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

Johannes Boehm
Sciences Po
johannes.boehm@sciencespo.fr

Ezra Oberfield
Princeton University & NBER
ezraoberfield@gmail.com

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Abstract

How costly is weak contract enforcement? Using microdata on Indian manufacturing plants, we show that in states with weaker enforcement, as measured by judicial lags, production and sourcing decisions appear systematically distorted. We document that among plants in industries that tend to rely more heavily on inputs that require customization, those in states with more congested courts shift their expenditures away from intermediate inputs, whereas we find the opposite in industries that tend to rely on standardized inputs. 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.

KEYWORDS: Intermediate Inputs, Misallocation, Productivity, Contract Enforcement, Production Networks
JEL:

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1 Introduction

The last two decades of research have found that legal institutions play a key role for development.[1] This paper studies theoretically and empirically how weak legal institutions—more precisely, slow contract enforcement due to congestion of the courts—shapes the organization of production, and quantifies the importance of these frictions for aggregate productivity. While contracts can alleviate holdup problems, frictions that impede contract enforcement increase the effective cost of some inputs. These, along with frictions in the enforcement of employment contracts, affect firms' how firms organize production.

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 172th (out of 190) when it comes to the enforcement of contracts, behind countries such as the Democratic Republic of Congo (171th) 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 detailed plant-level data from India's Annual Survey of Industries, we document several facts about how the quality of courts 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,[2] 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 and those that require customization or are relationship specific, using the classification from Rauch (1999). It is users (or potential users) of relationship-specific inputs that are most likely to benefit from 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 homogenous inputs.

To interpret these facts and to quantitatively evaluate their ramifications for aggregate produc-

[1] See Rajan and Zingales (1998), La Porta et al. (1997), Djankov et al. (2003), Acemoglu and Johnson (2005), and many others

[2] 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.

tivity 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, match-specific productivities. Both primary inputs and relationship-specific inputs are subject to wedges that reflect weak contract enforcement. Each firm chooses the the production technique that minimizes effective cost. The cost delivered by any single technique depends on its productivity and wedge draws, but also on the production cost of the chosen suppliers. Wedges hence 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 also may lead firms to switch to techniques that have lower productivity but do not require good courts.

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 strongly correlated with the observed speed of the regional courts, in line with the motivating reduced-form regressions. 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.

Our preliminary results suggest that courts may be important in shaping aggregate productivity, and that reducing congestion in the most congested state to be in line with the least congested state would raise the state's aggregate productivity by 6%. The overall wedges we back out are much larger, but it is less clear whether there is a policy that could improve the allocation further.

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), Ponticelli and Alencar (2016) among many others). Most relevant to our work, perhaps, is the paper by Johnson, McMillan and Woodruff (2002), who provide micro evidence on the role of courts for vertical relationships between firms. By embedding these mechanisms into a general equilibrium model, we explore their quantitative importance on the macro scale. Boehm (2016) provides cross-country evidence on the aggregate impact of enforcement costs through firms' make-or-buy decisions, but omits the role of within-sector firm heterogeneity, which may be quantitatively important, as emphasized by the trade literature (most directly by Blaum, Lelarge and Peters (2015)).

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 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). 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. Secondly, we confront the fact that firms produce in very different ways even in narrowly defined industries by explicitly modeling this heterogeneity in two ways. We allow firm to choose among several types of technologies (recipes) in the theory and by identifying different recipes in the data through the application of techniques from statistics/data mining. In addition, among firms that use the same broad technology may use inputs with varying intensities even in the absence of distortions. Third, we identify wedges (mostly) from first moments, which helps to alleviate concerns about mismeasurement being interpreted as misallocation.

Our model relates to recent models of firm linkages in general equilibrium (Oberfield (2017), Eaton, Kortum and Kramarz (2015), Lim (2017), Lu, Mariscal and Mejia (2013), and Chaney (2014)), and uses aggregation techniques pioneered by Houthakker (1955). 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. Pavcnik (2002), Khandelwal and Topalova (2011), Goldberg et al. (2010), Bas and Strauss-Kahn (2015)).

2 Input Use among Indian Manufacturing Plants

2.1 Background and Data

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.[3] 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 8,000 people. The conviction took place some 25 years after the disaster; one of the eight executives had already passed away beforehand, and the remaining seven appealed the conviction.[4]

The slowness of the Indian courts is at least partly due to the uneven distribution of workload across its three tiers.[5] The lowest tier are the Subordinate (District) Courts, which have courthouses in district capitals and major cities.[6] The next instance 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 are also administering the subordinate courts in their jurisdiction. The highest instance is the Supreme

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

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

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

[6] 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.

Court of India. All three instances 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.[7] 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.[8] 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, 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 (see Law Commission of India (2014)). Appendix C.3 provides detailed information on the construction of our court quality variable, along with summary statistics. It also shows that our measure is correlated with other commonly used measures, such as pendency ratios.

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.

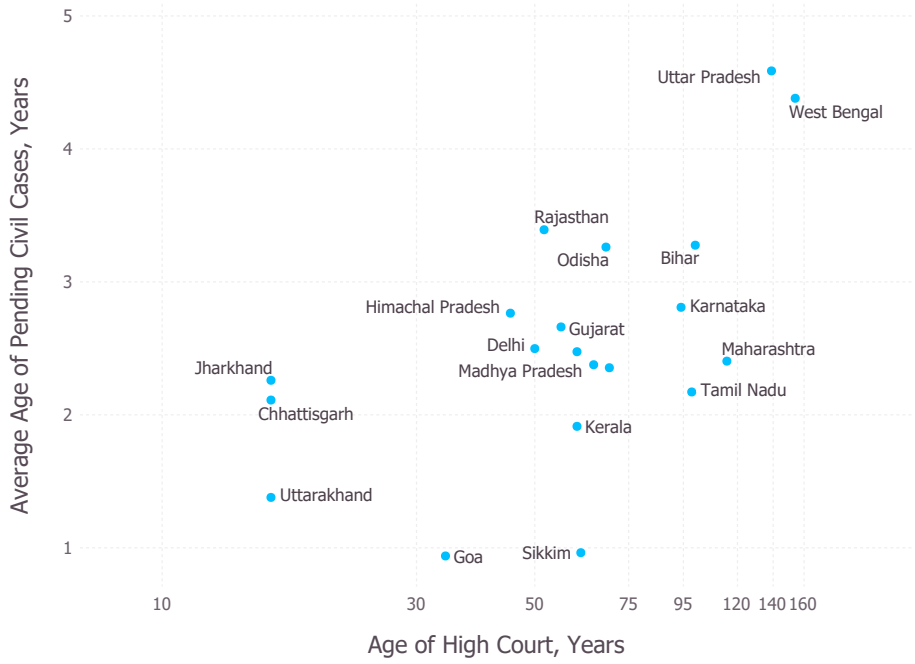
The main explanation for why court speed varies so much across states lies in the history of India's political subdivisions. The first high courts (Madras, Bombay, and Calcutta) were set up by the British in the 1861 Indian High Courts Act, and served as the precursor for India's post-independence high 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

[7] 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.

[8] 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)).

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.[9] The age of the high court is hence a strong determinant of its speed of enforcement (see Figure 1). We will later use the age of high courts as an instrument for its quality.

Figure 1 Age of the High Court, and Speed of Enforcement



Our industrial data is the Annual Survey of Industry (ASI), the official annual survey of India's formal manufacturing sector. The ASI is a panel that covers all 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), and the product classification remains largely unchanged during the period that we study, the years 2000/01 to 2009/10. For the sake of preciseness we restrict our attention here to single-product plants; all facts also hold when including multi-product plants as well. See Appendix C for more details on the data and for a description of our sample.

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

2.2 Intermediate Input Use

We first turn to documenting the correlation between court quality and plants' intermediate input use.

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

Figure 2 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). 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. Table I shows this result formally using linear regression. The difference in the slope of the regression line remains statistically significant when controlling for district characteristics such as income per capita, population density, or district dummies more generally.

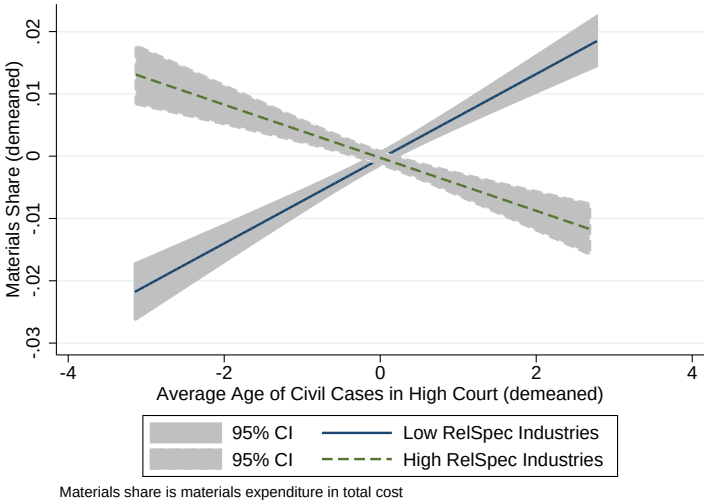
The relatively lower materials share suggests that these plants may be doing more of the production process in-house, as opposed to outsourcing it. A plant that produces cars might both manufacture and assemble its components in the same vertically intgrated facility. The regressions in Table II show this result formally. We first define a "vertical distance" between an output ω and an input ω' as the average number of production processes required to turn ω' into ω, weighted by the product of the input-output table materials shares along each production chain, and excluding any instances of roundabout production.[10] The left-hand side in the regressions in Table II is the plant's average vertical distance of its inputs from its output, weighted by each inputs's share in the plant's total materials expenditure. A higher values thus means that the plant produces its output using inputs that require on average more production steps (according to aggregate materials shares) to be turned into the output; the plant is more strongly vertically integrated. Table II shows that plants are on average more vertically integrated in states with worse courts if production relies heavily on relationship-specific inputs.

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

Not only the overall use of intermediate inputs is correlated with court quality; the composition of the intermediate input basket too. Figure 3 shows the model fit when the log ratio of aggregate expenditure on relationship-specific intermediate inputs to homogenous intermediate inputs by

[10] Appendix E gives the precise mathematical definition of vertical distance.

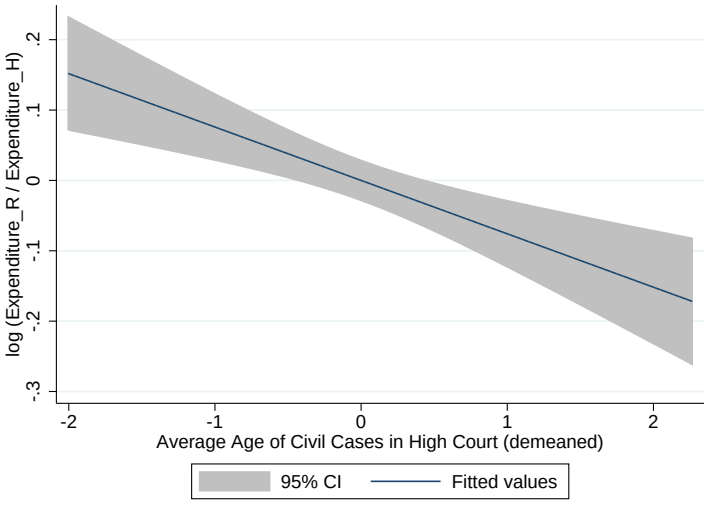
Figure 2 Court quality and materials shares



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.

state-industry is regressed on court quality. In states where courts are faster, plant's intermediate input baskets are tilted towards relationship-specific intermediate inputs. As Table III shows, this correlation remains statistically significant when controlling for district income per capita and population density.

Figure 3 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 I Materials Shares and Court Quality (Fact 1)

	Dependent variable: Materials Expenditure in Total Cost				
	(1)	(2)	(3)	(4)	(5)
Avg age of Civil HC cases	0.00115	0.00743*	0.00826*		
	(0.0017)	(0.0034)	(0.0035)		
Avg Age Of Civil Cases * Rel. Spec.		-0.0134*	-0.00348	-0.0167**	-0.0155*
		(0.0052)	(0.0059)	(0.0046)	(0.0066)
Log district GDP/capita			-0.00178		
			(0.0036)		
LogGDPC * Rel. Spec.			0.0385**		-0.00159
			(0.0076)		(0.012)
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes
District FE				Yes	Yes
R^2	0.456	0.456	0.461	0.480	0.482
Observations	223674	223674	201505	208527	199544

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

2.3 Endogeneity, and the Historical Determinants of Indian Court Efficiency

The main caveat in the above regressions in 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 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[11]—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 2.1, 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 1 in

[11]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.

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

	Dependent variable: Vertical Distance of Inputs from Output				
	(1)	(2)	(3)	(4)	(5)
Avg age of Civil HC cases	0.0122**	0.00144	-0.00594		
	(0.0032)	(0.0070)	(0.0071)		
Avg Age Of Civil Cases * Rel. Spec.		0.0230+	0.0319*	0.0195+	0.0341*
		(0.012)	(0.013)	(0.011)	(0.014)
Log district GDP/capita			-0.0372**		
			(0.0070)		
LogGDPC * Rel. Spec.			0.0355*		0.0517+
			(0.017)		(0.029)
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes
District FE				Yes	Yes
R^2	0.432	0.432	0.441	0.443	0.451
Observations	163344	163344	156198	163334	156191

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

Section 2.1 shows the strong correlation between court age and speed of enforcement.

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 is 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.

Tables IV, V, and VI repeat the regressions from above using the instrumented speed of enforcement. The point estimates of the coefficient of the interaction term is usually slightly larger than in the OLS estimates.

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.

Table III Input Mix and Court Quality (Fact 2)

	Dependent variable: $X_j^R/(X_j^R + X_j^H)$		
	(1)	(2)	(3)
Avg age of Civil HC cases	-0.00547*	-0.00572**	-0.00731**
	(0.0022)	(0.0022)	(0.0024)
Log district GDP/capita			-0.00645
			(0.0053)
logpopdensity2001		0.00223	0.00302+
		(0.0014)	(0.0017)
5-digit Industry FE	Yes	Yes	Yes
Estimator	OLS	OLS	OLS
R^2	0.441	0.451	0.452
Observations	225590	203624	196037

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

Table IV Materials Shares and Court Quality, Instrumented

	Dependent variable: Materials Expenditure in Total Cost		
	(1)	(2)	(3)
Avg age of Civil HC cases	-0.00381		
	(0.0061)		
Avg Age Of Civil Cases * Rel. Spec.	-0.0314**	-0.0156+	-0.0206*
	(0.010)	(0.0085)	(0.0098)
Log district GDP/capita	0.000764		
	(0.0039)		
LogGDPC * Rel. Spec.	-0.0245**		-0.00836
	(0.0089)		(0.016)
5-digit Industry FE	Yes	Yes	Yes
District FE		Yes	Yes
Estimator	IV	IV	IV
R^2	0.457	0.480	0.482
Observations	201505	208527	199544

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

Table V Vertical Distance of Inputs on Court Quality, Instrumented

	Dependent variable: Vertical Distance of Inputs from Output				
	(1)	(2)	(3)	(4)	(5)
Avg age of Civil HC cases	0.0122**	0.00144	-0.00594		
	(0.0032)	(0.0070)	(0.0071)		
Avg Age Of Civil Cases * Rel. Spec.		0.0230+	0.0319*	0.0195+	0.0341*
		(0.012)	(0.013)	(0.011)	(0.014)
Log district GDP/capita			-0.0372**		
			(0.0070)		
LogGDPC * Rel. Spec.			0.0355*		0.0517+
			(0.017)		(0.029)
5-digit Industry FE	Yes	Yes	Yes	Yes	Yes
District FE				Yes	Yes
Estimator	IV	IV	IV	IV	IV
R^2	0.432	0.432	0.441	0.443	0.451
Observations	163344	163344	156198	163334	156191

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

Table VI Input Mix and Court Quality, Instrumented

	Dependent variable: $X_j^R/(X_j^R + X_j^H)$		
	(1)	(2)	(3)
Avg age of Civil HC cases	-0.0144**	-0.0180**	-0.0195**
	(0.0044)	(0.0046)	(0.0048)
Log district GDP/capita			-0.0158*
			(0.0062)
logpopdensity2001		0.00370**	0.00556**
		(0.0014)	(0.0018)
5-digit Industry FE	Yes	Yes	Yes
Estimator	IV	IV	IV
R^2	0.441	0.450	0.451
Observations	225590	203624	196037

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

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. These 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.[12] 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, 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. It is not obvious ex-ante how to extract information about distortions by comparing their input bundles. Fortunately the ASI provides an extremely detailed characterization of firms' input bundles. As such, one goal is to use an analytical framework that is up to the task of leveraging this feature of the data so that, to the extent possible, we compare apples to apples.

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 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. It will be useful to use all of the variation across those firms to help us identify model parameters. The natural heterogeneity gives rise to a structural error term in our estimating equations that we can interpret as arising from productivity differences rather than distortions.

[12] 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.

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 of the varieties in each industry, maximizing consumption of the bundle C defined as

$$\begin{aligned} C &= \left[\sum_{\omega} \beta_\omega^{\frac{1}{\eta}} (C_\omega)^{\frac{\eta-1}{\eta}}\right]^{\frac{\eta}{\eta-1}} \\ C_\omega &= \left[\int_0^{J_\omega} c_{\omega j}^{\frac{\varepsilon_\omega - 1}{\varepsilon_\omega}} dj\right]^{\frac{\varepsilon_\omega}{\varepsilon_\omega - 1}} \end{aligned}$$

where $\{\beta_\omega\}$ 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.

To produce, a firm must use a *technique*. A technique is a production function with which the firm can produce her product using labor and a particular bundle of intermediate inputs. A firm may have several techniques with which it can produce its good, in which case it will produce using the one that is most cost effective. For each industry, there are several broad classes of technologies, which we call *recipes*, denoted by $\rho \in \varrho_\omega$. A recipe is delineated by the bundle of intermediate inputs; all firms that produce using the same recipe use intermediate inputs from the same set of industries.

More formally, a recipe ρ is defined by a bundle of intermediates indexed by $1, ..., n^\rho$ that correspond to a vector of sourcing industries, $\{\hat{\omega}_1^\rho, ..., \hat{\omega}_{n^\rho}^\rho\}$ and a production function F_ρ. We denote a technique by ϕ. A technique of recipe $\rho \in \varrho(\omega)$ is an instance of such a production function in which one firm (the "buyer", denoted $b(\phi)$) in industry ω can produce her good using labor and particular set of randomly drawn varieties. The first variety is produced by a "supplier," denoted $s_1(\phi)$ that is randomly drawn from industry $\hat{\omega}_1^\rho$, the second variety is produced by a supplier $s_2(\phi)$ that is is drawn from industry $\hat{\omega}_2^\rho$, etc. The production function is

$$y_b = F_\rho\left(z_l l, z_{x1} x_{s_1}, ..., z_{xn^\rho} x_{s_{n^\rho}}\right)$$

where where y_b units of the buyer's good can be using l units of labor, x_{s_1} units of the first supplier's variety, x_{s_2} units of the second supplier's variety, etc. The technique's productivity can be summarized by the vector $\{z_l, z_{x1}, ..., z_{xn^\rho}\}$ which augment labor and each intermediate input. These factor-augmenting productivities are specific to the technique. The technique can thus be summarized by the identity of the buyer, $b(\phi)$, the vector of suppliers, $\{s_1(\phi), ..., s_{n^\rho}(\phi)\}$ and the vector of input augmenting productivities, $\{z_l(\phi), z_{x1}(\phi), ..., z_{xn^\rho}(\phi)\}$.

For now, the only restrictions we place on the production function F_ρ 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 to be more important than the second. Further, 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 pries charged by the suppliers.

A firm may have many techniques with which she can produce her good. The arrival of techniques is governed by a stochastic process described by Assumption 1. In stating the assumption, we make use of the following definition: For any two vectors, we say that a vector $(x_0, x_1, ..., x_n)$ strictly dominates the vector $(y_0, y_1, ..., y_n)$ if $x_0 > y_0$, $x_1 > y_1$,...,$x_n > y_n$.

Assumption 1 *1. For a firm in industry ω, the number of techniques of recipe $\rho \in \varrho_\omega$ with match-specific productivities that strictly dominate z_l, z_{x1}, z_{x2},...,z_{xn^ρ} follows a Poisson distribution with mean $m_{\omega\rho} z_l^{-\zeta_l^\rho} z_{x1}^{-\zeta_{x1}^\rho} ... z_{xn^\rho}^{-\zeta_{xn^\rho}^\rho}$.*

2. For each industry ω, there is a $\gamma_\omega > \varepsilon_\omega - 1$ such that for every recipe $\rho \in \varrho_\omega$, $\zeta_l^\rho + \zeta_{x1}^\rho + ... + \zeta_{xn^\rho}^\rho = \gamma_\omega$.

The first part of Assumption 1 implies above any threshold, factor-augmenting productivities follow independent power laws.[13] The second part of Assumption 1 says that for each recipe, the sum of the power law exponents is the same, equal to γ_ω. This restriction keeps the model tractable, but for reasons we will discuss later, we do not believe it is quantitatively important. The restriction that $\gamma_\omega > \varepsilon_\omega - 1$ is necessary to keep utility finite.

$m_{\omega\rho}$ summarizes the frequency with which firms in industry ω draw recipes of type ρ. 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.

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

$$\alpha_l^\rho = \frac{\zeta_l^\rho}{\gamma_\omega}, \qquad \alpha_{xi}^\rho \equiv \frac{\zeta_{xi}^\rho}{\gamma_\omega}, \qquad i = 1, ..., n^\rho$$

Note that this implies that $\alpha_l^\rho + \sum_{i=1}^{n^\rho} \alpha_{xi}^\rho = 1$.

3.2 Market Structure

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

[13] 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 (2017), and Buera and Oberfield (2016). Note that the expected number of techniques per firm is unbounded. Formally, an economy satisfying Assumption 1 can be thought of as the limit of a sequence of economies that satisfy more standard assumptions. To see this, suppose that the number of techniques of recipe ρ is given by a Poisson distribution with mean $M_{\omega\rho}$, and that for each such technique, the match specific productivities were drawn from independent Pareto distributions. i.e., from the joint CDF $Z(z_l, z_{x1}, ...z_{xn^\rho}) = \left[1 - (z_l/\underline{z}_l)^{-\zeta_l^\rho}\right] \prod_{i=1}^{n^\rho} \left[1 - (z_{xi}/\underline{z}_{xi})^{-\zeta_{xi}^\rho}\right]$. Define the normalizing constant $m_{\omega\rho} \equiv M_{\omega\rho} \underline{z}_l^{\zeta_l^\rho} \underline{z}_{x1}^{\zeta_{x1}^\rho} ... \underline{z}_{xn^\rho}^{\zeta_{xn^\rho}^\rho}$. An economy satisfying Assumption 1 can be thought of as the limit in which $\underline{z}_l$, $\{\underline{z}_{xn^\rho}\} \to 0$, holding $m_{\omega\rho}$ fixed. In the this limit, the number of techniques per firm grows arbitrarily large, but the productivities associated with any single technique are drawn from an arbitrarily poor distribution. The limit is well behaved because the probability of drawing a technique with match specific productivities greater than $z_l, z_{x1}, z_{x2}, ...z_{xn^\rho}$ does not change as $\underline{z}_l$, $\{\underline{z}_{xn^\rho}\} \to 0$.

also assume that sales of goods for intermediate use are priced at the supplier's marginal cost.[14] Firms remit all profit to the household.

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 an iceberg cost. Appendix D.1 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 D.1 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 is isomorphic to an iceberg cost.

Specifically, for each technique there are random input wedges $t_l, \{t_{xi}\}_{i=1}^{n^\rho} \in (0, 1]$ that distort the use of labor and each of the intermediate inputs. These wedges are drawn from the joint distribution with CDF $T_\rho(t_l, t_{x1}, ..., t_{xn^\rho})$. If a technique is subject to the input wedge $t_{xi}(\phi)$, then if the supplier's marginal cost of providing the input is $\lambda_{s(\phi)}$, the effective cost of the input to the buyer is $\lambda_{s(\phi)}/t_{xi}(\phi)$. Similarly, if the technique is subject to the labor wedge $t_l(\phi)$, then if a worker receives the wage w, the effective cost to the firm is $w/t_l(\phi)$.

The joint distribution $T_\rho(t_l, t_{x1}, ..., t_{xn^\rho})$ summarizes the quality of enforcement. Note that the distribution may be specific to a recipe. Perfect enforcement of contracts would imply that $T_\rho(t_l, t_{x1}, ..., t_{xn^\rho}) = 0$ except for $t_l = t_{x1} = ... = t_{xn^\rho} = 1$. We interpret worse enforcement as a stochastically dominated distribution of wedges. Later, we will divide industries into those that produce homogenous inputs and those that produce relationship-specific inputs. We will assume that for any technique, there is no wedge on a homogenous input, i.e., $t_{xi}(\phi) = 1$.

[14] In the appendix (to be written, although see Oberfield (2017) for an detailed treatment in a simpler environment) we describe 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. More generally, for any bargaining power, our quantitative results would be identical.

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_{xi} and t_l should be interpreted as the wedges that prevails after all forms of enforcement are exhausted. For example, if formal enforcement would leave the wedge t_{xi}^{formal} while informal enforcement would leave the wedge t_{xi}^{informal}, then the parties would use whichever form of enforcement is better, i.e., $t_{xi} = \min\{t_{xi}^{\text{formal}}, t_{xi}^{\text{informal}}\}$ (and similarly for t_l).[15] Improving the quality of courts would reduce the wedges t_x^{formal} but would not change t_x^{informal}.

Second, there are two reasons why 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 is likely to mitigate the hold-up problem. With others, the holdup problem will be more severe. A secondary reason is that techniques may differ in how easily one may detect a breach of the contract.

Third, we model the wedges as an iceberg cost rather than an implicit tax or subsidy as in Hsieh and Klenow (2009). This is consequential, because the iceberg costs use up resources whereas implicit taxes do not. An implicit tax may stand in for rationing or the 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. In contrast, iceberg costs raise the buyer's shadow cost by wasting resources.

Both iceberg costs and implicit taxes would generate identical predictions consistent with the findings of Section 2. However, there is at least 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. With iceberg costs, those subject to larger wedges should have weakly lower ratios of revenue to cost.[16] In Appendix B.3 we ask whether those firms that we believe to subject to larger wedges have higher or lower revenue-cost ratios, and across specifications, and our findings are consistent with iceberg costs: larger distortions are associated with lower revenue-cost ratios.

3.5 Production Decisions

Let $\mathcal{C}_\rho$ be the cost function that is the dual of the production function F_ρ. Thus if the price paid by the buyer for the i^{th} input is p_{s_i}, then

$$C_\rho\left(w, \{p_{s_i}\}\right) \equiv \min_{l,x} wl + \sum_i p_{s_i} x_{s_i} \text{ subject to } F_\rho\left(l, x_{s_1}, ..., x_{s_{n^\rho}}\right) \geq 1$$

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

[16] Whether iceberg costs predict no change or lower ratios of revenue to cost depends on the demand system. With a 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 higher iceberg costs would lower the ratio of revenue to cost.

Let λ_j be firm j's unit cost. Under the assumption that the price in all transactions equals the supplier's unit cost, $\lambda_j = p_j$. Then we have that the unit cost delivered by a technique ϕ is

$$\mathcal{C}_\rho\left(\frac{w}{t_l(\phi)z_l(\phi)}, \left\{\frac{\lambda_{s_i(\phi)}}{t_{xi}(\phi)z_{xi}(\phi)}\right\}\right)$$

The unit cost delivered by a technique depends on the input-augmenting productivities, the prices charged by each supplier, and the wedges that distort the use of each input. Let $U_{j\rho}$ is the set of techniques of recipe ρ that j can use to produce her good (i.e., those upstream from j), then j's unit cost is

$$\lambda_j = \min_{\rho\in\varrho(\omega)} \min_{\phi\in U_{j\rho}} \mathcal{C}_\rho\left(\frac{w}{t_l(\phi)z_l(\phi)}, \left\{\frac{\lambda_{s_i(\phi)}}{t_{xi}(\phi)z_{xi}(\phi)}\right\}\right)$$

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

It will be useful to define, for each firm j, the variable $q_j \equiv \frac{w}{\lambda_j}$ to be the inverse of firm j's unit cost in units of labor. We call q_j firm j's *efficiency*. This satisfies

$$q_j = \max_{\rho\in\varrho(\omega)} \max_{\phi\in U_{j\rho}} \mathcal{C}_\rho\left(\frac{1}{t_l(\phi)z_l(\phi)}, \left\{\frac{1}{t_{xi}(\phi)z_{xi}(\phi)q_{s_i(\phi)}}\right\}\right)^{-1} \tag{1}$$

Among firms that produce product ω, let $G_\omega(q)$ be the fraction of firms with efficiency no greater than q. Proposition 1 shows the determinants of this distribution.

Proposition 1 *Under Assumption 1,*

$$G_\omega(q) = e^{-(q/Q_\omega)^{-\gamma_\omega}}$$

where

$$\begin{aligned} Q_\omega &= \left\{\sum_{\rho\in\varrho(\omega)} \kappa_{\omega\rho} m_{\omega\rho}\left(t^*_{\omega\rho}\prod_{i=1}^{n} Q_{\hat{\omega}_i^\rho}^{\alpha_{xi}^\rho}\right)^{\gamma_\omega}\right\}^{\frac{1}{\gamma_\omega}} \\ t^*_{\omega\rho} &= \left[\int\left(t_l^{\alpha_l^\rho} t_{x1}^{\alpha_{x1}^\rho}...t_{xn}^{\alpha_{xn}^\rho}\right)^{\gamma_\omega} T\left(dt_l, dt_{x1}, ..., dt_{xn}\right)\right]^{\frac{1}{\gamma_\omega}} \end{aligned} \tag{2}$$

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

Proposition 1 shows that the distribution of efficiencies takes the simple form of a Frechet distribution with shape parameter γ_ω and scale determined by Q_ω. Q_ω summarizes the level of efficiency in the industry; with a higher Q_ω the distribution improves 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 $t^*_{\omega\rho}$, which summarizes the impact of imperfect enforcement on those that produce the inputs used in recipe ρ. $t^*_{\omega\rho}$ accounts for both the direct impact of the wedges, but also

for the indirect impact: wedges might cause firms to switch to a technique with lower productivity or that uses more costly intermediate inputs.

(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 Assumption 1, the household's utility is*

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

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 Assumption 1 holds. Among firms that produce using recipe ρ, let the share of total expenditures that is spent on inputs from industry $\hat{\omega}_i^\rho$ is*

$$\frac{\alpha_{xi}^\rho \bar{t}_{xi}^\rho}{\alpha_l^\rho \bar{t}_l^\rho + \sum_i \alpha_{xi}^\rho \bar{t}_{xi}^\rho}$$

and the share of expenditures spent on labor is

$$\frac{\alpha_l^\rho \bar{t}_l^\rho}{\alpha_l^\rho \bar{t}_l^\rho + \sum_i \alpha_{xi}^\rho \bar{t}_{xi}^\rho}$$

where $\bar{t}_l^\rho$ and $\bar{t}_{xi}^\rho$ are particular moments of the wedge distribution, defined as:

$$\begin{aligned} \bar{t}_{xi}^\rho &= \int_t t_{xi} \tilde{T}_\rho(dt) \\ \bar{t}_l^\rho &= \int_t t_l \tilde{T}_\rho(dt) \end{aligned}$$

and $\tilde{T}_\rho(t_l, t_{x1}, ...t_{xn}) = \frac{\int_1^{t_l}\int_1^{t_{x1}}...\int_1^{t_{xn}} \tilde{t}_l^{\zeta_l^\rho} \tilde{t}_{x1}^{\zeta_{x1}^\rho}...\tilde{t}_{xn}^{\zeta_{xn}^\rho} T_\rho(d\tilde{t})}{\int_1^{\infty}\int_1^{\infty}...\int_1^{\infty} \tilde{t}_l^{\zeta_l^\rho} \tilde{t}_{x1}^{\zeta_{x1}^\rho}...\tilde{t}_{xn}^{\zeta_{xn}^\rho} T_\rho(d\tilde{t})}$.

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.[17] We require only that the production function exhibits constant

[17] 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 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.

returns to scale and that all inputs are asymptotically complements.[18]

Imperfect enforcement, on the other hand, reduces the expenditure share on 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, where as 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. Supposed 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 $m_{\omega\rho}$ as primitives[19], 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. Among those of type ω, let $R_{\omega\rho}$ be the share of total revenue of those that use recipe ρ.

Proposition 4 *If the quality of enforcement change so that the distribution of wedges changes from* $\{T_{\omega\rho}\}$ *to* $\{T'_{\omega\rho}\}$ *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 satisfy the following system of equations

$$\left(\frac{Q'_\omega}{Q_\omega} \right)^{\gamma_\omega} = \sum_{\rho \in \varrho(\omega)} R_{\omega\rho} \left(\frac{t^{*\prime}_{\omega\rho}}{t^{*}_{\omega\rho}} \prod_{i=1}^{n^\rho} \left(\frac{Q'_{\hat{\omega}_i^\rho}}{Q_{\hat{\omega}_i^\rho}} \right)^{\alpha^\rho_{xi}} \right)^{\gamma_\omega} \tag{3}$$

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

[18] 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.

[19] An alternative exercise is asking what would happen if J and m were allowed to evolve as well.

the economy are important for determining the first order impact of a change of the quality of enforcement.

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

$$d\log Q_\omega = \sum_{\rho\in\varrho_\omega} R_{\omega\rho}\left[d\log t^*_{\omega\rho} + \sum_{i=1}^{n^\rho} \alpha^\rho_{xi} d\log Q_{\hat{\omega}^\rho_i}\right]$$

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 $\{\gamma_\omega\}$ or η.

4 Identification

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.

In addition to this, we make several auxiliary assumptions that, in principle, we could relax. First, we assume that there is no trade across state borders.[20] While it would be fairly straightforward to incorporate interstate trade, we lack the relevant data. 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 (see ....), as we lack the data that indicates which inputs are used in the production of which products. Third, we treat service inputs and energy inputs as primary inputs.

While we allow preferences $\{\beta_\omega\}$, the arrival rates/productivities of different types of recipes $\{m_{\omega\rho}\}$, the measure of firms of each type $\{J_\omega\}$, and the distribution of wedges T_ρ to vary freely

[20] 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.

across states, we impose that the technological parameters $\{F_\rho\}$ and $\{\zeta_l^\rho, \zeta_{x1}^\rho, ..., \zeta_{xn^\rho}^\rho\}$ are the same across all states.

In addition, we also makes several distributional assumptions.

Assumption 2 *The production function F_ρ has a constant elasticity of substitution, i.e.,*

$$F_\rho(l, x_1, ..., x_n) = \left[\nu_l l^{\frac{\sigma_\rho - 1}{\sigma_\rho}} + \nu_1 x_1^{\frac{\sigma_\rho - 1}{\sigma_\rho}} + ... + \nu_n x_n^{\frac{\sigma_\rho - 1}{\sigma_\rho}}\right]^{\frac{\sigma_\rho}{\sigma_\rho - 1}}$$

Second, for each technique, a firm draws two wedges, t_l that applies to the use of labor and t_x that applies to every relationship-specific input.[21] The upshot of the assumption that there is a single intermediate input wedge is that it greatly reduces the number of production function parameters needed to identify the quality of enforcement. In particular, if $\mathcal{H}^\rho$ and $\mathcal{R}^\rho$ are the sets of inputs that are homogenous and relationship-specific respectively, we can define $\alpha_H^\rho \equiv \sum_{i \in \mathcal{H}^\rho} \alpha_{xi}^\rho$ and $\alpha_R^\rho \equiv \sum_{i \in \mathcal{R}^\rho} \alpha_{xi}^\rho$. It must therefore be that for each recipe $\rho \in \varrho(\omega)$, $\alpha_L^\rho + \alpha_H^\rho + \alpha_R^\rho = 1$. We further assume that the reciprocals of the two wedges are drawn from independent Pareto distributions, where the shape parameter is specific to a state-recipe.

Assumption 3 *The distribution of wedges in state d for recipe ρ is $T_{\rho d}(t_l, t_x) = t_l^{\tau_{\rho dl}} t_x^{\tau_{\rho dx}}$.*

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 $t_x^{\tau_{\rho dx}^{\text{formal}}}$ and the probability that the informal wedge is no greater than t_x is $t_x^{\tau_{\rho dx}^{\text{informal}}}$, then the probability that the effective wedge is no greater than t_x is $t_x^{\tau_{\rho dx}}$, where $\tau_{\rho dx} = \tau_{\rho dx}^{\text{formal}} + \tau_{\rho dx}^{\text{informal}}$.[22] This will lead to a clean interpretation of the counterfactual of interest.

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 Assumption 1, the first moments of revenue shares among firms that use recipe ρ satisfy:*

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

If, in addition, assumptions (2) and (3) hold, then $\frac{1}{\bar{t}_x^\rho} = 1 + \frac{1}{\zeta_R^\rho + \tau_x}$ and $\frac{1}{\bar{t}_l^\rho} = 1 + \frac{1}{\zeta_L^\rho + \tau_l}$ and the

[21] This is a special case of the assumption in Section 3; the wedges t_{xi} are perfectly correlated across relationship-specific inputs.

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

second moments of revenue shares satisfy:

$$\mathbb{E}\left[\left(\frac{2}{\bar{t}_x^\rho}-1\right)\frac{s_{Rj}^2}{\alpha_R^\rho\left(\alpha_R^\rho+\frac{1-\sigma_\rho}{\gamma_\omega}\right)}-\frac{s_{Hj}^2}{\alpha_H^\rho\left(\alpha_H^\rho+\frac{1-\sigma_\rho}{\gamma_\omega}\right)}\right] = 0$$

$$\mathbb{E}\left[\left(\frac{2}{\bar{t}_l^\rho}-1\right)\frac{s_{Lj}^2}{\alpha_L^\rho\left(\alpha_L^\rho+\frac{1-\sigma_\rho}{\gamma_\omega}\right)}-\frac{s_{Hj}^2}{\alpha_H^\rho\left(\alpha_H^\rho+\frac{1-\sigma_\rho}{\gamma_\omega}\right)}\right] = 0$$

Our algorithm for identification is thus as follows:

1. Identify recipes (see next section for details).[23]
2. Use Proposition 5 to estimate the production parameters that are common across locations $\left\{\alpha_l^\rho, \alpha_H^\rho, \alpha_R^\rho, \frac{\gamma_\omega}{1-\sigma_\rho}\right\}_{\rho\in\varrho_\omega}, \omega \in \Omega$ and the state-recipe specific variables, $\{\bar{t}_x^{\rho d}, \bar{t}_l^{\rho d}\}$.
3. Calibrate η and $\{\gamma_\omega\}$ externally.
4. Use estimates to back out $\{\tau_x^{\rho d}, \tau_l^{\rho d}\}$.
5. For each recipe, pool data across states to estimate the remaining production function parameters, α_{xi}, by using the aggregate expenditures. For example, if the sourcing industry $\hat{\omega}_i^\rho$ is relationship specific, then α_{xi}^ρ is equal α_R^ρ multiplied by the ratio of total expenditure on input i by those that use recipe ρ to total expenditure on relationship-specific inputs.
6. For each state-recipe, directly measure $\{R_{\omega\rho}\}$, and for each state, directly measure $\{HH_\omega\}$.

4.1 The Role of Stochastic Distortions

The model captures the idea that buyer-supplier relationships differ susceptibility to imperfect contract enforcement. Some buyer-supplier pair is able to enforce contracts informally, or transact in such a way that avoids a holdup problem. 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. This section shows that, given our identification 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.

Formally, we show in Appendix D.2 that for each recipe,

$$t_{\omega\rho}^* \leq (\bar{t}_l^\rho)^{\alpha_l}(\bar{t}_{x1}^\rho)^{\alpha_{x1}}...(\bar{t}_{xn}^\rho)^{\alpha_{xn}} \tag{4}$$

with equality only if the distortions are degenerate. Our identification strategy consists of measuring $\{\bar{t}_l^\rho, \bar{t}_{xi}^{\alpha_{xi}}\}$ and then using these along with our functional form assumptions to compute t^*. The

[23] It would be preferable to identify the recipes and the wedges simultaneously. We are working on this.

derivation of (4) uses Jensen's inequality to show that $(\bar{t}_l^\rho)^{\alpha_l}(\bar{t}_{x1}^\rho)^{\alpha_{x1}}...(\bar{t}_{xn}^\rho)^{\alpha_{xn}}$ is an upper bound for $t_{\omega\rho}^*$, and this upper bound is attained only if the wedges $\{t_l^\rho, t_{xi}^{\alpha_{xi}}\}$ are degenerate. In other words, given the data and our strategy, if we had assumed, instead, that each buyer faced the same wedge when purchasing a particular input from any supplier, then the industry-level efficiency loss would attain this lower bound.

4.2 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.

5 Estimating Wedges

5.1 Bringing the model to the data: 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: each input-output combination that produces an output ω corresponds to a recipe $\rho \in \rho(\omega)$. In order to use 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.

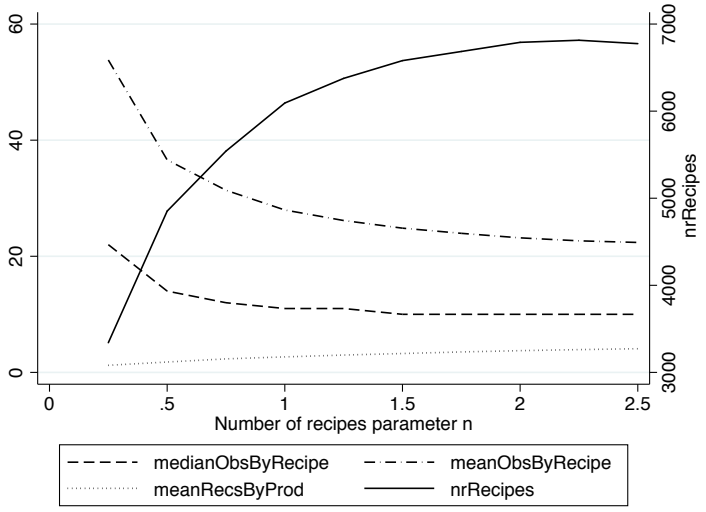
Our preferred method is due to Ward (1963), and constructs clusters recursively, starting with the partition where every cluster is a singleton. In each step, two clusters are merged to minimize the sum squared errors:

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

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.

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. Furthermore, we discard recipes that consist of less than five firm-year observations. Figure 4 shows summary statistics when the number of potential recipes (i.e. prior to discarding small recipes) is set to $\lceil n \log((\#\text{Observations})_w) \rceil$, for varying parameters n.

Figure 4 Summary statistics on recipes by fineness parameter



The figure shows the median number of observations by recipe (dashed line), mean number of observations by recipe (dash-dotted line), mean number of recipes by product (dotted line; all left vertical axis), and the number of created recipes (solid line; right vertical axis) when the number of potential recipes is set to $\lceil n \log((\#\text{Observations})_w) \rceil$.

We inspect the cluster hierarchy and choose $n = 1.5$, where we find that the resulting recipes correspond well to different modes of organization. To give an example, Table 5.1 shows the resulting recipes for product 63303 (cloth, bleached, cotton), which correspond to different ways of producing bleached cotton cloth: either by weaving bleached cotton yarn (recipe 1), by bleaching

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

	input value, %	Description	# firm-years
Recipe 1	95	yarn bleached, cotton	54
	2	grey cloth (bleached / unbleached)	
	2	chemical & allied substances & products, n.e.c	
	1	colour, chemicals	
Recipe 2	35	grey cloth (bleached / unbleached)	39
	13	yarn, finished / processed - cotton (knitted)	
	6	fabrics, cotton	
	5	colour, chemicals	
	5	yarn dyed, synthetic	
	35	(others)	
Recipe 3	98	yarn unbleached, cotton	22
	1	cotton raw - others (pressed)	
	1	colour, chemicals	
Recipe 4	90	yarn, grey-cotton	18
	6	dye stuff	
	2	cotton woven	
	1	maize atta/flour/maida/sooji	
	1	benders (starch)	

and dyeing greige cloth (recipe 2), and by weaving and bleaching unbleached cotton yarn (recipes 3 and 4).

6 Quantitative Results (Preliminary)

This section shows preliminary results from the estimation and counterfactual. We define recipes by clustering using Ward's method on the 3-digit and 5-digit cost shares of the materials basket. We then estimate the ζ_R^ρ, ζ_H^ρ, ζ_L^ρ, σ_ρ and $\kappa_{s\rho}$ from the first and second moment conditions in Proposition 5 using one-stage GMM subject to the constraints that $\zeta \geq 0$, $\kappa_x^s, \kappa_l^s \geq 1$, $\sigma \in [0;1]$, and that the implied τ's are non-negative, while assuming that $\gamma = 2$.

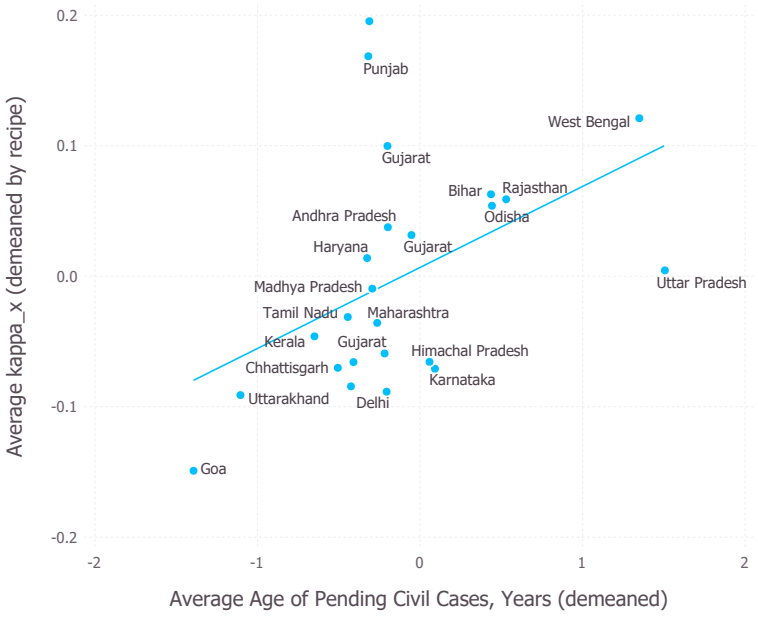
Figure 5 shows the correlation between the estimated $\kappa_x^\rho = 1/\bar{t}_x^\rho$, projected on recipe dummies and averaged within states, and the quality of high courts as measured by the average age of pending civil cases. In states with slower courts, firms face larger distortions κ_x^ρ when sourcing relationship-specific intermediate inputs.

For the counterfactual, we calibrate the household's outer-tier utility to be Cobb-Douglas in the industry baskets ($\eta = 1$). We set the consumption aggregator's expenditure shares on each product to be calculated from the nonnegative part of the difference between total sales and total intermediate input purchases in the pooled data (and the fraction of that difference in the sum over all products).

We then back out wedge parameters $\tau_x^{\rho d}$ and $\tau_l^{\rho d}$ and regress x-wedges on court quality:

$$\log \tau_x^{\rho d} = \nu_1^\rho + \nu_2 (\text{avg age})^d + \varepsilon_{\rho d}$$

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



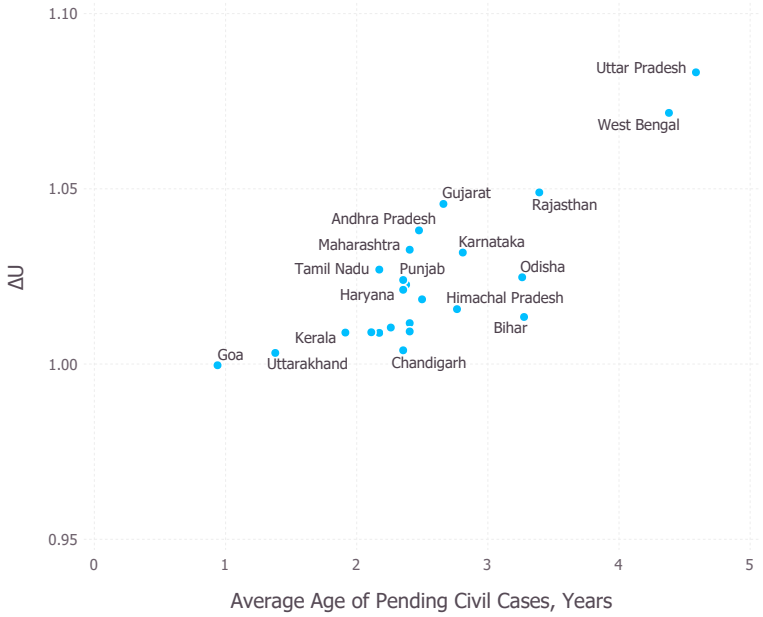
The figure shows the correlation between within-state averages of $1/\bar{t}_x^\rho$ and the average age of pending civil cases in the state's high court. Both variables are de-meaned within recipes.

where ν_1^ρ denotes a set of recipe fixed effects. The point estimate for ν_2 is .32, with a standard error of .12. In the following counterfactual, we reduce x-wedges to the level that the above regression predicts when the average age of pending cases is set to one year. Inputs which do not show up in our data as outputs are assumed to have unchanged productivity distributions. Figure 6 shows the associated proportional increase in the household's consumption aggregate U. The numbers are in the range of zero to nine percent, suggesting that the gains from improving contract enforcement institutions can be large.

7 Conclusion

This paper studies the quantitative importance of contracting frictions between buyers and sellers in the context of the Indian manufacturing sector. 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 organization form optimally to minimize the cost of production, and estimate the relative distortions associated with the use of relationship-specific inputs. 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.

Figure 6 Counterfactural increases in aggregate productivity



The figure shows the counterfactual increase in U when the τ_x^ρ are reduced by the fraction of $\log \tau_x^\rho$ that is explained by court quality in a linear regression.

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Appendix

A Comparison between US and Indian Product Codes

Table VIII Numbers of Distinct Products, Industries and Sectors

	US	ASI
Products	1,440	5,204 5-digit/ 1,108 4-digit
Industries	455	262
Sectors	20	64 2-digit/9 1-digit
Classification	5,4,2 digit SIC	5,4,3,2,1 digit ASIC

US classification refers to Census data as reported by Bernard, Redding, and Schott (2010).

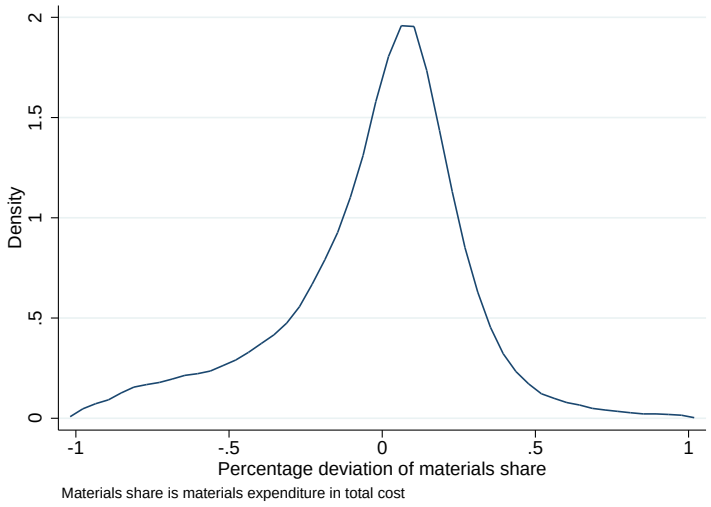
B Robustness / Further results

B.1 Two facts about the intra-industry variation in materials shares

Fact 1: Intermediate Input shares vary substantially across plants even within narrowly defined industries.

Figure 7 shows the dispersion of materials shares – the fraction of expenditure on materials intermediate inputs in total cost – around their 5-digit industry mean. The average standard deviation of materials shares is 17 percentage points. Similar dispersion arises when using the share of materials expenditures in the value of production output, or in sales. Of course, these differences in materials shares within industries are *not* evidence for inefficiencies per se: differences in input prices, production technology, and organizational choice, as well as measurement error could be driving this variation.

Figure 7 Within-industry dispersion of materials shares

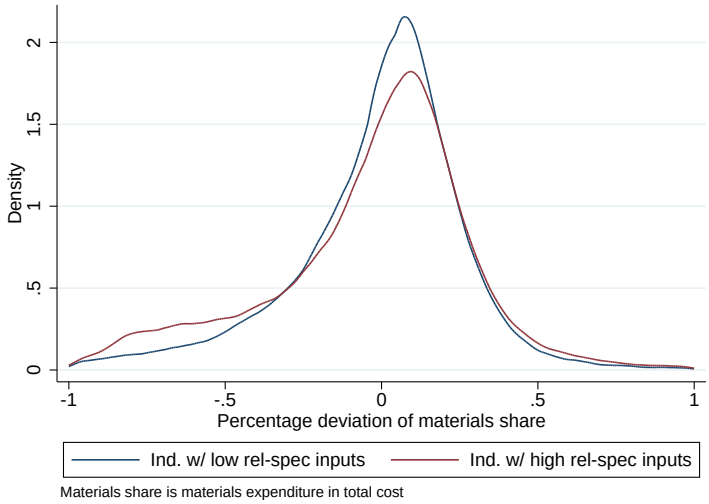


The figure shows the percentage deviation of a plant's materials share from the mean of its 5-digit industry. The sample consists of single-product plants only.

Fact 2: The dispersion of materials shares is higher in industries that rely heavily on relationship-specific intermediate inputs.

Figure 8 compares the intra-industry distribution of materials shares by the industry's dependency on intermediate inputs that are not traded on an organized exchange, or whose price is listed in trade publications ("relationship-specific" inputs). Industries that require such intermediate inputs will typically rely more heavily on formal enforcement of contracts in courts because the scope for hold-ups is higher. Figure 8 shows that the materials share in these industries is more dispersed and has a fatter left tail. This is consistent with firms reducing their intermediate input use when frictions in the markets for relationship-specific inputs increase their cost of production.

Figure 8 Industries that are more vs less intensive in relationship-specific inputs



The figure shows the percentage deviation of a plant's materials share from its 5-digit industry mean. The sample is divided into industries whose expenditure share on relationship-specific inputs at the national level is above the median (red) and below the median (blue). The classification of relationship-specificity is from Rauch (1999).

B.2 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 IX 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 IX shows that this estimated relationship is stronger when we use our instrumental variables strategy with court age as an instrument for congestion.

Table X 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 XI 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.

B.3 Distortions and Markups

Table XII 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

Table IX 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^{+}	-0.0116	-0.0349**	-0.0325**
	(0.0057)	(0.0074)	(0.0097)	(0.010)
LogGDPC * Rel. Spec.		-0.00178		-0.0296
		(0.015)		(0.018)
Trust * Rel. Spec.		-0.0431		-0.0365
		(0.043)		(0.043)
Language HHI * Rel. Spec.		-0.00544		-0.00630
		(0.044)		(0.044)
Caste HHI * Rel. Spec.		0.0367		0.0503
		(0.071)		(0.070)
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.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table X 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^{+}	-0.00433	0.0222**	0.0193**	0.00847^{+}
	(0.0045)	(0.0035)	(0.0068)	(0.0062)	(0.0045)
LogGDPC * Rel. Spec.		-0.00674			0.0104
		(0.0076)			(0.0089)
Trust * Rel. Spec.		0.0680**			0.0639*
		(0.026)			(0.026)
Language HHI * Rel. Spec.		0.0400			0.0405
		(0.030)			(0.030)
Caste HHI * Rel. Spec.		0.0727			0.0643
		(0.049)			(0.048)
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 × industry level.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

Table XI 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**	0.0189**	0.0112**	0.0127**
	(0.0023)	(0.0024)	(0.0016)	(0.0017)
Log district GDP/capita		0.0392**		0.0301**
		(0.0033)		(0.0027)
logpopdensity2001		-0.00665**		-0.00618**
		(0.0014)		(0.0011)
5-digit Industry FE	Yes	Yes	Yes	Yes
Estimator	IV	IV	IV	IV
R^2	0.227	0.251	0.180	0.198
Observations	168120	145305	168953	147017

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.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

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.

B.4 Materials Shares with Size and Age

B.5 Controlling for Fractionalization

C Data Appendix

C.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).

Table XII 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 XIII 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 XIV 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.

Table XV 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**	-0.0159*	-0.0156+	-0.0240*
	(0.0046)	(0.0067)	(0.0085)	(0.0095)
LogGDPC * Rel. Spec.		-0.00852		-0.0193
		(0.013)		(0.016)
Trust * Rel. Spec.		0.0249		0.0274
		(0.038)		(0.038)
Language HHI * Rel. Spec.		0.0345		0.0342
		(0.033)		(0.033)
Caste HHI * Rel. Spec.		0.109*		0.115*
		(0.051)		(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.
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$

- *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 E.
- *Labor Regulations:* From the STICERD/EOPP Indian States website (as constructed by Besley and Burgess (2004)). The labor regulations variable is "1" if the number of pro-worker amendments to the IDA exceeds the number of pro-employer amendments, "0" if the number of pro-worker and pro-employer amendments is equal, or no amendments were passed, and "-1" if the state passed more pro-employer amendments than pro-worker amendments.

Table XVI 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	-0.00844		-0.00490	0.000701	
	(0.0070)	(0.0075)		(0.011)	(0.011)	
Avg Age Of Civil Cases * Rel. Spec.	0.0230^{+}	0.0358**	0.0344*	0.0294	0.0424*	0.0423^{+}
	(0.012)	(0.013)	(0.014)	(0.020)	(0.020)	(0.022)
Log district GDP/capita		-0.0364**			-0.0373**	
		(0.0072)			(0.0072)	
LogGDPC * Rel. Spec.		0.0351*	0.0496		0.0633**	0.0601
		(0.017)	(0.032)		(0.019)	(0.038)
Trust		0.0583			0.0524	
		(0.057)			(0.058)	
Language Herfindahl		0.128**			0.121**	
		(0.044)			(0.044)	
Caste Herfindahl		0.0843			0.0839	
		(0.067)			(0.066)	
Trust * Rel. Spec.		-0.189*	-0.114		-0.183*	-0.116
		(0.091)	(0.089)		(0.093)	(0.090)
Language HHI * Rel. Spec.		-0.249**	-0.192**		-0.238**	-0.192**
		(0.074)	(0.072)		(0.074)	(0.072)
Caste HHI * Rel. Spec.		-0.197	-0.272*		-0.206^{+}	-0.278*
		(0.12)	(0.12)		(0.12)	(0.12)
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 XVII 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*	-0.00604*	-0.0144**	-0.0197**
	(0.0022)	(0.0025)	(0.0044)	(0.0046)
Log district GDP/capita		-0.00690		-0.0163**
		(0.0053)		(0.0061)
logpopdensity2001		0.00254		0.00530**
		(0.0018)		(0.0018)
Trust		-0.0125		-0.00836
		(0.019)		(0.020)
Language HHI		-0.0401*		-0.0342*
		(0.017)		(0.016)
Caste HHI		-0.0372		-0.0436
		(0.027)		(0.028)
5-digit Industry FE	Yes	Yes	Yes	Yes
Estimator	OLS	OLS	IV	IV
R^2	0.441	0.453	0.441	0.452
Observations	225590	193217	225590	193217

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

- *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.[24]

C.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 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

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

expenditures are non-positive.

C.3 High court case data and correlations with other measures

C.4 Details on High Court and State creation

Table XVIII 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	

D Model

D.1 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 uses $g^x(\psi^x)$. Both the buyer and supplier recognize that the supplier will save on cost by producing a defective input, and the price will be $p_s(\psi^x) = g^x(\psi^x)\lambda_s$ where λ_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

$$\left[\left(z^l \min\left\{l, \frac{\tilde{y}^l}{\psi^l}\right\}\right)^{\frac{\sigma-1}{\sigma}} + \left(z^x \min\left\{x, \frac{\tilde{y}^x}{\psi^x}\right\}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}} - \tilde{y}^l - \tilde{y}^x \geq y_b$$

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 λ_b, which satisfies

$$\lambda_b^{1-\sigma} = \left(\frac{\omega\left(\psi^l\right) + \psi^l\lambda_b}{z^l}\right)^{1-\sigma} + \left(\frac{p_s\left(\psi^x\right) + \psi^x\lambda_b}{z^x}\right)^{1-\sigma}$$

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 $\lambda_b\psi^l l$ and the value of the transaction is $\omega(\psi^l)l$. It is assumed that if the damage ratio $\frac{\lambda_b\psi^l l}{\omega(\psi^l)l}$ 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 $\lambda_b\psi^x x$ 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 $\frac{\lambda_b\psi^x x}{p_s(\psi^x)x}$ 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

$$\lambda_b^{1-\sigma} = \left(\frac{\omega(\psi^l)}{t_l z^l}\right)^{1-\sigma} + \left(\frac{p_s(\psi^x)}{t_x z^x}\right)^{1-\sigma}$$

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 $p_s(\psi^x) \to \lambda_x$, which means that the buyer's marginal cost is

$$\lambda_b^{1-\sigma} = \left(\frac{w}{t_l z^l}\right)^{1-\sigma} + \left(\frac{\lambda_s}{t_x z^x}\right)^{1-\sigma}$$

but the payments to labor and the supplier are wl and λ_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.

D.2 Stochastic vs. Deterministic Distortions

For this section, we omit the subscripts ω and ρ. We have defined:

$$\begin{aligned} t^* &= \left[\int \left(t_l^{\alpha_l} t_{x1}^{\alpha_{x1}} ... t_{xn}^{\alpha_{xn}}\right)^\gamma T\left(dt_l, dt_{x1}, ..., dt_{xn}\right)\right]^{1/\gamma} \\ \bar{t}_{x_i} &= \frac{\int t_{xi}\left(t_l^{\alpha_l} t_{x1}^{\alpha_{x1}} ... t_{xn}^{\alpha_{xn}}\right)^\gamma T\left(dt_l, dt_{x1}, ..., dt_{xn}\right)}{\int \left(t_l^{\alpha_l} t_{x1}^{\alpha_{x1}} ... t_{xn}^{\alpha_{xn}}\right)^\gamma T\left(dt_l, dt_{x1}, ..., dt_{xn}\right)} \end{aligned}$$

Proof.

$$\begin{aligned}\int t_{xi}\left(t_l^{\alpha_l}t_{x1}^{\alpha_{x1}}...t_{xn}^{\alpha_{xn}}\right)^{\gamma}T\left(dt_l,dt_{x_1},...,dx_n\right) &= \int\left(t_{xi}^{\zeta_{xi}}\right)^{\frac{1+\zeta_{xi}}{\zeta_{xi}}}\left(t_l^{\alpha_l}t_{x1}^{\alpha_{x1}}.t_{xi-1}^{\alpha_{xi-1}}t_{xi+1}^{\alpha_{xi+1}}..t_{xn}^{\alpha_{xn}}\right)^{\gamma}T\left(dt_l,dt_{x_1},...,dx_n\right)\\ &\geq \left[\int\left(t_{x_i}^{\zeta_{xi}}\right)\left(t_l^{\alpha_l}t_{x1}^{\alpha_{x1}}.t_{xi-1}^{\alpha_{xi-1}}t_{xi+1}^{\alpha_{xi+1}}..t_{xn}^{\alpha_{xn}}\right)^{\gamma}T\left(dt_l,dt_{x_1},...,dx_n\right)\right]^{\frac{1+\zeta_{xi}}{\zeta_{xi}}}\end{aligned}$$

where the last inequality uses Jensen's inequality and holds only if the distribution of t_{xi} is degenerate. With this we can bound $\bar{t}_{xi}$:

$$\begin{aligned}\bar{t}_{xi} &= \frac{\int t_{x_i}\left(t_l^{\alpha_l}t_{x1}^{\alpha_{x1}}...t_{xn}^{\alpha_{xn}}\right)^{\gamma}T\left(dt_l,dt_{x_1},...,dx_n\right)}{\int\left(t_l^{\alpha_l}t_{x1}^{\alpha_{x1}}...t_{xn}^{\alpha_{xn}}\right)^{\gamma}T\left(dt_l,dt_{x_1},...,dx_n\right)}\\ &\geq \frac{\int\left(t_l^{\alpha_l}t_{x1}^{\alpha_{x1}}...t_{xn}^{\alpha_{xn}}\right)^{\gamma}T\left(dt_l,dt_{x_1},...,dx_n\right)^{\frac{1+\zeta_{xi}}{\zeta_{xi}}}}{\int\left(t_l^{\alpha_l}t_{x1}^{\alpha_{x1}}...t_{xn}^{\alpha_{xn}}\right)^{\gamma}T\left(dt_l,dt_{x_1},...,dx_n\right)}\\ &= \int\left(t_l^{\alpha_l}t_{x1}^{\alpha_{x1}}...t_{xn}^{\alpha_{xn}}\right)^{\gamma}T\left(dt_l,dt_{x_1},...,dx_n\right)^{\frac{1}{\zeta_{xi}}}\\ &= \left(t^*\right)^{\frac{1}{\alpha_{xi}}}\end{aligned}$$

We can then multiply these across inputs to get

$$\bar{t}_l^{\alpha_l}\bar{t}_{x_1}^{\alpha_{x1}}...\bar{t}_{x_n}^{\alpha_{xn}} \geq t^*$$

■

E Vertical Distance

E.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 II, 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

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

E.2 Examples

Table XIX 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 XX 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 XIX 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 XX 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