's Ministry of Finance challenges this conventional wisdom.

Table IV Statistics on recipes

	Count
Products (5-digit ASIC)	4,530
Products with ≥ 3 plants	3,573
Products with ≥ 5 plants	3,034
Recipes	18,838
Recipes with ≥ 3 plants	10,985
Recipes with ≥ 5 plants	7,894
Avg. plants per recipe	11.8
SD plants per recipe	41.3

"Products" are the 5-digit ASIC codes in our data, "Recipes" are the output from our clustering procedure. Plant counts include only single-product plants.

Table V Recipe classification: cloth, bleached, cotton (63303)

Recipe	Description	Value, %	N	Recipe	Description	Value, %	N
# 1	Yarn bleached, cotton	98	50	# 3	Yarn unbleached, cotton	> 99	19
	Grey cloth (bleached / unbleached)	2			Colour, chemicals	< 1	
	Thread, others, cotton	< 1			Gen. purpose machinery, n.e.c	< 1	
	Colour (r.c) special blue	< 1			Dye, vat	< 1	
# 2	Yarn dyed, cotton	41	21	# 4	Grey cloth	42	16
	Yarn, finished / processed (knitted)	23			Colour, chemicals	10	
	Yarn bleached, cotton	16			Yarn dyed, synthetic	10	
	Yarn, grey-cotton	3			Kapas (cotton raw)	5	
	Chemical & allied substances, n.e.c	3			Grey cotton - others	5	
	Fabrics, cotton	3			Fabrics, cotton	4	
	Thread, others, cotton	2			Cotton raw, ginned & pressed	4	
	Colour, chemicals	2			Colour, ink, n.e.c	4	
	Dye stuff	2			Other	16	
	Other	5					

Our implementation of the clustering procedure to identify recipes uses not only the five-digit materials shares, but also three-digit shares to allow for the possibility of misclassification of inputs within three-digit baskets. We set the number of potential recipes within each industry ω to $\lceil n \log((\#\text{Observations})_\omega) \rceil$, for varying parameters n. This allows industries with more plant-year observations to have more recipes. We inspect the cluster hierarchy and choose $n = 1.5$, where we find that the resulting recipes correspond well to different modes of organization.[29] Table 4.1 shows statistics on the number and size of clusters (recipes) that we define.

To give a example of the usefulness of our procedure, Table V shows the resulting four most important recipes for product 63303 (bleached cotton cloth), which correspond to different ways of producing bleached cotton cloth: either by weaving bleached or dyed cotton yarn (recipes 1 and 2), by weaving and bleaching unbleached cotton yarn (recipe 3), and by bleaching and dyeing greige cloth (recipe 4).

Once we have defined recipes, we assign plants to belong to a recipe with a probability that is

[29] In Section D.2 of Appendix D we show results for varying degrees of recipe fineness.

proportional to the inverse Euclidean distance to the recipe center:

$$P\left(j \in \rho\right) = \frac{\frac{1}{\sqrt{\sum_{\omega'}(m_{j\omega'} - \overline{m}_{\rho\omega'})^2}}}{\sum_{\rho' \in \rho(\omega)} \frac{1}{\sqrt{\sum_{\omega'}(m_{j\omega'} - \overline{m}_{\rho'\omega'})^2}}} \tag{4}$$

We use these assigned probabilities as weights in the estimation below.

4.2 Estimation

We estimate the $\bar{t}_x^d$, t_l^d, α_R^ρ, α_H^ρ, and α_L^ρ from the moment conditions in Proposition 5 using our algorithm described above. To identify the level of the $\bar{t}_x$ and t_l, we set the largest $\bar{t}_x$ and t_l, respectively, to one, thereby making the assumption that the least distorted state in each distortion is undistorted.[30] We also exclude state-recipe pairs where the average share of relationship-specific inputs in sales is more than one hundred times the one of homogeneous inputs (and vice versa).

Figure 5 shows the estimated $\kappa_x^d = 1/\bar{t}_x^d$ and their correlation with the quality of high courts as measured by the average age of pending civil cases. Frictions are large: κ exceeds two in the most heavily distorted states. Some of that variation is explained by the quality of courts. In states with slower courts, firms face larger distortions κ_x when sourcing relationship-specific intermediate inputs. The solid line is the fit of an OLS regression of κ_x on court quality; the dashed line the fit of an IV regressions where we instrument court quality using the log age of the high court. The estimated IV slope coefficient is similar to the one in the OLS. This relationship between κ_x and the age of pending court cases is closely related to the fact that intermediate input bundles are tilted towards homogeneous inputs in states where enforcement is weak (Fact 2 in Section 2.3). The main difference here (beyond the fact that the κ_x are coming from a nonlinear regression) is that the κ_x are identified from within-recipe variation in the input mix, whereas Fact 2 is about within-product variation.

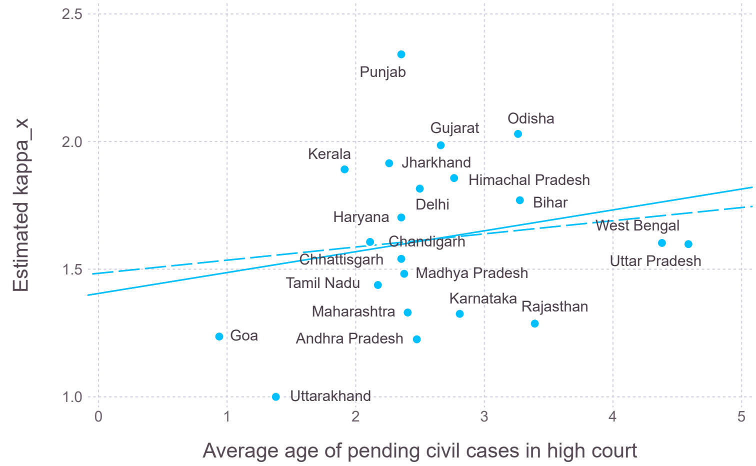
4.3 Counterfactual

To perform a counterfactual where we assess the aggregate impact of a change in the wedge distribution T, Proposition 4 tells us that we need to know the change in the moment t_x^* of the wedge distribution that is relevant for the industry's cost distribution, which depends on the parameter ζ_R and, under our parameterization of the wedge distribution, on its Pareto tail τ_d. We also need to know the parameters $\alpha_{\hat{\omega}}^\rho$, the within-industry sales shares $R_{\omega\rho}$ of each recipe, the household's expenditure shares HH_ω, and the elasticities γ and η.

The parameter ζ_R, which allows us to back out τ_x^d from $\bar{t}_x$, also governs the elasticity of substitution across sets of suppliers. We estimate it as the elasticity of substitution between foreign and domestically sourced inputs in a pair of inputs and outputs:

[30] We view this as conservative. Given the expenditure shares we see in the data, more severe distortions (smaller $\bar{t}_x$) would raise the estimated output elasticities of relationship-specific inputs (higher α_R^ρ). This would amplify the responses to changes in enforcement.

Figure 5 Correlation between $1/\bar{t}_x$ and court quality



The figure shows the correlation between $\kappa_x^d \equiv 1/\bar{t}_x^d$ and the average age of pending civil cases in the state's high court. The solid line is the OLS regression line; the dashed line is fit of an IV regression where the age of pending cases is instrumented using the log age of the high court.

Table VI Estimating ζ

	Dependent variable: $\log(X_{i\omega}^{DOM}/X_{i\omega}^{IMP})$		
	(1)	(2)	(3)
$\log(1+\iota_{it})$	0.617	0.218	1.209*
	(0.45)	(0.78)	(0.56)
Industry × Input FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Level	5-digit	5-digit	5-digit
Sample	All inputs	R only	H only
R^2	0.601	0.580	0.623
Observations	23692	12002	11690

Robust errors in parentheses, clustered at the state × industry level
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

$$\log\left(\frac{X_{i\omega t}^{DOM}}{X_{i\omega t}^{IMP}}\right) = \zeta \log(1+\iota_{it}) + \lambda_t + \lambda_{i\omega} + \eta_{i\omega t}$$

where $\iota_{i\omega t}$ is the import tariff on i at time t, and the λ's are fixed effects. Table VI shows the results for this regression. We use the point estimate of 0.214 for ζ_R.[31]

The elasticities $\alpha_{\hat{\omega}}$ can be recovered as the product of the input-type elasticity (α_R^ρ or α_H^ρ) and the average cost shares of plants that produce using recipe ρ:

$$\alpha_{\hat{\omega}}^\rho = \alpha_R^\rho \frac{\overline{m}_{\rho\hat{\omega}}}{\sum_{\omega' \in \Omega^R} \overline{m}_{\rho\hat{\omega}'}} \text{ if } \hat{\omega} \text{ relationship-specific}, \qquad \alpha_{\hat{\omega}}^\rho = \alpha_H^\rho \frac{\overline{m}_{\rho\hat{\omega}}}{\sum_{\omega' \in \Omega^H} \overline{m}_{\rho\hat{\omega}'}} \text{ if } \hat{\omega} \text{ homogenous}.$$

[31]Choosing a low ζ_R is conservative; see the discussion in 4.4 below. We conduct sensitivity checks in Appendix D.1.

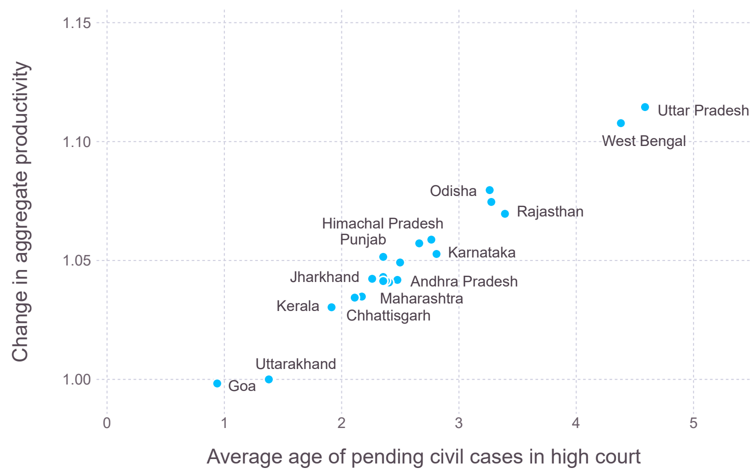
We target the demand aggregator's expenditure shares HH_ω and the recipe revenue shares $R_{\omega\rho}$ to represent the aggregate of India's formal manufacturing sector. We calculate HH_ω as total sales of ω minus total intermediate consumption (excluding imports) of ω (or zero, if this difference is negative), divided by the sum of this difference over all products. To calculate the recipe revenue shares $R_{\omega\rho}$, we also take into account the output of multi-product plants: we choose each multi-product plants' recipe shares to minimize the Euclidean distance of its cost share vector from the weighted average of the recipe centers' cost shares. When calculating HH_ω and $R_{\omega\rho}$, we pool observations across years, but weigh each plant-year observation by the inverse of the number of times the plant shows up in the ASI. This weighting allows us to construct parameters that better represent the aggregate of India's formal manufacturing sector.[32]

Finally, we calibrate the household's outer-tier utility to be Cobb-Douglas in the industry baskets ($\eta = 1$), and choose $\gamma = 1$, which amounts to a first-order approximation of the change in the efficiency levels Q_ω. Inputs which do not show up in our data as outputs (predominantly agricultural and mineral commodities) are assumed to have unchanged productivity distributions.

We then perform a counterfactual where we reduce $\kappa_x^d = 1/\bar{t}_x^d$ for each state by the amount that is implied by the IV regression in Figure 5, down to a point where the average age of pending cases is one year (which is roughly the level of court quality enjoyed by the best state, Goa). Using our estimate for ζ_R, we back out τ_x at the original and counterfactual level, and compute the change in the welfare-relevant moment $t^* = (\tau_x/(\zeta_R + \tau_x))^{1/\zeta_R}$. We then simulate the corresponding change in household's utility aggregate as given by Proposition 4.

Figure 6 shows the counterfactual increase in the household's consumption aggregate C. The numbers are in the range of zero to more than eleven percent, suggesting that the gains from improving contract enforcement institutions can be large.

Figure 6 Counterfactural increases in aggregate productivity



The figure shows the counterfactual increase in C when the wedges on relationship-specific inputs are reduced according to the fraction of $1/\bar{t}_x$ that is explained by court quality in a linear regression.

[32]Recall that in the ASI, large plants are surveyed every year, while smaller plants are surveyed every five years.

4.4 The Role of Stochastic Distortions

The model captures the idea that buyer-supplier relationships differ in their susceptibility to imperfect contract enforcement. Some buyer-supplier pairs are able to enforce contracts informally, or transact in such a way that avoids holdup problems. As a reduced form, we modeled this by assuming that for each supplier, the buyer draws a wedge from a distribution that deteriorates when formal enforcement is less reliable. Given our identification strategy and conditioning on the data, the fact that wedges are stochastic and differ across suppliers raises the implied welfare loss from imperfect enforcement relative to what we would have inferred if we had assumed that the wedges were the same for each supplier of an input. Our identification strategy consists of measuring $\{t_l, \bar{t}_x\}$ and then using these along with our functional form assumptions to compute t_x^*. Jensen's inequality implies that $\bar{t}_x$ is an upper bound for t_x^* that is attained only if the wedge is the same for all suppliers.[33]

4.5 Entry and Exit

In our benchmark model, we assumed that the number of producers of each product is given exogenously. Of course we would expect that if the formal enforcement improved, profitability would increase more in industries that rely more heavily on relationship-specific inputs. We do, in fact observe that as formal enforcement deteriorates, the number of firms decreases relatively more in the industries that rely more heavily on relationship-specific inputs. Thus it is likely the quality of enforcement affects firms' entry and exit decisions.

How would our estimates differ if firms could endogenously enter and exit? The answer depends on the specifics of entry and exit and the particular counterfactual. Consider the following two possibilities. First suppose firms were committed to enter, but could choose which industry to enter. Then the additional adjustment after formal enforcement improved would raise aggregate productivity even more than a benchmark model suggests. Second, suppose that firms were committed to producing in a particular industry but choose which state to locate in. Here, if formal enforcement improves in one state, aggregate productivity in that state would rise as firms for other states moved in. However, aggregate productivity in other states would fall as firms moved out. This suggests that the response to nation-wide improvement in formal enforcement would differ from the response to a single state improving enforcement. Further, systematic differences across states in how the number of firms responds to cross-sectional difference in legal enforcement may not be informative about the economy's response to a nationwide improvement.

[33]Since $t^{\frac{\zeta}{\zeta+1}}$ is a strictly concave function of t, Jensen's Inequality gives $\int_0^1 t_x^{\zeta+1} dT(t_x) \geq \left\{\int_0^1 \left(t_x^{\zeta+1}\right)^{\frac{\zeta}{\zeta+1}} dT(t_x)\right\}^{\frac{\zeta+1}{\zeta}}$. This implies

$$\bar{t}_x = \frac{\int_0^1 t_x^{\zeta+1} dT(t_x)}{\int_0^1 t_x^{\zeta} dT(t_x)} \geq \frac{\left\{\int_0^1 t_x^{\zeta} dT(t_x)\right\}^{\frac{\zeta+1}{\zeta}}}{\int_0^1 t_x^{\zeta} dT(t_x)} = t_x^*$$

with equality only if the distribution of t_x is degenerate.

5 Conclusion

This paper studies the organization of production in the Indian manufacturing sector, and how it relates to the quality of formal contract enforcement institutions. We make two main points: one about the within-industry heterogeneity and measurement of the organization of production, and a second one on how institutions are shaping it.

Firstly, we show that there is considerable amount of heterogeneity in technology and organization even within narrowly-defined industries. These differences should be reflected in the level of aggregation at which researchers assume a homogeneous shape of the production function. We argue that information on input use can be helpful in understanding differences in organization and technology within industries: a plant that produces cotton cloth from raw cotton is vertically integrated and performs both spinning and weaving, whereas a plant that produces cotton cloth from cotton yarn will only perform the weaving, and might therefore have different factor intensities. We provide a simple and flexible way of defining homogeneous technologies using a statistical clustering algorithm.

Secondly, we find that the organization of production is shaped by the contracting environment. We find that slow enforcement of contracts impedes the use of relationship-specific materials. As a result, firms tilt their input basket towards the use of more standardized inputs, for which spot markets exist, and for which enforcement by courts in not necessary. Firms also respond by performing a larger chunk of the value chain within the plant. We develop a multi-industry general equilibrium model where firms source multiple inputs and choose the organizational form optimally to minimize the cost of production. We estimate the relative distortions associated with the use of relationship-specific inputs from first moments of cost shares, which, compared to the standard approaches of estimating input wedges, is more robust to potentially imprecise measurement of input use. Preliminary results suggest that the fraction of the distortions that is associated with poor courts is sizable and implies substantial welfare gains if courts were improved: for each year reduction in the average age of pending cases, the state's aggregate productivity would increase by about three percent.

References

Acemoglu, Daron, and Pablo D Azar. 2017. "Endogenous Production Networks." National Bureau of Economic Research.

Acemoglu, Daron, and Simon Johnson. 2005. "Unbundling Institutions." *Journal of Political Economy*, 113: 5.

Acemoglu, Daron, Pol Antràs, and Elhanan Helpman. 2007. "Contracts and Technology Adoption." *American Economic Review*, 97(3): 916–943.

Alfaro, Laura, Pol Antràs, Davin Chor, and Paola Conconi. 2015. "Internalizing Global Value Chains: A Firm-Level Analysis." Working paper, Harvard University.

Amirapu, Amrit. 2017. "Justice Delayed is Growth Denied: The Effect of Slow Courts on Relationship-Specific Industries in India." School of Economics, University of Kent.

Antràs, Pol, and Alonso de Gortari. 2017. "On the Geography of Global Value Chains." National Bureau of Economic Research.

Antràs, Pol, Davin Chor, Thibault Fally, and Russell Hillberry. 2012. "Measuring the upstreamness of production and trade flows." *American Economic Review*, 102(3): 412–16.

Antras, Pol, Teresa C Fort, and Felix Tintelnot. 2017. "The Margins of Global Sourcing: Theory and Evidence from US Firms." *American Economic Review*, 107(9): 2514–64.

Baqaee, David Rezza, and Emmanuel Farhi. 2017. "Productivity and Misallocation in General Equilibrium." National Bureau of Economic Research.

Bartelme, Dominick, and Yuriy Gorodnichenko. 2014. "Linkages and Economic Development." Mimeo, UC Berkeley.

Bas, Maria, and Vanessa Strauss-Kahn. 2015. "Input-trade liberalization, export prices and quality upgrading." *Journal of International Economics*, 95(2): 250–262.

Bigio, Saki, and Jennifer La'O. 2016. "Financial frictions in production networks." National Bureau of Economic Research.

Bils, Mark, Peter J Klenow, and Cian Ruane. 2017. "Misallocation or Mismeasurement?" Society for Economic Dynamics.

Boehm, Johannes. 2016. "The Impact of Contract Enforcement Costs on Outsourcing and Aggregate Productivity."

Buera, Francisco J, and Ezra Oberfield. 2016. "The Global Diffusion of Ideas." National Bureau of Economic Research.

Caliendo, Lorenzo, Fernando Parro, and Aleh Tsyvinski. 2017. "Distortions and the Structure of the World Economy." National Bureau of Economic Research.

Caprettini, Bruno, and Antonio Ciccone. 2015. "Turnover Taxes and Productivity: Evidence from a Brazilian Tax Reform."

Chaney, Thomas. 2014. "The network structure of international trade." *The American Economic Review*, 104(11): 3600–3634.

Chemin, Matthieu. 2012. "Does court speed shape economic activity? Evidence from a court reform in India." *Journal of Law, Economics, and Organization*, 28(3): 460–485.

Costinot, Arnaud, Jonathan Vogel, and Su Wang. 2012. "Global Supply Chains and Wage Inequality." *American Economic Review*, 102(3): 396–401.

Djankov, Simeon, Rafael La Porta, Florencio Lopez de Silanes, and Andrei Shleifer. 2003. "Courts." *The Quarterly Journal of Economics*, 118(2): 453–517.

Eaton, Jonathan, Samuel Kortum, and Francis Kramarz. 2015. "Firm-to-Firm Trade: Imports, Exports, and the Labor Market."

Fadinger, Harald, Christian Ghiglino, and Mariya Teteryatnikova. 2016. "Income differences and input-output structure."

Fally, Thibault, and Russell Hillberry. 2015. "A Coasian Model of International Production Chains." National Bureau of Economic Research.

Goldberg, Pinelopi Koujianou, Amit Kumar Khandelwal, Nina Pavcnik, and Petia Topalova. 2010. "Imported intermediate inputs and domestic product growth: Evidence from India." *The Quarterly Journal of Economics*, 125(4): 1727–1767.

Grossman, Gene M., and Elhanan Helpman. 2002. "Integration versus Outsourcing in Industry Equilibrium." *The Quarterly Journal of Economics*, 117(1): 85–120.

Hazra, Arnab Kumar, and Bibek Debroy. 2007. *Judicial reforms in India: Issues and aspects.* Academic Foundation.

Hopenhayn, Hugo A. 2014. "Firms, misallocation, and aggregate productivity: A review." *Annu. Rev. Econ.*, 6(1): 735–770.

Houthakker, Hendrik. 1955. "The Pareto Distribution and the Cobb-Douglas Production Function in Activity Analysis." *The Review of Economic Studies*, 23(1): pp. 27–31.

Hsieh, Chang-Tai, and Peter J Klenow. 2009. "Misallocation and manufacturing TFP in China and India." *The quarterly journal of economics*, 124(4): 1403–1448.

Iyer, Rajkamal, and Antoinette Schoar. 2008. "The Importance of Holdup in Contracting: Evidence from a Field Experiment."

Johnson, Simon, John McMillan, and Christopher Woodruff. 2002. "Courts and relational contracts." *Journal of Law, Economics, and organization*, 18(1): 221–277.

Jones, Charles I. 2005. "The shape of production functions and the direction of technical change." *The Quarterly Journal of Economics*, 120(2): 517–549.

Jones, Charles I. 2013. "Misallocation, Economic Growth, and Input-Output Economics." Vol. 2, 419, Cambridge University Press.

Khandelwal, Amit, and Petia Topalova. 2011. "Trade liberalization and firm productivity: The case of india." *Review of Economics and Statistics*, 93(3): 995–1009.

Kortum, Samuel S. 1997. "Research, Patenting, and Technological Change." *Econometrica*, 65(6): 1389–1420.

Laeven, Luc, and Christopher Woodruff. 2007. "The quality of the legal system, firm ownership, and firm size." *The Review of Economics and Statistics*, 89(4): 601–614.

La Porta, Rafael, Florencio Lopez de Silanes, Andrei Shleifer, and Robert W. Vishny. 1997. "Legal Determinants of External Finance." *The Journal of Finance*, 52(3): 1131–50.

Law Commission of India. 2014. "Report No. 245. Arrears and Backlog: Creating Additional Judicial (wo)manpower."

Levchenko, Andrei A. 2007. "Institutional quality and international trade." *The Review of Economic Studies*, 74(3): 791–819.

Lim, Kevin. 2017. "Firm-to-firm Trade in Sticky Production Networks."

Liu, Ernest. 2017. "Industrial policies and economic development."

Lu, Dan, Asier Mariscal, and Luis Fernando Mejia. 2013. "Imports Switching and the Impact of Large Devaluation."

Narasappa, Harish, and Shruti Vidyasagar. 2016. *State of the Indian Judiciary: A Report by Daksh.* Eastern Book Company.

Nunn, Nathan. 2007. "Relationship-specificity, incomplete contracts, and the pattern of trade." *The Quarterly Journal of Economics*, 122(2): 569–600.

Oberfield, Ezra. 2018. "A Theory of Input-Output Architecture." *Econometrica*, 86(2): 559–589.

Pavcnik, Nina. 2002. "Trade liberalization, exit, and productivity improvements: Evidence from Chilean plants." *The Review of Economic Studies*, 69(1): 245–276.

Ponticelli, Jacopo, and Leonardo S. Alencar. 2016. "Court Enforcement, Bank Loans, and Firm Investment: Evidence from a Bankruptcy Reform in Brazil." *The Quarterly Journal of Economics*, 131(3): 1365–1413.

Rauch, James E. 1999. "Networks versus markets in international trade." *Journal of International Economics*, 48(1): 7–35.

Robinson, Nick. 2016. "Judicial Architecture and Capacity." In *The Oxford Handbook of the Indian Constitution.* , ed. Sujit Choudhry, Madhav Khosla and Pratap Bhanu Mehta. Oxford:Oxford University Press.

Rotemberg, Martin, and T Kirk White. 2017. "Measuring Cross-Country Differences in Misallocation."

Taschereau-Dumouchel, Mathieu. 2017. "Cascades and fluctuations in an economy with an endogenous production network."

Tintelnot, Felix, Ken Kikkawa, Magne Mogstad, and Emmanuel Dhyne. 2017. "Trade and Domestic Production Networks." *Unpublished Manuscript, University of Chicago.*

Appendix

A Data Appendix

A.1 Data Sources and Variable Definitions

- *Plant-level data:* Our plant data is India's Annual Survey of Industries (ASI), published by the Central Statistics Office, Ministry of Statistics and Program Implementation. The data is at annual frequency, each reporting year starts on April 1st and ends on March 31st. Our data covers the years 2000/01 to 2012/13. The input and output product codes for 2008/09 and 2009/10 are different to the ones from earlier years; we created a concordance using the product names (which often match perfectly), and concord the few remaining ones by hand. The years 2010/11 to 2012/13 use the NPCMS product classification, which we convert to ASIC 2007/08 product codes using the concordance published by the Ministry.

- *Total cost:* Sum of the user cost of capital, the total wage bill, energy, services, and materials inputs. Total cost is set to be missing if and only if the user cost of capital, the wage bill, or total materials are missing. The user cost of capital is constructed using the perpetual inventory method as in the Appendix of Greenstreet (2007), using depreciation rates of 0%, 5%, 10%, 20%, and 40% for land, buildings, machinery, transportation equipment, and computers & software, respectively. Capital deflators are from the Ministry's wholesale price index, and the nominal interest rate is the India Bank Lending Rate, from the IMF's International Financial Statistics (on average about 11%).

- *Materials expenditure in total cost:* (as used in Table I and subsequent tables) Total expenditure on intermediate inputs which are associated with a product code (that excludes services and most energy inputs) divided by total cost (see above).

- *Pending High Court cases:* From Daksh India (www.dakshindia.org). Daksh collects and updates pending cases by scraping High Court websites. Cases were retrieved on 11 June 2017. To eliminate biases resulting from possible delays in the digitisation, we exclude all cases that were filed after 1/1/2017. We divide cases into civil and criminal based on state-specific case type codes (which are part of the case identifiers), and a correspondence between case types and whether they are civil or criminal cases (from High Courts, where available).

- *Rauch classification of goods*: From James Rauch's website, for 5-digit SITC codes. Concorded from SITC codes to ASIC via the SITC-CPC concordance from UNSTATS, and the NPCMS-ASIC concordance from the Indian Ministry of Statistics (NPCMS is based on CPC codes).

- *Dependence on relationship-specific inputs, by industry:* (as used in Table I) Total expenditure of single-product plants in an industry on relationship-specific inputs (according to the concorded Rauch classification), by 3-digit industry, divided by total expenditures on intermediate inputs that are associated with a 5-digit product code (which excludes services and most energy intermediate inputs).

- *Gross domestic product per capita, by district* District domestic product was assembled from various state government reports, for the year 2005 (to maximize coverage). Missing for Goa and Gujarat and some union territories, and for some individual districts in the other states. Population data from the 2001 and 2011 Census of India, interpolated to 2005 assuming a constant population growth rate in each district. Whenever district domestic product per capita was unavailable, we used gross state domestic product per capita, as reported by the Ministry of Statistics and Program Implementation.

- *Population density, by district:* population and district size from the 2001 Census of India.

- *Vertical Distance to Output:* See Appendix B. Due to the change in product classification from ASIC to NPCMS after 2010, we construct vertical distance only for the pre-2011 years.

- *Trust:* Fraction of respondents that answer "Most people can be trusted" in the World Value Survey's trust question: "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" Data from waves 4, 5, and 6 of the World Values Survey, except for Himachal Pradesh, Puducherry, and Uttarakhand, which are only available in wave 6. Data is missing for Goa and the UT's, except for Delhi and Puducherry.

- *Language:* Data on population by mother tongue in each state, from the 2001 Census of India, as published by the Office of the Registrar General and Census Commissioner.
- *Caste:* Data on caste from the 2014 round of CMIE's Consumer Pyramids Survey (as made available by ICPSR), covering all states of India except the northeastern states and the UT's of Andaman and Nicobar, Lakshadweep, Dadra and Nagar Haveli and Daman and Diu. Observations have been weighted to be representative at the level of a "homogeneous region", which is "a set of neighbouring districts that have similar agro-climatic conditions, urbanisation levels and female literacy" (CPS 2014 User guide). Data covers 364 castes and caste categories. Herfindahls are constructed at the level of a homogeneous region, and mapped to districts.[34]
- *Corruption:* Number of self-reported bribes per 1,000 inhabitants. Data on bribes is the full history of 35,391 self-reported bribes paid from IPaidABribe.com (as of 03/28/2018), which we aggregate at the state level. Population by state is from the 2011 Census of India.
- *Capital Intensity:* Average plant-level cost share of capital inputs (user cost of capital, see above), by 5-digit industry.
- *Wage Premium:* Average plant-level wage bill divided by the total number of man-days worked, by 5-digit industry.
- *Contract Labor Share:* Average plant-level cost share of contract (non-permanent) workers in the total wage bill, by 5-digit industry.
- *Upstreamness:* Upstreamness as defined by Antràs et al. (2012) of 3-digit industries, calculated by year and averaged across years. Some goods show up mostly as inputs and not as outputs because as outputs they fall outside of the scope of the ASI (chiefly agricultural and mining goods); for these inputs total observed intermediate consumption exceeds total observed production by plants in our sample. We set total production of these goods equal to total intermediate consumption (hence assuming zero sales to final goods consumers).[35] The resulting variable looks very similar to those constructed by Antràs et al. (2012) for industrialized countries.
- *Household consumption shares HH_ω:* Define total net production as the total production of ω (from the ASI, pooled across all years, with each plant-year observation weighted by the inverse of the number of times the plant shows up in the ASI), minus the total consumption of ω as intermediate inputs by ASI firms (constructed and weighted analogously). If total net production of a good is negative, we set it equal to zero. The value of HH_ω is then the fraction of total net production of ω is the sum of total net production of all goods $\omega' \in \Omega$.
- *Recipe revenue shares $R_{\omega\rho}$:* Share of sales of ω using recipe ρ in total sales of ω. The sales of ω using ρ of a single-product plant j are the sales of ω by j multiplied by the probability that j produces using ρ (equation (4)). To construct the sales of ω using ρ of a multi-product plant j, we choose plant-specific recipe shares to minimize the Euclidean distance of the plant's vector of observed cost shares from the weighted average of the recipes' mean cost shares $\overline{m}_{\rho\omega}$, where the weights are the plant-specific recipe shares (subject to the constraint that weights have to sum up to one for each product ω). To construct $R_{\omega\rho}$, we weigh all plant-year observations by the inverse of the number of times the plant shows up in the ASI.

[34]We are grateful to Renuka Sané and CMIE for helping us to get a description of the homogeneous regions.

[35]While this may make these goods look more upstream than they actually are, the biases incurred are likely to be small: minerals are usually not directly sold to households; agricultural goods are either very upstream in the value chain of processed foods, or directly sold to households, but do not appear "in the middle" of the value chain.

A.2 Sample

For the linear regressions in Section 2, the sample consists of all plants are reported as operating, produce a single 5-digit product, and have materials shares of output strictly between zero and two. We also drop the few observations from Sikkim and the Seven Sister States in North East India (Assam, Meghalaya, Manipur, Mizoram, Nagaland, and Tripura; Arunachal Pradesh is not covered by the ASI) because they have a different sampling methodology in the ASI, and Jammu and Kashmir, because coverage of its court cases is inadequate, and because many federal laws do not apply to it due to its special status within the union.

For the structural estimation, we also remove observations where the shares of relationship-specific materials, homogeneous materials, or labor in *sales* exceed two, and observations where sales or non-materials expenditures are non-positive. To construct the households consumption shares HH_ω and the recipe sales shares $R_{\omega\rho}$ in the counterfactual, we weigh each plant-year observation by the inverse of the number of times the plant shows up in our sample.

The regression to estimate ζ (Table VI) is the only one where we identify parameters from time variation. Our sample consists of all census plants that have positive imports, between 2001 and 2010 (to avoid noise from the change in the product classification to NPCMS after 2010).

A.3 Details on High Court and State creation

Table VII Details on High Court Creation

Name	Jurisdiction over States/UT's	Year founded	Created with State	Notes on High Court creation	Reasons for State creation
Allahabad High Court	Uttar Pradesh	1866	no	Created as HC of Judicature of the Northwestern Provinces by the Indian High Courts Act 1861.	
High Court of Judicature at Hyderabad	Andhra Pradesh, Telangana	1956	yes	Created when Andhra Pradesh was created as part of the State Reorganization Act 1956	Creation of Andhra Pradesh was triggered by the independence movement of the Telugu-speaking population of Madras Presidency.
Mumbai High Court	Goa, Dadra and Nagar Haveli,Daman and Diu, Maharashtra	1862	no	Created by the Indian High Courts Act 1861.	
Kolkata High Court	Andaman and Nicobar Islands,West Bengal	1862	no	Created by the Indian High Courts Act 1861.	
Chhattisgarh High Court	Chhattisgarh	2000	yes	Created when Chhattisgarh state was carved out of Mandhya Pradesh in 2000 (Madhya Pradesh Reorganisation Act)	Chhattisgarh was a separate division in the Central Provinces under British rule. Demand for a separate state goes back to 1920.
Delhi High Court	Delhi	1966	no	At the time of independence, Punjab HC had jurisdiction for Delhi. With the State Reorganisation Act 1956, Punjab merged with Pepsu. Given Delhi's importance as capital, it was decided that they should have their own HC.	
Gauhati High Court	Arunachal Pradesh, Assam,Mizoram, Nagaland *	1948	yes	Created as HC of Assam in 1948, with the Indian constitution; renamed Gauhati HC in 1971 with the North East Areas Reorganization Act. Lost jurisdiction over Meghalaya, Manipur, and Tripura in 2013	
Gujarat High Court	Gujarat	1960	yes	Created when Gujarat split from Bombay State with the Bombay Reorganisation Act 1960.	Gujarat was created following the demand of Gujarati-speaking people for their own state (Mahagujarat movement).
Himachal Pradesh High Court	Himachal Pradesh	1971	yes	Created with Himachal Pradesh becoming a state (and therefore should have a separate HC under the Indian constitution)	
Jammu and Kashmir High Court	Jammu and Kashmir	1928	no	Created by the Maharaja in 1928. Special status: Laws passed by the Indian parliament generally do not apply to J&K (except foreign policy, communication, defense).	
Jharkhand High Court	Jharkhand	2000	yes	Created when Jharkhand state was carved out of Bihar in 2000 (Bihar Reorganisation Act)	Jharkhand was richer in natural resources than the rest of Bihar; Jharkhand Mukti Morcha independence movement, and political considerations by ruling parties.

Name	Jurisdiction over States/UT's	Year founded	Created with State	Notes on High Court creation	Reasons for State creation
Karnataka High Court	Karnataka	1884	no	Founded by the British as the Chief Court of Mysore in 1884.	
Kerala High Court	Kerala, Lakshadweep	1956	yes	Created when Kerala was created as part of the State Reorganization Act 1956	Idea of Kerala was to combine Malayalam-speaking regions.
Madhya Pradesh High Court	Madhya Pradesh	1936	no	Established as Nagpur High Court by King George V through a Letters Patent on 2 Jan 1936. Moved to its present location at Jabalpur with the State Reorganization Act 1956.	
Chennai High Court	Puducherry, Tamil Nadu	1862	no	Created by the Indian High Courts Act 1861.	
Odisha High Court	Odisha/Orissa	1948	no	Orissa was split off from Bihar in 1936, but did not get its own high court until the drafting of the Indian constitution (1948).	
Patna High Court	Bihar	1916	yes	Created when Bihar and Orissa were split off from Bengal Presidency.	Bengal nationalism and the undoing of the 1905 Partition of Bengal.
Punjab and Haryana High Court	Chandigarh, Haryana, Punjab	1947	yes	Created with the independence of India in 1947 (former HC of Punjab in Lahore was mostly relevant for modern-day Pakistan)	
Rajasthan High Court	Rajasthan	1949	yes	Created with the foundation of Rajasthan (1948-1950)	
Sikkim High Court	Sikkim	1955	no	Established by the Maharaja of Sikkim in 1955, became an Indian High Court in 1975 when Sikkim joined India and the monarchy was abolished	
Uttarakhand High Court	Uttarakhand	2000	yes	Created when Uttaranchal was carved out of Uttar Pradesh	Uttarakhand Kranti Dal independence movement.
High Court of Mumbai, Goa Bench	Goa, Daman and Diu, Dadra and Nagar Haveli	1982	no	Prior to the HC, a Judicial Commissioner's court existed in Goa. HC was established to safeguard the judge's independence (see Bombay HC at Goa website).	
Manipur High Court	Manipur	2013	no	Parties in Manipur demanded their own high court	
Meghalaya High Court	Meghalaya	2013	no	Parties in Meghalaya demanded their own high court	
High Court Of Tripura	Tripura	2013	no	Parties in Tripura demanded their own high court	

B Vertical Distance

B.1 Definition

Let $x_{j\omega'}$ be the expenditure of plant j on $\omega' \in \Omega$, then define for products $\omega, \omega' \in \Omega$, and a set $B \subset \Omega$

$$\beta^B_{\omega\omega'} = \frac{\sum_{j \in J_\omega} x_{j\omega'}}{\sum_{j \in J_\omega} \sum_{\omega'' \in \Omega \setminus B} x_{j\omega''}}$$

if $\omega' \notin B$, and $\beta^B_{\omega\omega'} = 0$ otherwise. $\beta^B_{\omega\omega'}$ is the share of ω' in industry ω's materials basket that excludes inputs from B.

Denote by $A^n_{\omega\omega'}$ the set of $(n+1)$-tuples $(\omega^{(0)}, \omega^{(1)}, \ldots, \omega^{(n)}) \in \Omega^{n+1}$ such that

$$\omega^{(0)} = \omega, \quad \omega^{(n)} = \omega', \tag{5}$$

$$\omega^{(i)} \neq \omega^{(j)} \quad \forall (i,j) \in \{0, \ldots, n\}^2, i \neq j. \tag{6}$$

Intuitively, $A^n_{\omega\omega'}$ is the set of all possible non-circular product chains of length n between ω and ω'. Then let

$$\delta_{\omega\omega'} = \sum_{n=1}^{\infty} \sum_{a \in A^n_{\omega\omega'}} \frac{\lambda(a)}{\sum_{n'=1}^{\infty} \sum_{a' \in A^{n'}_{\omega\omega'}} \lambda(a')} \cdot n$$

where

$$\lambda : A^n_{\omega\omega'} \to \mathbb{R}, \ \lambda(\omega^{(0)}, \omega^{(1)}, \ldots, \omega^{(n)}) = \prod_{i=1}^{n} \beta^{\{(\omega^{(0)}, \omega^{(1)}, \ldots, \omega^{(i-1)})\}}_{\omega^{(i-1)}\omega^{(i)}}$$

is the share of ω' in ω's input mix through a given product chain. Hence, $\delta_{\omega\omega'}$ is the average number of production steps between an output ω and an input ω', weighted by the overall expenditure of each product chain in industry ω's mix of materials, and excluding any circular product chains.

The plant-level measure of vertical integration, and the left-hand side of Table III, is then the average distance of its inputs from the output, weighted by each inputs' share in the plants materials expenditure: let $j \in J_\omega$, then

$$VI_j = \sum_{\omega' \in \Omega} \frac{x_{j\omega'}}{\sum_{\omega'' \in \Omega} x_{j\omega''}} \delta_{\omega\omega'}.$$

To understand why we exclude circular product chains, consider the following example: Some plants sell aluminum and use aluminum scrap as an input, whereas some other plants use aluminum as an input and sell aluminum scrap. Thus in the production of aluminum scrap, aluminum would show up as an input one stage away, three stages away, five stages away, etc.

When we see a plant selling aluminum scrap and using aluminum as an input, we believe that it is the distance of one that is relevant, not the distances of three, five, etc. In other words, we believe the plant is turning the aluminum into scrap, but not turning the aluminum into scrap then back to aluminum and then back to scrap. Therefore we believe the circular part of the production chain is not relevant for constructing a plant's distance to its inputs.

B.2 Examples

Table VIII shows the average vertical distance of several input groups (defined as all inputs that contain the strings "fabric"/"cloth", "yarn", or "cotton, raw" in their description") from the output "cotton shirts". Fabrics and cloths are closest to the final output; yarns, which are used in the production of cloths and fabrics, are further upstream, and raw cotton inputs are even further upstream.

Table IX shows vertical distances between aluminium ingots as an output, and several intermediate inputs. Aluminium ingots can be made both by recycling castings and alloys, but also by casting molten aluminium. The latter also serves as an intermediate input in the production of castings and alloys, and is hence vertically more distant than the inputs which undergo recycling. Aluminium itself is produced from aluminium oxide using electrolytic reduction (Hall-Heroult process). In turn, aluminium oxide is produced by dissolving bauxite in caustic soda at high temperatures (hence the coal inputs).

Table VIII Vertical distance examples for 63428: Cotton Shirts

Input group	Average vertical distance
Fabrics Or Cloths	1.67
Yarns	2.78
Raw Cotton	3.55

Table IX Vertical distance examples for 73107: Aluminium Ingots

ASIC code	Input description	Vertical distance
73105	Aluminium Casting	1.23
73104	Aluminium Alloys	1.46
73103	Aluminium	1.92
22301	Alumina (Aluminium Oxide)	2.92
31301	Caustic Soda (Sodium Hydroxide)	3.81
23107	Coal	3.85
22304	Bauxite, raw	3.93

C Additional Reduced Form Results

C.1 Distortions and International Sourcing

This section presents three tables describing how plants' usage of domestically- and foreign-sourced inputs varies with distortions. The fourth row of Table X shows that, relative to those in industries that tend to use standardized inputs, the expenditure shares on domestic inputs of plants in industries that use relationship-specific inputs declines as courts get more congested. The second row of Table X shows that this estimated relationship is stronger when we use our instrumental variables strategy with court age as an instrument for congestion.

Table XI shows the same regressions but with the cost share of imported intermediates. Here, the OLS and IV specifications point to opposite results, and further investigation is required. The OLS specifications indicate that among those that rely more on more relationship-specific inputs, more congestion leads to lower shares of imported inputs relative to those that rely on standardized inputs. The IV specification indicates that more congestion leads to relatively higher imported input shares in those that rely on relationship-specific inputs, indicating that firms respond to distortions by substituting from domestic to foreign suppliers.

Table XII shows the results on the share of imports in the basket of relationship-specific (first three columns) and homogenous (last three columns) inputs. More congestion leads to a higher share of imports in both baskets, but the substitution is stronger in the basket of relationship-specific goods.

C.2 Distortions and Markups

Table XIII shows how measured markups, plants ratio of sales to cost vary with the level of distortions. Court congestion should increase distortions for plant industries that tend to rely on relationship-specific relative to those in industries that tend to rely on homogeneous inputs. The first row of the table indicates that, across all measures, ratios of sales to cost decline with distortions. The second and third column shows that this appears to be the direct impact of the distortions rather than the indirect of distortions on size or age.

Table X Domestic Materials Shares and Court Quality (Fact 3)

	Dependent variable: Dom. Mat. Exp. in Total Cost			
	(1)	(2)	(3)	(4)
Avg Age Of Civil Cases * Rel. Spec.	-0.0110^{+}	-0.0119	-0.0349**	-0.0323**
	(0.0057)	(0.0075)	(0.0097)	(0.010)
LogGDPC * Rel. Spec.		-0.00366		-0.0321^{+}
		(0.016)		(0.019)
Trust * Rel. Spec.		-0.0411		-0.0333
		(0.043)		(0.043)
Language HHI * Rel. Spec.		0.00528		0.0122
		(0.056)		(0.056)
Caste HHI * Rel. Spec.		0.0439		0.0623
		(0.076)		(0.075)
Corruption * Rel. Spec.		0.0490		0.0843
		(0.13)		(0.13)
5-digit Industry FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	IV	IV
R^2	0.432	0.439	0.431	0.439
Observations	208527	196748	208527	196748

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

C.3 Materials Shares with Size and Age

Table XIV shows that materials cost shares do not correlate much with size and age of the plant. Table XV shows correlations of input wedges with various plant-level characteristics.

C.4 Plant-level substitutability of inputs

Table XVI uses the interaction of court quality with the average dependency on relationship-specific inputs among an industry's upstream industries to stand in for a shifter to the cost of intermediate inputs. The IV coefficient estimates are positive, giving support to our assumption that inputs are complements at the plant-level.

C.5 Do wedges get paid in another factor?

Table XVII shows regressions of the cost share of labor/capital/services/other inputs in total non-material inputs on the interaction of court quality and relationship-specificity. If wedges were paid in terms on another factor, the cost share of that factor should be systematically correlated with wedges. This does not seem to be the case.

C.6 Controlling for Interactions with State and Industry Characteristics

Tables XVIII, XIX, and XX show the main regressions of materials cost shares, input mixes, and vertical distance with a full set of controls. See Appendix A for definitions of the variables.

Tables XXI and XXIII also include interactions of industry characteristics with court quality. Tables XXII and XXIV show IV regressions where the court quality × industry characteristic interactions are instrumented by the interaction of log court age and the corresponding industry characteristic.

Table XI Import Shares and Court Quality, OLS + IV

	Dependent variable: Imported Materials Expenditure in Total Cost				
	(1)	(2)	(3)	(4)	(5)
Avg age of Civil HC cases	-0.00105		0.000444		
	(0.0017)		(0.0032)		
Avg Age Of Civil Cases * Rel. Spec.	-0.00848^{+}	-0.00466	0.0222**	0.0193**	0.00856^{+}
	(0.0045)	(0.0035)	(0.0068)	(0.0062)	(0.0045)
LogGDPC * Rel. Spec.		-0.00934			0.00905
		(0.0090)			(0.0098)
Trust * Rel. Spec.		0.0707**			0.0656*
		(0.026)			(0.026)
Language HHI * Rel. Spec.		0.0548			0.0504
		(0.041)			(0.041)
Caste HHI * Rel. Spec.		0.0826			0.0707
		(0.055)			(0.053)
Corruption * Rel. Spec.		0.0678			0.0450
		(0.083)			(0.082)
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes
District FE		Yes		Yes	Yes
Estimator	OLS	OLS	IV	IV	IV
R^2	0.276	0.342	0.265	0.329	0.342
Observations	223674	196748	223674	208527	196748

Standard errors in parentheses, clustered at the state $\times$ industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

C.7 Time variation: creation of new High Court benches

C.7.1 Background

Two new benches of the Karnataka High Court were set up Dharwad and Gulbarga in July 2008. They have jurisdiction over Belgaum, Balgakot, Koppal, Gadag, Dharwad, Uttara Kannada, Haveri, and Bellary (Dharwad bench), and Bijapur, Gulbarga, Bidar, and Raichur (Gulbarga bench). The purpose was explicitly to improve access to justice in remote areas.

In July 2004, the Chennai High Court set up a bench in Madurai, which has jurisdiction over Kanniyakumari, Tirunelveli, Tuticorin, Madurai, Dindigul, Ramanathapuram, Virudhunagar, Sivaganga, Pudukkottai, Thanjavur, Tiruchirappalli and Karur districts.

C.7.2 Results

The regressions in Table XXV look at whether wedges on relationship-specific inputs have decreased differentially in districts that are under the jurisdiction of the new benches. The coefficients are not very precisely estimated, since the districts with new benches account on average only for about 6% of the plants in the respective states.

C.7.3 Figures

Figures 7 and 8 show the relative changes in the input mix in treated vs. untreated districts before and after the new high court benches were installed.

Table XII Substitution into Importing

	R-Imports in Total R		H-Imports in Total H	
	(1)	(2)	(3)	(4)
Avg age of Civil HC cases	0.0193**	0.00925**	0.0112**	0.00440**
	(0.0023)	(0.0018)	(0.0016)	(0.0013)
Log district GDP/capita		0.0224**		0.0180**
		(0.0027)		(0.0019)
Trust in other people (WVS)		0.110**		0.0564**
		(0.012)		(0.011)
Language Herfindahl		0.0162		-0.0292**
		(0.019)		(0.0093)
Caste Herfindahl		0.0584*		0.0171
		(0.028)		(0.013)
Corruption		0.0315		-0.0912**
		(0.028)		(0.022)
5-digit Industry FE	Yes	Yes	Yes	Yes
Estimator	IV	IV	IV	IV
R^2	0.227	0.251	0.180	0.197
Observations	168120	148165	168953	149623

Standard errors in parentheses, clustered at the state × industry level.
Dependent variable in columns (1) and (2) (resp. (3) and (4)) is the share of relationship-specific (homogeneous) imports in total relationship-specific (homogeneous) materials.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table XIII Sales over Total Cost

	Dependent variable: Sales/Total Cost					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Age Of Civil Cases * Rel. Spec.	-0.0353**	-0.0347**	-0.0345**	-0.0494*	-0.0496*	-0.0508*
	(0.0097)	(0.0094)	(0.0093)	(0.022)	(0.022)	(0.022)
Plant Age		0.000574**	0.000258^{+}		0.000575**	0.000259^{+}
		(0.00014)	(0.00014)		(0.00014)	(0.00014)
Log Employment			0.0314**			0.0314**
			(0.0016)			(0.0016)
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	OLS	IV	IV	IV
R^2	0.114	0.110	0.115	0.114	0.110	0.115
Observations	208527	205109	204767	208527	205109	204767

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table XIV Plant Age and Size

	Dependent variable: Mat. Exp in Total Cost		
	(1)	(2)	(3)
Plant Age	-0.000695**		-0.000679**
	(0.000065)		(0.000063)
Log Employment		-0.00257**	-0.00176*
		(0.00086)	(0.00083)
5-digit Industry FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Estimator			
R^2	0.481	0.481	0.482
Observations	205109	208179	204767

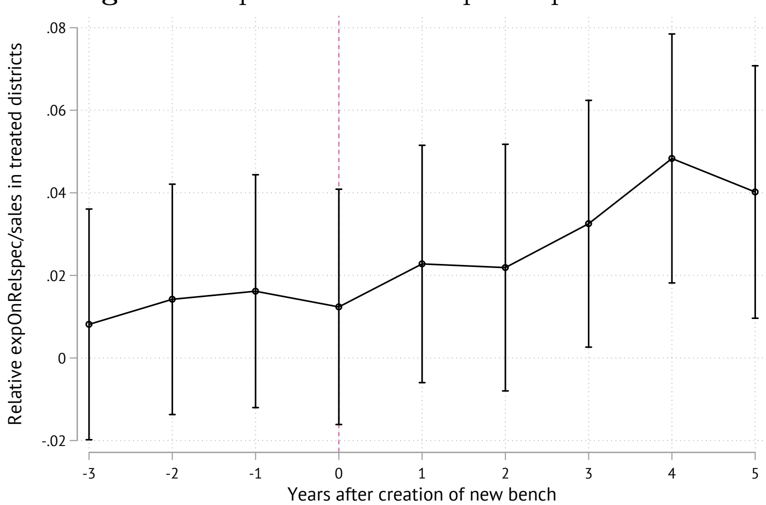
Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table XV Wedges and Plant Characteristics

	Age	Size	Multiproduct	# Products
	(1)	(2)	(3)	(4)
Avg Age Of Civil Cases * Rel. Spec.	0.617^{+}	-0.0252	-0.0122	-0.0585
	(0.32)	(0.040)	(0.0076)	(0.037)
5-digit Industry FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
R^2	0.214	0.339	0.301	0.295
Observations	353392	359820	360316	360316

Note: Sample includes multiproduct plants. Industry dummies refer to the 5-digit industry with the plants' highest production value.

Figure 7 Expenditure on rel.spec. inputs in sales



The figure shows the evolution of the share of relationship-specific inputs in sales, in treated districts relative to non-treated districts. Treatment happens at the start of period 0. Regression includes firm × product fixed effects and year dummies.

Table XVI Plant-level elasticity of substitution

	Dependent variable: Materials Expenditure in Total Cost			
	(1)	(2)	(3)	(4)
Avg Age Of Civil Cases * Rel. Spec.	-0.0147^{+}	-0.0174^{+}	-0.0397**	-0.0421**
	(0.0080)	(0.0098)	(0.013)	(0.014)
LogGDPC * Rel. Spec.		-0.00849		-0.0178
		(0.013)		(0.017)
Avg Age Of Civ. Cases * Rel. Spec. of Upstream Sector	-0.00360	0.00265	0.0450*	0.0345^{+}
	(0.011)	(0.012)	(0.019)	(0.019)
Trust * Rel. Spec.		0.0250		0.0287
		(0.038)		(0.038)
Language HHI * Rel. Spec.		0.0346		0.0349
		(0.033)		(0.033)
Caste HHI * Rel. Spec.		0.109*		0.110*
		(0.050)		(0.050)
5-digit Industry FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	IV	IV
R^2	0.480	0.484	0.480	0.484
Observations	208527	196748	208527	196748

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table XVII Cost share of factors in equipped labor

	Labor	Capital	Services	Rest
	(1)	(2)	(3)	(4)
Avg Age Of Civil Cases * Rel. Spec.	-0.000504	0.00405	-0.000248	-0.00355
	(0.0054)	(0.0030)	(0.0046)	(0.0049)
5-digit Industry FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
R^2	0.310	0.232	0.341	0.269
Observations	208527	208527	208527	208527

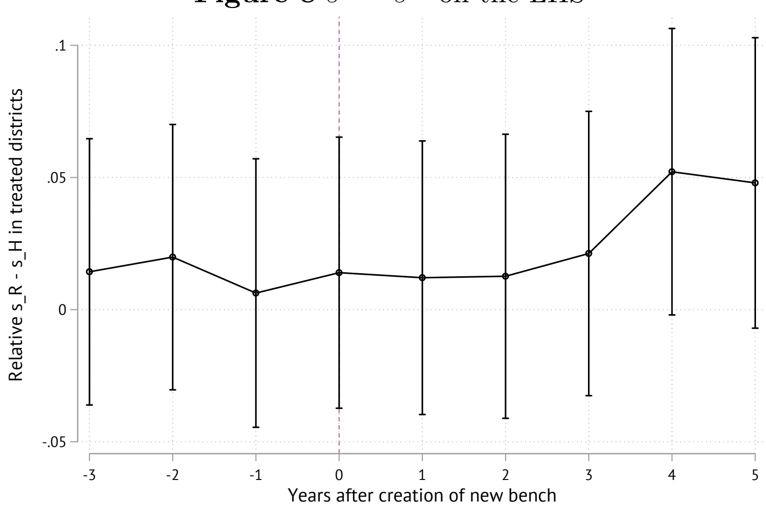
Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
The dependent variable is the cost share of the factor in the total cost of non-material inputs.

Table XVIII Additional Controls – Materials Cost Share

	Dependent variable: Materials Expenditure in Total Cost			
	(1)	(2)	(3)	(4)
Avg Age Of Civil Cases * Rel. Spec.	-0.0167**	-0.0165*	-0.0156^{+}	-0.0237*
	(0.0046)	(0.0069)	(0.0085)	(0.0094)
LogGDPC * Rel. Spec.		-0.0130		-0.0230
		(0.015)		(0.018)
Trust * Rel. Spec.		0.0295		0.0323
		(0.038)		(0.038)
Language HHI * Rel. Spec.		0.0601		0.0625
		(0.040)		(0.039)
Caste HHI * Rel. Spec.		0.126*		0.133*
		(0.053)		(0.053)
Corruption * Rel. Spec.		0.117		0.129
		(0.11)		(0.11)
5-digit Industry FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	IV	IV
R^2	0.480	0.484	0.480	0.484
Observations	208527	196748	208527	196748

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Figure 8 $s^R - s^H$ on the LHS



The figure shows the evolution of $s^R - s^H$, in treated districts relative to non-treated districts. Treatment happens at the start of period 0. Regression includes firm × product fixed effects and year dummies.

Table XIX Additional Controls – Vertical Distance

	Dependent variable: Vertical Distance of Inputs from Output					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg age of Civil HC cases	0.00144	-0.00843		-0.00490	0.000687	
	(0.0070)	(0.0075)		(0.011)	(0.011)	
Avg Age Of Civil Cases * Rel. Spec.	0.0230^{+}	0.0356^{**}	0.0320^{*}	0.0294	0.0423^{*}	0.0437^{*}
	(0.012)	(0.013)	(0.014)	(0.020)	(0.020)	(0.021)
Log district GDP/capita		-0.0364^{**}			-0.0372^{**}	
		(0.0072)			(0.0072)	
LogGDPC * Rel. Spec.		0.0341^{*}	0.0309		0.0640^{**}	0.0471
		(0.017)	(0.034)		(0.020)	(0.040)
Trust		0.0586			0.0521	
		(0.057)			(0.057)	
Language Herfindahl		0.128^{**}			0.121^{**}	
		(0.044)			(0.044)	
Caste Herfindahl		0.0840			0.0841	
		(0.067)			(0.066)	
Trust * Rel. Spec.		-0.188^{*}	-0.0941		-0.183^{*}	-0.0979
		(0.092)	(0.090)		(0.093)	(0.091)
Language HHI * Rel. Spec.		-0.244^{**}	-0.0885		-0.243^{**}	-0.0928
		(0.084)	(0.092)		(0.085)	(0.093)
Caste HHI * Rel. Spec.		-0.193	-0.202^{+}		-0.210^{+}	-0.213^{+}
		(0.12)	(0.12)		(0.12)	(0.12)
Corruption * Rel. Spec.		0.0228	0.463^{+}		-0.0217	0.442^{+}
		(0.14)	(0.25)		(0.14)	(0.25)
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE			Yes			Yes
Estimator	OLS	OLS	OLS	IV	IV	IV
R^2	0.432	0.443	0.453	0.432	0.443	0.453
Observations	163344	154028	154021	163344	154028	154021

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table XX Additional Controls – Input Mix

	Dependent variable: $X_j^R/(X_j^R + X_j^H)$			
	(1)	(2)	(3)	(4)
Avg age of Civil HC cases	-0.00547*	-0.00530*	-0.0144**	-0.0167**
	(0.0022)	(0.0024)	(0.0044)	(0.0045)
Log district GDP/capita		-0.00384		-0.00980^{+}
		(0.0046)		(0.0051)
Trust		-0.00740		-0.00160
		(0.018)		(0.019)
Language HHI		-0.0553**		-0.0567**
		(0.021)		(0.022)
Caste HHI		-0.0428		-0.0525^{+}
		(0.028)		(0.029)
Corruption		-0.0676		-0.0844^{+}
		(0.044)		(0.045)
5-digit Industry FE	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	IV	IV
R^2	0.441	0.449	0.441	0.449
Observations	225590	199339	225590	199339

Standard errors in parentheses, clustered at the state $\times$ industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table XXI Materials Cost Share: Industry Characteristic Interactions

	Dependent variable: Materials Expenditure in Total Cost				
	(1)	(2)	(3)	(4)	(5)
Avg Age Of Civil Cases * Rel. Spec.	-0.0161*	-0.0146*	-0.0165*	-0.0157*	-0.0137*
	(0.0067)	(0.0063)	(0.0068)	(0.0069)	(0.0064)
Capital Intensity * Avg. age of cases	-0.110**				-0.103**
	(0.038)				(0.037)
Industry Wage Premium * Avg. age of cases		-0.00140			-0.00139^{+}
		(0.0011)			(0.00084)
Industry Contract Worker Share * Avg. age of cases			-0.00152		-0.0105
			(0.030)		(0.029)
Upstreamness * Avg. age of cases				0.00284^{+}	0.00222
				(0.0015)	(0.0015)
State $\times$ Rel. Spec. Controls	Yes	Yes	Yes	Yes	Yes
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
R^2	0.484	0.484	0.484	0.484	0.484
Observations	196748	196748	196748	196748	196748

Standard errors in parentheses, clustered at the state $\times$ industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
"State $\times$ Rel. Spec. controls" are interactions of GDP/capita, trust, language herfindahl, caste herfindahl, and corruption with relationship-specificity.

Table XXII Materials Cost Share: Industry Characteristic Interactions (IV)

	Dependent variable: Materials Expenditure in Total Cost					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Age Of Civil Cases * Rel. Spec.	-0.0237*	-0.0236*	-0.0177*	-0.0235*	-0.0216*	-0.0162^{+}
	(0.0094)	(0.0093)	(0.0089)	(0.0092)	(0.0097)	(0.0092)
Capital Intensity * Avg. age of cases		-0.0236				0.0139
		(0.065)				(0.064)
Industry Wage Premium * Avg. age of cases			-0.00398*			-0.00349*
			(0.0017)			(0.0015)
Industry Contract Worker Share * Avg. age of cases				0.0300		0.0192
				(0.040)		(0.039)
Upstreamness * Avg. age of cases					0.00657*	0.00657*
					(0.0032)	(0.0032)
State × Rel. Spec. Controls	Yes	Yes	Yes	Yes	Yes	Yes
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.484	0.484	0.484	0.484	0.484	0.484
Observations	196748	196748	196748	196748	196748	196748

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
"State × Rel. Spec. controls" are interactions of GDP/capita, trust, language herfindahl, caste herfindahl, and corruption with relationship-specificity.

Table XXIII Vertical Distance: Industry Characteristic Interactions

	Dependent variable: Vertical Distance of Inputs from Output				
	(1)	(2)	(3)	(4)	(5)
Avg Age Of Civil Cases * Rel. Spec.	0.0318*	0.0269^{+}	0.0315*	0.0310*	0.0261^{+}
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Capital Intensity * Avg. age of cases	0.0255				-0.00400
	(0.073)				(0.073)
Industry Wage Premium * Avg. age of cases		0.00363^{+}			0.00329
		(0.0021)			(0.0021)
Industry Contract Worker Share * Avg. age of cases			-0.0257		-0.0151
			(0.026)		(0.025)
Upstreamness * Avg. age of cases				-0.00428	-0.00436
				(0.0036)	(0.0036)
State × Rel. Spec. Controls	Yes	Yes	Yes	Yes	Yes
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
R^2	0.453	0.453	0.453	0.453	0.453
Observations	154021	154021	154021	154021	154021

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
"State × Rel. Spec. controls" are interactions of GDP/capita, trust, language herfindahl, caste herfindahl, and corruption with relationship-specificity.

Table XXIV Vertical Distance: Industry Characteristic Interactions (IV)

	Dependent variable: Vertical Distance of Inputs from Output					
	(1)	(2)	(3)	(4)	(5)	(6)
Avg Age Of Civil Cases * Rel. Spec.	0.0437^{*}	0.0416^{+}	0.0268	0.0429^{*}	0.0427^{*}	0.0253
	(0.021)	(0.021)	(0.022)	(0.021)	(0.022)	(0.022)
Capital Intensity * Avg. age of cases		0.252^{+}				0.213
		(0.15)				(0.15)
Industry Wage Premium * Avg. age of cases			0.0110^{**}			0.0106^{*}
			(0.0042)			(0.0043)
Industry Contract Worker Share * Avg. age of cases				-0.0468		0.00351
				(0.047)		(0.048)
Upstreamness * Avg. age of cases					-0.00359	-0.00169
					(0.0070)	(0.0070)
State × Rel. Spec. Controls	Yes	Yes	Yes	Yes	Yes	Yes
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.453	0.453	0.453	0.453	0.453	0.453
Observations	154021	154021	154021	154021	154021	154021

Standard errors in parentheses, clustered at the state × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$
"State × Rel. Spec. controls" are interactions of GDP/capita, trust, language herfindahl, caste herfindahl, and corruption with relationship-specificity.

Table XXV Identification from Time Variation: Diff-in-Diff

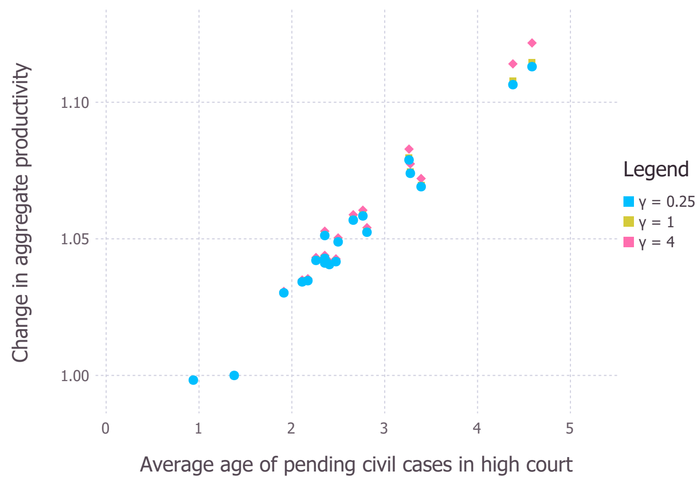
	X^R/Sales	$s_R - s_H$	Materials/TotalCost	Vert. Distance
	(1)	(2)	(3)	(4)
(New Bench in District)$_d$× (Post)$_t$	0.0126^{**}	0.00960	-0.00305	0.00678
	(0.0043)	(0.0076)	(0.0033)	(0.010)
(New Bench in District)$_d$× (Post)$_t$× (Rel.Spec)$_\omega$			0.0142	-0.0764^{*}
			(0.010)	(0.031)
Plant × Product FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	0.832	0.824	0.906	0.813
Observations	80427	74696	78462	77995

D Additional Structural Results

D.1 Counterfactual: Robustness to different parameter values

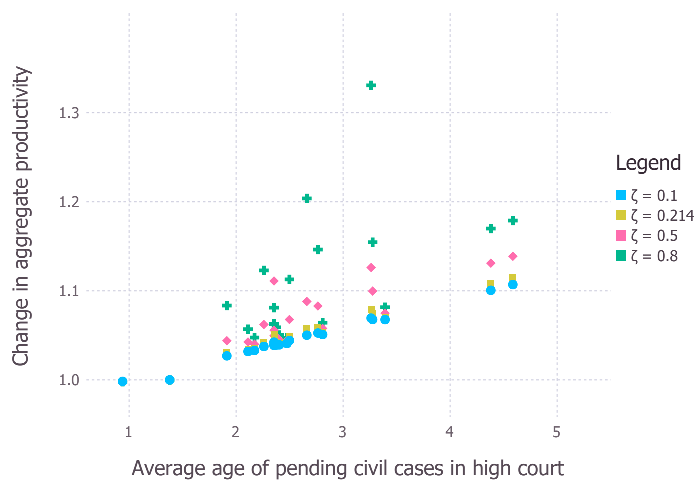
Figures 9 and 10 show the results from the welfare counterfactual for different values of γ and ζ.

Figure 9 Welfare counterfactual for different elasticities γ



The figure shows the counterfactual increase in U for each state for different values of γ.

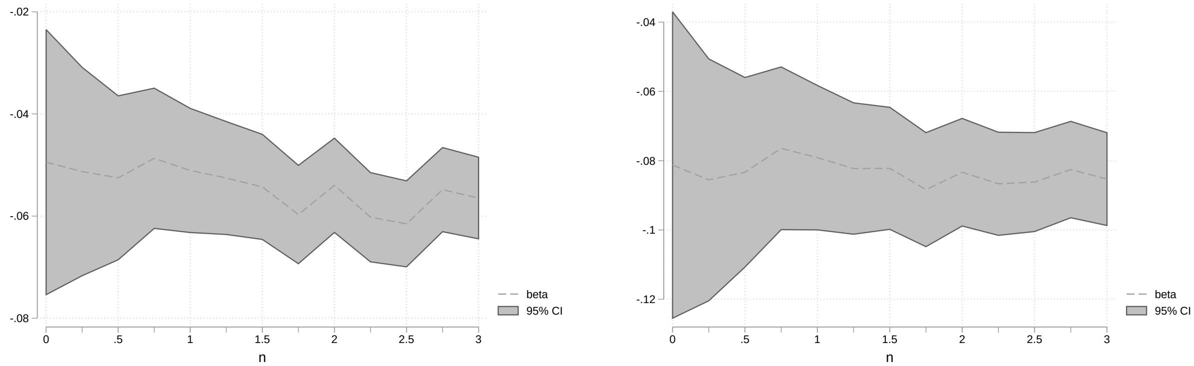
Figure 10 Welfare counterfactual for different elasticities ζ



The figure shows the counterfactual increase in U for each state for different values of ζ.

D.2 Fineness of recipes

This subsection explores the robustness of our estimates to the choice of how finely to define recipes. In our clustering procedure that defines recipes, we have to choose the number of clusters (recipes) within each product. In the baseline results, we choose $\lceil n \log((\#\text{observations})_\omega) \rceil$ clusters, where $\#\text{observations}_\omega$ is the number of single product plant-year observations that produce ω, and set $n = 1.5$.



(a) OLS (b) IV

Figure 11 Regression coefficients for different levels of recipe fineness

We now explore how much this choice of $n = 1.5$ matters. To do so, we run linear regressions that most closely mimic the structural regressions (cf. the GMM moment conditions in Proposition 5):

$$\log\left(\frac{\overline{s}_R^{\rho d}}{\overline{s}_H^{\rho d}}\right) = \beta \cdot (\text{Court quality})_d + \nu_\rho + \varepsilon_{\rho d}$$

where $\overline{s}_R^{\rho d}$ (and $\overline{s}_H^{\rho d}$) is the weighted average sales share of relationship-specific (homogeneous) inputs of plants that produce using recipe rho in state d (weights are the probability weights as in the GMM procedure), and ν_ρ is a set of fixed effects. The estimate for β has a negative sign: Among plants that use a particular recipe, the sales shares of relationship-specific inputs is low compared to homogeneous inputs when courts are slow (i.e., when the average age of pending cases is high). The same holds when we instrument for court quality with the log age of court.

Figure D.2 shows that the point estimates do not change much with the fineness of our recipe classification. For $n = 0$, each product category has only a single recipe, so the total number of recipes equals the number of products (which is 4,530). For $n = 3$, each product category has on average 7.3 recipes, resulting in a total of 33,225 recipes. With more recipes, the estimates become more precise: the clustering procedure assigns outliers their own recipe, so that no longer contaminate the within-recipe variation in average sales shares.

E Model

Lemma 1 *Under Assumption 2, for a firm of type ω,*

$$\Pr(\lambda_{\hat{\omega}}(\phi) \geq \lambda) = e^{-(\lambda/\Lambda_{\omega\hat{\omega}})^{\zeta}}$$

where

$$\frac{\Lambda_{\omega\hat{\omega}}}{w} = \begin{cases} (t_x^*)^{-1}\left[Z\int_0^\infty q^{\zeta_R} dF_{\hat{\omega}}(q)\right]^{-1/\zeta_R} & \hat{\omega} \in \Omega_R^\rho \\ \left[Z\int_0^\infty q^{\zeta_H} dF_{\hat{\omega}}(q)\right]^{-1/\zeta_H} & \hat{\omega} \in \Omega_H^\rho \end{cases}$$

and

$$t_x^* \equiv \left(\int_0^1 t_x^{\zeta_R} dT(t_x)\right)^{1/\zeta_R}$$

.

Proof. Consider first a relationship-specific input $\hat{\omega} \in \hat{\Omega}_R^\rho$. Fix any $\underset{\sim}{z} > 0$ and consider for now only suppliers with match-specific productivities greater than $\underline{z}$. The number of such techniques follows a Poisson distribution with mean $Z\underline{z}^{-\zeta_R}$, and the distribution of the match specific productivities follows a Pareto distribution, $1-(z/\underline{z})^{-\zeta_R}$. The probability that a single such supplier delivers effective cost weakly greater than λ is $\int_{\underline{z}}^{\infty}\int_0^1 F_{\hat{\omega}}\left(\frac{w}{\lambda t_x z}\right) dT(t_x)\zeta^R \underline{z}^{\zeta_R} z^{-\zeta_R-1}dz$. To see this note first that the effective cost delivered by supplier s with match productivity z and wedge t_x is $\frac{p_s}{zt_x}$, and since $p_s=\frac{w}{q_s}$, effective cost is $\frac{w}{t_x z q_s}$. Thus for a supplier with match-specific productivity z and wedge t_x, the probability that the supplier delivers effective cost greater than λ is the same as the probability that $\frac{w}{t_x z q_s}\geq\lambda$, or $q_s\leq\frac{w}{\lambda t_x z}$. We thus have that the effective cost delivered by the best supplier with match productivity greater than $\underline{z}$ is

$$\begin{aligned}
\Pr(\lambda_{\hat{\omega}}(\phi)\geq\lambda|z>\underline{z}) &= \sum_{n=0}^{\infty}\Pr(\lambda_{\hat{\omega}}(\phi)\geq\lambda|z>\underline{z}, n\text{ suppliers with }z>\underline{z})\Pr(n\text{ suppliers with }z>\underline{z})\\
&= \sum_{n=0}^{\infty}\left[\int_{\underline{z}}^{\infty}\int_0^1 F_{\hat{\omega}}\left(\frac{w}{\lambda t_x z}\right)dT(t_x)\underline{z}^{\zeta_R}\zeta_R z^{-\zeta_R-1}dz\right]^n \frac{e^{-Z\underline{z}^{-\zeta_R}}(Z\underline{z}^{-\zeta_R})^n}{n!}\\
&= e^{-Z\int_{\underline{z}}^{\infty}\int_0^1\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda t_x z}\right)\right]dT(t_x)\zeta_R z^{-\zeta_R-1}dz}
\end{aligned}$$

Taking a limit as $\underline{z}\to 0$, making a change of variables, and integrating by parts yields

$$\begin{aligned}
\Pr(\lambda_{\hat{\omega}}(\phi)\geq\lambda) &= e^{-Z\int_0^{\infty}\int_0^1\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda t_x z}\right)\right]dT(t_x)\zeta_R z^{-\zeta_R-1}dz}\\
&= e^{-Z\int_0^{\infty}\int_0^1[1-F_{\hat{\omega}}(u)](\lambda t_x/w)^{\zeta_R}dT(t_x)\zeta_R u^{\zeta_R-1}du}\\
&= e^{-(\lambda/w)^{\zeta_R}Z\int_0^{\infty}\int_0^1 u^{\zeta_R}t_x^{\zeta_R}dT(t_x)dF_{\hat{\omega}}(u)}\\
&= e^{-(\lambda/\Lambda_{\omega\hat{\omega}})^{\zeta_R}}
\end{aligned}$$

The logic for homogeneous inputs is the same.

Proposition 6 *Under Assumptions 1, 2, 3, and 4, the fraction of firms with efficiency no greater than q among those that produce good ω is*

$$F_\omega(q)=e^{-(q/Q_\omega)^{-\gamma}}$$

where

$$\begin{aligned}
Q_\omega &= \left\{\sum_{\rho\in\varrho(\omega)}\kappa_{\omega\rho}\left((t_x^*)^{\alpha_R^\rho}(t_l)^{\alpha_l^\rho}\prod_{\hat{\omega}\in\hat{\Omega}^\rho}Q_{\hat{\omega}}^{\alpha_{\hat{\omega}}^\rho}\right)^\gamma\right\}^{\frac{1}{\gamma}} && (7)\\
t_x^* &= \left(\int_0^1 t_x^{\zeta^R}dT(t_x)\right)^{1/\zeta_R}
\end{aligned}$$

and $\kappa_{\omega\rho}$ is a constant that depends on $B_{\omega\rho}$ and technological parameters.

Proof. Consider recipe ρ that uses inputs $\hat{\Omega}^\rho=\{\hat{\omega}_1,...,\hat{\omega}_n\}$. Fix a vector of input-augmenting productivities, $\underline{b}=\left\{\underline{b}_l,\underline{b}_{\hat{\omega}_1},...,\underline{b}_{\hat{\omega}_n}\right\}$, and consider for now only techniques that dominate $\underline{b}$. Let $H_{\omega\rho}(q;\underline{b})$ be the probability that a single such technique delivers to the buyer efficiency weakly less than q, and let $F_{\omega\rho}(q;\underline{b})$ be the probability that a firm in industry ω has no such techniques that deliver efficiency greater than q.

Then we are interested in

$$F_\omega(q)=\prod_{\rho\in\varrho(\omega)}F_{\omega\rho}(q;0) \tag{8}$$

Since the number of such techniques follows a Poisson distribution with mean $B_{\omega\rho}\underline{b}_l^{-\beta_l^\rho}\underline{b}_{\hat{\omega}_1}^{-\beta_{\hat{\omega}_1}^\rho}...\underline{b}_{\hat{\omega}_n}^{-\beta_{\hat{\omega}_n}^\rho}$, we have

$$
\begin{aligned}
F_{\omega\rho}(q;\underline{b}) &= \sum_{k=0}^{\infty} \Pr(k \text{ techniques that dominate } \underline{b}) \Pr(\text{all } k \text{ deliver efficiency } \leq q) && (9) \\
&= \sum_{k=0}^{\infty} \frac{\left[B_{\omega\rho}\underline{b}_l^{-\beta_l^\rho} \underline{b}_{\hat{\omega}_1}^{-\beta_{\hat{\omega}_1}^\rho} ... \underline{b}_{\hat{\omega}_n}^{-\beta_{\hat{\omega}_n}^\rho}\right]^k e^{-B_{\omega\rho}\underline{b}_l^{-\beta_l^\rho} \underline{b}_{\hat{\omega}_1}^{-\beta_{\hat{\omega}_1}^\rho} ... \underline{b}_{\hat{\omega}_n}^{-\beta_{\hat{\omega}_n}^\rho}}}{k!} H_{\omega\rho}(q;\underline{b})^k \\
&= e^{-B_{\omega\rho}\underline{b}_l^{-\beta_l^\rho} \underline{b}_{\hat{\omega}_1}^{-\beta_{\hat{\omega}_1}^\rho} ... \underline{b}_{\hat{\omega}_n}^{-\beta_{\hat{\omega}_n}^\rho}[1-H_{\omega\rho}(q;\underline{b})]} && (10)
\end{aligned}
$$

To find $H_{\omega\rho}(q;\underline{b})$, we can integrate over possible realizations of input-augmenting efficiencies (which follow independent Pareto distributions) and effective cost for each intermediate input

$$
\begin{aligned}
H_{\omega\rho}(q;\underline{b}) &= \int_0^\infty ... \int_0^\infty \int_{\underline{b}_{\omega_n}}^\infty ... \int_{\underline{b}_{\omega_1}}^\infty \int_{\underline{b}_l}^\infty 1\left\{\mathcal{C}_{\omega\rho}\left\{\frac{w/t_l}{b_l}, \frac{\lambda_1}{b_1}, ..., \frac{\lambda_n}{b_n}\right\} \geq \frac{w}{q}\right\} \\
&\quad \times \beta_l^\rho \underline{b}_l^{\beta_l^\rho} b_l^{-\beta_l^\rho - 1} db_l \beta_{\hat{\omega}_1}^\rho \underline{b}_{\hat{\omega}_1}^{\beta_{\hat{\omega}_1}^\rho} b_1^{-\beta_{\hat{\omega}_1}^\rho - 1} db_1 ... \beta_{\hat{\omega}_n}^\rho \underline{b}_{\hat{\omega}_n}^{\beta_{\hat{\omega}_n}^\rho} b_n^{-\beta_{\hat{\omega}_n}^\rho - 1} db_n \\
&\quad \times d\left[e^{-\left(\lambda_1/\bar{\Lambda}_{\omega\hat{\omega}_1}\right)^{\zeta_{\hat{\omega}_1}}}\right] ... d\left[e^{-\left(\lambda_n/\Lambda_{\omega\hat{\omega}_n}\right)^{\zeta_{\hat{\omega}_n}}}\right]
\end{aligned}
$$

With this, (10) can be expressed as

$$
\begin{aligned}
-\log F_{\omega\rho}(q;\underline{b}) &= B_{\omega\rho} \int_0^\infty ... \int_0^\infty \int_{\underline{b}_{\omega_n}}^\infty ... \int_{\underline{b}_{\omega_1}}^\infty \int_{\underline{b}_l}^\infty 1\left\{\mathcal{C}_{\omega\rho}\left\{\frac{w/t_l}{b_l}, \frac{\lambda_1}{b_1}, ..., \frac{\lambda_n}{b_n}\right\} \geq \frac{w}{q}\right\} \\
&\quad \times \beta_l^\rho b_l^{-\beta_l^\rho - 1} db_l \beta_{\hat{\omega}_1}^\rho b_1^{-\beta_{\hat{\omega}_1}^\rho - 1} db_1 ... \beta_{\hat{\omega}_n}^\rho b_n^{-\beta_{\hat{\omega}_n}^\rho - 1} db_n \\
&\quad \times d\left[e^{-\left(\lambda_1/\bar{\Lambda}_{\omega\hat{\omega}_1}\right)^{\zeta_{\hat{\omega}_1}}}\right] ... d\left[e^{-\left(\lambda_n/\Lambda_{\omega\hat{\omega}_n}\right)^{\zeta_{\hat{\omega}_n}}}\right]
\end{aligned}
$$

Taking the limit as $\underline{b} \to 0$ gives

$$
\begin{aligned}
-\log F_{\omega\rho}(q;0) &= B_{\omega\rho} \int_0^\infty ... \int_0^\infty \int_0^\infty ... \int_0^\infty \int_0^\infty 1\left\{\mathcal{C}_{\omega\rho}\left\{\frac{w/t_l}{b_l}, \frac{\lambda_1}{b_1}, ..., \frac{\lambda_n}{b_n}\right\} \geq \frac{w}{q}\right\} \\
&\quad \times \beta_l^\rho b_l^{-\beta_l^\rho - 1} db_l \beta_{\hat{\omega}_1}^\rho b_1^{-\beta_{\hat{\omega}_1}^\rho - 1} db_1 ... \beta_{\hat{\omega}_n}^\rho b_n^{-\beta_{\hat{\omega}_n}^\rho - 1} db_n \\
&\quad \times d\left[e^{-\left(\lambda_1/\bar{\Lambda}_{\omega\hat{\omega}_1}\right)^{\zeta_{\hat{\omega}_1}}}\right] ... d\left[e^{-\left(\lambda_n/\Lambda_{\omega\hat{\omega}_n}\right)^{\zeta_{\hat{\omega}_n}}}\right]
\end{aligned}
$$

Using the change of variables $u_l = \frac{q}{t_l b_l}$, $u_i = \frac{\lambda_i q}{b_i w}$, $v_i = \left(\lambda_i/\bar{\Lambda}_{\omega\hat{\omega}_i}\right)^{\zeta_{\hat{\omega}_i}}$ gives

$$
\begin{aligned}
-\log F_{\omega\rho}(q;0) &= B_{\omega\rho}\left(\frac{q}{t_l}\right)^{-\beta_l^\rho} \left(\frac{\Lambda_{\omega\hat{\omega}_1} q}{w}\right)^{-\beta_{\hat{\omega}_n}^\rho} ... \left(\frac{\Lambda_{\omega\hat{\omega}_n} q}{w}\right)^{-\beta_{\hat{\omega}_n}^\rho} \\
&\quad \times \int_0^\infty ... \int_0^\infty 1\left\{\mathcal{C}_{\omega\rho}\{u_l, u_1, ..., u_n\} \geq 1\right\} \times \beta_l^\rho u_l^{\beta_l^\rho - 1} du_l \beta_{\hat{\omega}_1}^\rho u_1^{\beta_{\hat{\omega}_1}^\rho - 1} du_1 ... \beta_{\hat{\omega}_n}^\rho u_n^{\beta_{\hat{\omega}_n}^\rho - 1} du_n \\
&\quad \times \int_0^\infty ... \int_0^\infty v_1^{-\frac{\beta_{\hat{\omega}_n}^\rho}{\zeta_{\hat{\omega}_1}}} ... v_n^{-\frac{\beta_{\hat{\omega}_n}^\rho}{\zeta_{\hat{\omega}_n}}} e^{-v_1} dv_1 ... e^{-v_n} dv_n
\end{aligned}
$$

The integral on the second line is finite because the inputs are complements in production. The last integral is simply

$$\int_0^\infty ... \int_0^\infty v_1^{-\frac{\beta^\rho_{\hat\omega_n}}{\zeta_{\hat\omega_1}}} ... v_n^{-\frac{\beta^\rho_{\hat\omega_n}}{\zeta_{\hat\omega_n}}} e^{-v_1} dv_1 ... e^{-v_n} dv_n = \prod_{\hat\omega \in \hat\Omega^\rho} \int_0^\infty v^{-\frac{\beta^\rho_{\hat\omega}}{\zeta_{\hat\omega}}} e^{-v} dv$$
$$= \prod_{\hat\omega \in \Omega^\rho_R} \Gamma\left(1 - \frac{\beta^\rho_{\hat\omega}}{\zeta_R}\right) \prod_{\hat\omega \in \Omega^\rho_H} \Gamma\left(1 - \frac{\beta^\rho_{\hat\omega}}{\zeta_H}\right)$$

Or more simply,

$$-\log F_{\omega\rho}(q;0) = q^{-\gamma} B_{\omega\rho} t_l^{\beta^\rho_l} \left(\Lambda_{\omega\hat\omega_1}/w\right)^{-\beta^\rho_{\hat\omega_1}} ... \left(\Lambda_{\omega\hat\omega_n}/w\right)^{-\beta^\rho_{\hat\omega_n}} \tilde\kappa_{\omega\rho} \tag{11}$$

Define

$$Q_\omega \equiv \left[\sum_{\rho \in \varrho(\omega)} B_{\omega\rho} t_l^{-\beta^\rho_l} \left(\Lambda_{\omega\hat\omega_1}/w\right)^{-\beta^\rho_{\hat\omega_1}} ... \left(\Lambda_{\omega\hat\omega_n}/w\right)^{-\beta^\rho_{\hat\omega_n}} \tilde\kappa_{\omega\rho}\right]^{1/\gamma} \tag{12}$$

Then (8) implies that

$$F_\omega(q) = e^{-(q/Q_\omega)^{-\gamma}}$$

To complete the proof, we will derive expressions for $\Lambda_{\omega\tilde\omega}$ in terms of $Q_{\hat\omega}$ and substitute into (12). Note first that for $\zeta \in \{\zeta_R, \zeta_H\}$ we have

$$\int_0^\infty q^\zeta dF_\omega(q) = \int_0^\infty q^\zeta Q_\omega^\gamma \gamma q^{-\gamma-1} e^{-(q/Q_\omega)^{-\gamma}} dq$$
$$= Q_\omega^\zeta \int_0^\infty u^{-\frac{\zeta}{\gamma}} e^{-u} du$$
$$= Q_\omega^\zeta \Gamma\left(1 - \frac{\zeta}{\gamma}\right)$$

therefore Lemma 1 implies

$$\frac{\Lambda_{\omega\tilde\omega}}{w} = \begin{cases} \left(t_x^* Q_{\hat\omega}\right)^{-1} Z^{-1/\zeta_R} \Gamma\left(1 - \frac{\zeta_R}{\gamma}\right)^{-1/\zeta_R} & \hat\omega \in \hat\Omega_R \\ \left(Q_{\hat\omega}\right)^{-1} Z^{-1/\zeta_H} \Gamma\left(1 - \frac{\zeta_H}{\gamma}\right)^{-1/\zeta_H} & \hat\omega \in \hat\Omega_H \end{cases}$$

Plugging this into (12) and using $\alpha^\rho_{\hat\omega} = \frac{\beta^\rho_{\hat\omega}}{\gamma}$ gives the result.

E.1 Factor Shares

Consider a firm in industry ω. If, in equilibrium, the firm uses a technique of recipe ρ (with n intermediate inputs) with input-augmenting productivities $\{b_l, b_1, ..., b_n\}$, effective cost of intermediate inputs $\{\lambda_1, ..., \lambda_n\}$, then its payment to supplier of a relationship-specific input $\hat\omega_i$ with wedge $t_{\hat\omega x}$ is

$$p_s \hat x_s = t_{\hat\omega x} \frac{\lambda_{\hat\omega}}{b_{\hat\omega}} \mathcal{C}_{\omega\rho\hat\omega} \left\{\frac{w/t_l}{b_l}, \frac{\lambda_1}{b_1}, ..., \frac{\lambda_n}{b_n}\right\} y_j$$

. We characterize average revenue shares of each input in several in several intermediate steps.

Lemma 2 *Among firms in industry ω that, in equilibrium, use techniques in recipe ρ with efficiency q, the* *following equations holds*

$$E\left[\frac{\lambda_{\hat{\omega}}}{b_{\hat{\omega}}}\mathcal{C}_{\omega\rho\hat{\omega}}\left\{\frac{w/t_l}{b_l},\frac{\lambda_1}{b_1},...,\frac{\lambda_n}{b_n}\right\}\middle|q,\rho\right] = \alpha_{\hat{\omega}}^{\rho}E\left[\mathcal{C}_{\omega\rho}\left\{\frac{w/t_l}{b_l},\frac{\lambda_1}{b_1},...,\frac{\lambda_n}{b_n}\right\}\middle|q,\rho\right], \quad \forall\hat{\omega}\in\hat{\Omega}_{\rho}$$
$$E\left[\frac{w/t_l}{b_l}\mathcal{C}_{\omega\rho l}\left\{\frac{w/t_l}{b_l},\frac{\lambda_1}{b_1},...,\frac{\lambda_n}{b_n}\right\}\middle|q,\rho\right] = \alpha_{l}^{\rho}E\left[\mathcal{C}_{\omega\rho}\left\{\frac{w/t_l}{b_l},\frac{\lambda_1}{b_1},...,\frac{\lambda_n}{b_n}\right\}\middle|q,\rho\right]$$

Proof. To be filled in ■

Lemma 3 *Among firms that produce ω that, in equilibrium, use a supplier for relationship-specific input $\hat{\omega}\in\Omega_R^{\rho}$ that delivers effective cost $\lambda_{\hat{\omega}}$, the average wedge is*

$$\bar{t}_x = E\left[t_{x\hat{\omega}}|\lambda_{\hat{\omega}}\right] = \int_0^1 t_x d\tilde{T}(t_x)$$

where $\tilde{T}(t_x) \equiv= \frac{\int_0^{t_x} t^{\zeta_R}dT(t)}{\int_0^1 t^{\zeta_R}dT(t)}$.

Proof. Consider all suppliers drawn by j to supply input $\hat{\omega}$ for recipe ρ. Among those, consider first those for which the match specific productivity is greater than $\underline{z}$. The effective cost delivered by the supplier is $\lambda = \frac{p_s}{t_x z}$ where $p_s = \frac{w}{q_s}$ is the price charged by the supplier. Given the match-specific productivity z and wedge t_x, the probability that the supplier's efficiency is high enough to deliver an effective cost lower λ is the probability that q_s is large enough to so that $\frac{w/q_s}{t_x z} < \lambda$, i.e., $q_s > \frac{w}{\lambda t_x z}$, or $1 - F_{\hat{\omega}}\left(\frac{w}{\lambda t_x z}\right)$. Integrating over possible values of z and t_x, the probability that a supplier delivers effective cost lower than λ is $\int_{\underline{z}}^{\infty}\int_0^1\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda tz}\right)\right]dT(t)\zeta_R\underline{z}^{\zeta_R}z^{-\zeta_R-1}dz$. Second, the probability that such a supplier delivers effective cost less than λ and the wedge is less than t_x is $\int_{\underline{z}}^{\infty}\int_0^{t_x}\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda tz}\right)\right]dT(t)\zeta_R\underline{z}^{\zeta_R}z^{-\zeta_R-1}dz$. Together, these imply that, among such suppliers who deliver effective cost less than λ, the probability that the wedge is less than t_x is

$$\begin{aligned}\Pr\left(t_{xs}<t_x|\lambda_s\le\lambda,z_s>\underline{z}\right) &= \frac{\int_{\underline{z}}^{\infty}\int_0^{t_x}\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda tz}\right)\right]dT\left(t\right)\zeta_R\underline{z}^{\zeta_R}z^{-\zeta_R-1}dz}{\int_{\underline{z}}^{\infty}\int_0^{t_x}\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda tz}\right)\right]dT\left(t\right)\zeta_R\underline{z}^{\zeta_R}z^{-\zeta_R-1}dz}\\ &= \frac{\int_{\underline{z}}^{\infty}\int_0^{t_x}\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda tz}\right)\right]dT\left(t\right)z^{-\zeta_R-1}dz}{\int_{\underline{z}}^{\infty}\int_0^{t_x}\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda tz}\right)\right]dT\left(t\right)z^{-\zeta_R-1}dz}\end{aligned}$$

Taking the limit as $\underline{z}\to 0$, making the change of variable $u=\frac{w}{\lambda tz}$ and simplifying gives

$$\begin{aligned}\Pr\left(t_{xs}<t_x|\lambda_s\le\lambda\right) &= \frac{\int_0^{\infty}\int_0^{t_x}\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda tz}\right)\right]dT\left(t\right)z^{-\zeta_R-1}dz}{\int_0^{\infty}\int_0^{t_x}\left[1-F_{\hat{\omega}}\left(\frac{w}{\lambda tz}\right)\right]dT\left(t\right)z^{-\zeta_R-1}dz}\\ &= \frac{\int_0^{\infty}\int_0^{t_x}\left[1-F_{\hat{\omega}}\left(u\right)\right]t^{\zeta_R}dT\left(t\right)u^{\zeta_R-1}du}{\int_0^{\infty}\int_0^{t_x}\left[1-F_{\hat{\omega}}\left(u\right)\right]t^{\zeta_R}dT\left(t\right)u^{\zeta_R-1}du}\\ &= \frac{\int_0^{t_x}t^{\zeta_R}dT\left(t\right)}{\int_0^{t_x}t^{\zeta_R}dT\left(t\right)}\\ &= \tilde{T}\left(t_x\right)\end{aligned}$$

With this, we have that among suppliers that deliver effective cost weakly greater than λ, the average wedges is

$$E\left[t_{xs}|\lambda_s\le\lambda\right]=\bar{t}_x$$

Since $\bar{t}_x$ does not depend on λ, the expectation must be the same for each λ, i.e.,

$$E\left[t_{xs}|\lambda_s\right]=\bar{t}_x$$

Finally, this equation holds regardless of whether s is selected as a supplier. In other words,

$$E\left[t_{x\hat{\omega}}|\lambda_{\hat{\omega}}\right]=E\left[t_{xs}|\lambda_s, s \text{ selected as supplier}\right]=E\left[t_{xs}|\lambda_s\right]=\bar{t}_x$$

■

Proposition 7 *For a firm in industry ω that, in equilibrium uses recipe ρ and has efficiency q,*

$$E\left[s_{\hat{\omega}}|q,\rho\right]=\frac{\bar{t}_x\alpha_\omega^\rho}{\bar{t}_x\alpha_R^\rho+\alpha_H^\rho+t_l\alpha^\rho}$$

Proof. Let $\bar{p}_j$ be j's average price across all buyers. Note first that j's revenue share of input $\hat{\omega}$ is

$$s_j=\frac{p_s\hat{x}_s y_j}{\bar{p}_j y_j}=\frac{1}{\bar{p}_j}t_{\hat{\omega}x}\frac{\lambda_{\hat{\omega}}}{b_{\hat{\omega}}}\mathcal{C}_{\omega\rho\hat{\omega}}\left\{\frac{w/t_l}{b_l},\frac{\lambda_1}{b_1},...,\frac{\lambda_n}{b_n}\right\}$$

Note that conditional on q, $\bar{p}_j$ is independent of any feature of the firm's sourcing decision, and conditional on λ_i, t_{xi} is independent of any other feature of the firm's sourcing decision. Putting the pieces together, we have

$$\begin{aligned}
E\left[s_{\hat{\omega}}|q,\rho\right] &= E\left[\frac{1}{\bar{p}}t_{x\hat{\omega}}\frac{\lambda_{\hat{\omega}}}{b_{\hat{\omega}}}\mathcal{C}_{\omega\rho\hat{\omega}}\left\{\frac{w/t_l}{b_l},\frac{\lambda_1}{b_1},...,\frac{\lambda_n}{b_n}\right\}\middle| q,\rho_j=\rho\right]\\
&= E\left\{E\left[\frac{1}{\bar{p}}t_{x\hat{\omega}}\frac{\lambda_{\hat{\omega}}}{b_{\hat{\omega}}}\mathcal{C}_{\omega\rho\hat{\omega}}\left\{\frac{w/t_l}{b_l},\frac{\lambda_1}{b_1},...,\frac{\lambda_n}{b_n}\right\}\middle| q,\rho,b,\lambda\right]\middle| q,\rho\right\}\\
&= E\left\{E\left[\frac{1}{\bar{p}}\middle| q,\rho,b,\lambda\right]E\left[t_{x\hat{\omega}}|\, q,\rho,b,\lambda\right]\frac{\lambda_{\hat{\omega}}}{b_{\hat{\omega}}}\mathcal{C}_{\omega\rho\hat{\omega}}\left\{\frac{w/t_l}{b_l},\frac{\lambda_1}{b_1},...,\frac{\lambda_n}{b_n}\right\}\middle| q,\rho\right\}\\
&= E\left[\frac{1}{\bar{p}}\middle| q,\rho,b,\lambda\right]E\left[t_{x\hat{\omega}}|\, q,\rho,b,\lambda\right]E\left\{\frac{\lambda_{\hat{\omega}}}{b_{\hat{\omega}}}\mathcal{C}_{\omega\rho\hat{\omega}}\left\{\frac{w/t_l}{b_l},\frac{\lambda_1}{b_1},...,\frac{\lambda_n}{b_n}\right\}\middle| q,\rho\right\}\\
&= E\left[\frac{1}{\bar{p}}\middle| q,\rho\right]\bar{t}_x\alpha_{\hat{\omega}}^\rho\frac{w}{q}
\end{aligned}$$

■

Corollary 2 *For a firm in industry ω that, in equilibrium uses recipe ρ, the cost share of input $\hat{\omega}$ is*

$$\frac{\bar{t}_x\alpha_\omega^\rho}{\bar{t}_x\alpha_R^\rho+\alpha_H^\rho+t_l\alpha^\rho}$$

Proof. Integrating over realizations of q gives

$$E\left[s_{j\hat{\omega}}|\rho\right]=\alpha_{\hat{\omega}}^\rho\bar{t}_x E\left\{E\left[\frac{w}{q\bar{p}}\middle|\rho\right]\right\}$$

The corollary follows from the fact that the cost share is $\frac{s_{j\hat{\omega}}}{s_{jl}+s_{jR}+s_{jH}}$ ■

E.2 Counterfactuals

Given the household's preferences, let P_ω be the ideal price index for industry ω and let P be the overall ideal price index. These satisfy $P_\omega\equiv\left(\int_0^{J_\omega}p_j^{1-\varepsilon_\omega}dj\right)^{\frac{1}{1-\varepsilon_\omega}}$ and $P=\left(\sum_\omega\upsilon_\omega P_\omega^{1-\eta}\right)^{\frac{1}{1-\eta}}$.

Since each firm charges marginal cost, firm j in industry ω would charge a price of $\frac{w}{q_j}$. Thus the price index for ω satisfies

$$P_\omega^{1-\varepsilon_\omega}=\int_0^{J_\omega}\left(\frac{w}{q_j}\right)^{1-\varepsilon_\omega}dj=J_\omega\int_0^\infty(q/w)^{\varepsilon_\omega-1}dF_\omega(q)$$

Under Assumption **??**, $F_\omega(q) = e^{-(q/Q_\omega)^{-\gamma}}$. Integrating yields $\int_0^\infty q^{\varepsilon_\omega - 1} dF_\omega(q) = \Gamma\left(1 - \frac{\varepsilon_\omega - 1}{\gamma}\right) Q_\omega^{\varepsilon - 1}$, which implies that the industry price index can be expressed as

$$P_\omega = J_\omega^{\frac{1}{1-\varepsilon_\omega}} \Gamma\left(1 - \frac{\varepsilon_\omega - 1}{\gamma}\right)^{\frac{1}{1-\varepsilon_\omega}} \frac{w}{Q_\omega}$$

The overall price index is therefore

$$P = \left(\sum_\omega \upsilon_\omega J_\omega^{\frac{\eta-1}{\varepsilon_\omega - 1}} \Gamma\left(1 - \frac{\varepsilon_\omega - 1}{\gamma}\right)^{\frac{\eta-1}{\varepsilon_\omega-1}} (Q_\omega/w)^{\eta-1}\right)^{\frac{1}{1-\eta}}$$

Since firms do not earn profit, household income is simply labor income, so household utility is

$$U = \frac{wL}{P} = \left(\sum_\omega \upsilon_\omega J_\omega^{\frac{\eta-1}{\varepsilon_\omega - 1}} \Gamma\left(1 - \frac{\varepsilon_\omega - 1}{\gamma}\right)^{\frac{\eta-1}{\varepsilon_\omega-1}} Q_\omega^{\eta-1}\right)^{\frac{1}{\eta-1}} L$$

Claim 1 *A change in the distribution of relationship-specific intermediate input wedges from T to T' leads to a change in household utility that can be summarized by*

$$\frac{U'}{U} = \left(\sum_\omega HH_\omega \left(\frac{Q'_\omega}{Q_\omega}\right)^{\eta-1}\right)^{\frac{1}{\eta-1}} \tag{13}$$

and the change in industry efficiencies satisfy the following system of equations

$$\frac{Q'_\omega}{Q_\omega} = \left[\sum_{\rho\in\varrho(\omega)} R_{\omega\rho}\left(\left(\frac{t^{*\prime}}{t^*}\right)^{\alpha_R^\rho} \prod_{\hat\omega\in\hat\Omega_\rho}\left(\frac{Q'_{\hat\omega}}{Q_{\hat\omega}}\right)^{\alpha_{\hat\omega}^\rho}\right)^\gamma\right]^{\frac{1}{\gamma}} \tag{14}$$

Proof. The share of the household's spending on goods from ω is

$$HH_\omega = \frac{\upsilon_\omega P_\omega^{1-\eta}}{P^{1-\eta}} = \frac{\upsilon_\omega J_\omega^{\frac{1-\eta}{1-\varepsilon_\omega}} \Gamma\left(1 - \frac{\varepsilon_\omega - 1}{\gamma}\right)^{\frac{1-\eta}{1-\varepsilon_\omega}} \left(\frac{w}{Q_\omega}\right)^{1-\eta}}{P^{1-\eta}} \tag{15}$$

Using $U = wL/P$ and rearranging gives

$$HH_\omega = \frac{\upsilon_\omega J_\omega^{\frac{1-\eta}{1-\varepsilon_\omega}} \Gamma\left(1 - \frac{\varepsilon_\omega - 1}{\gamma}\right)^{\frac{1-\eta}{1-\varepsilon_\omega}} Q_\omega^{\eta-1}}{(U/L)^{\eta-1}}$$

Under the counterfactual, we have

$$\begin{aligned}
(U'/L)^{\eta-1} &= \sum_\omega \upsilon_\omega J_\omega^{\frac{\eta-1}{\varepsilon_\omega-1}} \Gamma\left(1 - \frac{\varepsilon_\omega - 1}{\gamma}\right)^{\frac{\eta-1}{\varepsilon_\omega-1}} (Q'_\omega)^{\eta-1} \\
&= \sum_\omega \upsilon_\omega J_\omega^{\frac{\eta-1}{\varepsilon_\omega-1}} \Gamma\left(1 - \frac{\varepsilon_\omega - 1}{\gamma}\right)^{\frac{\eta-1}{\varepsilon_\omega-1}} Q_\omega^{\eta-1} \left(\frac{Q'_\omega}{Q_\omega}\right)^{\eta-1} \\
&= \sum_\omega HH_\omega (U/L)^{\eta-1} \left(\frac{Q'_\omega}{Q_\omega}\right)^{\eta-1}
\end{aligned}$$

Rearranging gives (13).

We next show that the share of revenue is $R_{\omega\rho} = \left(\frac{Q_{\omega\rho}}{Q_\omega}\right)^\gamma$, where we define $Q_{\omega\rho} \equiv \kappa_{\omega\rho}\left(t_l^{\alpha_L^\rho} (t_x^*)^{\alpha_R^\rho} \prod_{\hat\omega\in\hat\Omega^\rho} (Q_{\hat\omega})^{\alpha_{\hat\omega}^\rho}\right)^\gamma$, so that $F_{\omega\rho}(q) = e^{-(q/Q_{\omega\rho})^{-\gamma}}$. This follows from two facts. First, among producers of ω that have efficiency q, the fraction that use recipe ρ is $\frac{Q_{\omega\rho}}{Q_{\omega}}$:

$$
\begin{aligned}
\Pr(\rho|q) &= \frac{\left(\prod_{\rho'} F_{\omega\rho'}(q)\right) F'_{\omega\rho}(q)}{F'_{\omega}(q)} \\
&= \frac{\left(\prod_{\rho'} e^{-(q/Q_{\omega\rho'})^{-\gamma}}\right) Q^{\gamma}_{\omega\rho}\gamma q^{-\gamma-1}e^{-(q/Q_{\omega\rho})^{-\gamma}}}{Q^{\gamma}_{\omega}\gamma q^{-\gamma-1}e^{-(q/Q_{\omega})^{-\gamma}}} \\
&= \left(\frac{Q_{\omega\rho}}{Q_{\omega}}\right)^{\gamma}
\end{aligned}
$$

The second fact is that, conditional on q revenue is independent of the recipe chosen by a firm or any other feature of the firm's sourcing decisions.

Finally, we have that the counterfactual industry efficiencies $\{Q'_{\omega}\}$ satisfy

$$
\begin{aligned}
Q'_{\omega} &= \left\{\sum_{\rho\in\varrho(\omega)} \kappa_{\omega\rho}\left(t_l^{\alpha^{\rho}_L}(t_x^{*\prime})^{\alpha^{\rho}_R}\prod_{\hat{\omega}\in\hat{\Omega}^{\rho}}(Q'_{\hat{\omega}})^{\alpha^{\rho}_{\hat{\omega}}}\right)^{\gamma}\right\}^{\frac{1}{\gamma}} \\
&= \left\{\sum_{\rho\in\varrho(\omega)} \kappa_{\omega\rho}\left(t_l^{\alpha^{\rho}_L}(t_x^{*})^{\alpha^{\rho}_R}\prod_{\hat{\omega}\in\hat{\Omega}^{\rho}}(Q_{\hat{\omega}})^{\alpha^{\rho}_{\hat{\omega}}}\right)^{\gamma}\left(\left(\frac{t^{*\prime}}{t^{*}}\right)^{\alpha^{\rho}_R}\prod_{\hat{\omega}\in\hat{\Omega}_{\rho}}\left(\frac{Q'_{\hat{\omega}}}{Q_{\hat{\omega}}}\right)^{\alpha^{\rho}_{\hat{\omega}}}\right)^{\gamma}\right\}^{\frac{1}{\gamma}} \\
&= \left\{\sum_{\rho\in\varrho(\omega)} R_{\omega\rho}Q^{\gamma}\left(\left(\frac{t^{*\prime}}{t^{*}}\right)^{\alpha^{\rho}_R}\prod_{\hat{\omega}\in\hat{\Omega}_{\rho}}\left(\frac{Q'_{\hat{\omega}}}{Q_{\hat{\omega}}}\right)^{\alpha^{\rho}_{\hat{\omega}}}\right)^{\gamma}\right\}^{\frac{1}{\gamma}}
\end{aligned}
$$

Rearranging yields (14). ∎

E.3 Imperfect Enforcement: Inputs are defective and Worker steals

There are two frictions. Workers can steal output and suppliers can deliver defective output that causes the buyer to waste output. If a worker earns wage ω and steals ψ^l units of output, she derives indirect utility $V(\omega,\psi^l) = v\left(\omega + h(\psi^l)\right)$. Suppose that the competitive wage is w. To attract workers, a firm must pay $\omega(\psi^l) \equiv w - h(\psi^l) + h(0)$. Define $g^l(\psi^l) \equiv 1 - \frac{h(\psi^l)-h(0)}{w}$, so that $\omega(\psi^l) = g^l(\psi^l)w$.

Suppose also that suppliers can sell a good that is defective or imperfectly customized to the buyer. If this happens, the buyer uses up output correcting the defect. The supplier can save on production cost by producing defective inputs. To produce one unit of the intermediate input that is defective enough so that the buyer must use up ψ^x units of output, the supplier must use $g^x(\psi^x)$. Both the buyer and supplier recognize that the supplier will save on cost by producing a defective input, and the price will be $p_s(\psi^x) = g^x(\psi^x)m_s$ where m_s is the supplier's marginal cost of producing a defect-free unit of the input.

The buyer takes as given prices, the defectiveness of the input and the amount each worker will steal and minimizes cost:

$$\min \omega\left(\psi^l\right) l + p_s\left(\psi^x\right) x$$

subject to

$$G\left(b_l \min\left\{l, \frac{\tilde{y}^l}{\psi^l}\right\}, b_{\hat{\omega}} z \min\left\{x, \frac{\tilde{y}^x}{\psi^x}\right\}\right) - \tilde{y}^l - \tilde{y}^x \geq y_b$$

where $\tilde{y}^l$ and $\tilde{y}^x$ are respectively the units of output lost to stealing and fixing defective inputs. The buyer's marginal cost is m_b, which satisfies

$$m_b = \mathcal{C}\left(\frac{\omega\left(\psi^l\right) + \psi^l m_b}{b_l}, \frac{p_s\left(\psi^x\right) + \psi^x m_b}{b_{\hat{\omega}} z}\right)$$

Weak enforcement means that the court will only enforce claims where the damage is large relative to the size of the transaction. With the worker stealing, the cost to the buyer (if the lost output is valued at the buyer's marginal cost) is $m_b\psi^l l$ and the value of the transaction is $\omega(\psi^l)l$. It is assumed that if the damage ratio $\frac{m_b\psi^l l}{\omega(\psi^l)l}$ is no greater than $1/t_l - 1$ then the court will not step in. For the defective inputs, the cost to the buyer is $m_b\psi^x x$ and the value of the transaction is $p_s(\psi^x)x$. It is assumed that the court will not step in unless the damage ratio $\frac{m_b\psi^x x}{p_s(\psi^x)x}$ is greater than $1/t_x - 1$.

The worker steals and the supplier shirks up to the point of the court stepping in. The buyers cost can thus be written as

$$m_b = \mathcal{C}\left(\frac{\omega(\psi^l)}{t_l b_l}, \frac{p_s(\psi^x)}{t_x b_{\hat{\omega}} z}\right)$$

Finally, we study the limiting economy as $g^l\left(\psi^l\right), g^x\left(\psi^x\right) \to 1$, In this limit, the payoff to the worker from stealing or to the supplier from shirking are almost zero, but the cost to the buyer may still be large. In this limit, we have $\omega(\psi^l) \to w$ and $p_s(\psi^x) \to m_x$, which means that the buyer's marginal cost is

$$m_b = \mathcal{C}\left(\frac{w}{t_l b_l}, \frac{m_s}{t_x b_{\hat{\omega}} z}\right)$$

but the payments to labor and the supplier are wl and m_s respectively.

In principle, the contracts can be written to get around this friction. However, the doctrine of *expectation damages* limits the damages the buyer can collect from the supplier. The damages cannot be more than what is needed so that the buyer's is as well off as she would have been had the contract been honored.