Internalizing Global Value Chains: A Firm-Level Analysis

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A key decision facing firms is the extent of control to exert over the different stages in their production processes. We develop and test a property rights model of firm boundary choices along the value chain. We construct firm-level measures of the upstreamness of integrated and nonintegrated inputs by combining information on firms' production activities in more than 100 countries with input-output tables. Whether a firm integrates upstream or downstream suppliers depends crucially on the elasticity of demand it faces. Moreover, integration is shaped by the relative contractibility of stages along the value chain, as well as by the firm's productivity.

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I. Introduction

Sequential production has been an important feature of modern manufacturing processes at least since Henry Ford introduced his Model T assembly line in 1913. The production of cars, computers, mobile phones, and most other manufacturing goods involves a sequencing of stages: raw materials are converted into basic components, which are then combined with other parts to produce more complex inputs, before being assembled into final goods. In recent decades, advances in information and communication technology and falling trade barriers have led firms to retain within their boundaries and in their domestic economies only a subset of these production stages. Research and development, design, production of parts, assembly, marketing, and branding, previously performed in close proximity, are increasingly fragmented across firms and countries.[1]

While fragmenting production across firms and countries has become easier, contractual frictions remain a significant obstacle to the globalization of value chains. On top of the inherent difficulties associated with designing richly contingent contracts, international transactions suffer from a disproportionately low level of enforcement of contract clauses and legal remedies (Antràs 2015). In such an environment, companies are presented with complex organizational choices. In this paper, we focus on a key decision faced by firms worldwide: the extent of control to exert over the different segments of their production process.

Although the global fragmentation of production has featured prominently in the trade literature (e.g., Johnson and Noguera 2012), much less attention has been placed on how the position of a given production stage in the value chain affects firm boundary choices and firm organi-

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[1] The semiconductor industry exemplifies these trends. The first semiconductor chips were manufactured in the United States by vertically integrated firms such as IBM and Texas Instruments. Firms initially kept the design, fabrication, assembly, and testing of integrated circuits within ownership boundaries. The industry has since undergone several reorganization waves, and many of the production stages are now outsourced to independent contractors in Asia (Brown and Linden 2005). Another example is the iPhone: while its software and product design are done by Apple, most of its components are produced by independent suppliers around the world (Xing 2011).

zational decisions more broadly. Most studies on this topic have been mainly theoretical in nature.[2] To a large extent, this theoretical bias is explained by the challenges one faces when taking models of global value chains to the data. Ideally, researchers would like to access comprehensive data sets that would enable them to track the flow of goods within value chains across borders and organizational forms. Trade statistics are useful in capturing the flows of goods when they cross a particular border, and some countries' customs offices also record whether goods flow in and out of a country within or across firm boundaries. Nevertheless, once a good leaves a country, it is virtually impossible with available data sources to trace the subsequent locations (beyond its first immediate destination) where the good will be combined with other components and services.

The first contribution of this paper is to show how available data on the activities of firms can be combined with information from standard input-output tables to study firm boundaries along value chains. A key advantage of this approach is that it allows us to study how the integration of stages in a firm's production process is shaped by the characteristics—in particular, the production line position (or "upstreamness")—of these different stages. Moreover, the richness of our data allows us to run specifications that exploit variation in organizational features across firms, as well as within firms across their various inputs. Available theoretical frameworks of sequential production are highly stylized and often do not feature asymmetries across production stages other than in their position along the value chain. A second contribution of this paper is to develop a richer framework of firm behavior that can closely guide our firm-level empirical analysis.

Toward this end, we build on the property rights model in Antràs and Chor (2013) by generalizing it to an environment that accommodates differences across input suppliers along the value chain on the technology and cost sides.[3] We focus on the problem of a firm controlling the manufacturing process of a final-good variety, which is associated with a constant price elasticity demand schedule. The production of the final good entails a large number of stages that need to be performed in a predetermined order. The different stage inputs are provided by suppliers, who each undertake relationship-specific investments to make their components compatible with those of other suppliers along the value chain. The setting is one of incomplete contracting, in the sense that contracts contingent on whether components are compatible or not cannot be en-

[2] See, among others, Dixit and Grossman (1982), Yi (2003), Antràs and Chor (2013), Baldwin and Venables (2013), Costinot, Vogel, and Wang (2013), Antràs and de Gortari (2017), Fally and Hillberry (2018), and Kikuchi, Nishimura, and Stachurski (2018).

[3] The property rights approach builds on the seminal work of Grossman and Hart (1986) and has been employed to study the organization of multinational firms. See Antràs (2015) for a comprehensive overview of this literature.

forced by third parties. As a result, the division of surplus between the firm and each supplier is governed by bargaining, after a stage has been completed and the firm has had a chance to inspect the input. The firm must decide which input suppliers (if any) to own along the value chain. As in Grossman and Hart (1986), the integration of suppliers does not change the space of contracts available to the firm and its suppliers, but it affects the relative ex post bargaining power of these agents. A key feature of our model is that organizational decisions have spillovers along the value chain because relationship-specific investments made by upstream suppliers affect the incentives of suppliers in downstream stages.

Perhaps surprisingly, we show that the key predictions of Antràs and Chor (2013) continue to hold in this richer environment with input asymmetries. In particular, a firm's decision to integrate upstream or downstream suppliers depends crucially on the relative size of the elasticity of demand for its final good and the elasticity of substitution across production stages. When demand is elastic or inputs are not particularly substitutable, inputs are sequential complements, in the sense that the marginal incentive of a supplier to undertake relationship-specific investments is higher the larger are the investments by upstream suppliers. In this case, the firm finds it optimal to integrate only the most downstream stages, while it chooses to contract at arm's length with upstream suppliers in order to incentivize their investment effort. When instead demand is inelastic or inputs are sufficiently substitutable, inputs are sequential substitutes, and the firm chooses to integrate relatively upstream stages while engaging in outsourcing with downstream suppliers. While the profile of marginal productivities and costs along the value chain does not detract from this core prediction, it does shape the measure of stages (i.e., how many inputs) the firm ends up finding optimal to integrate in both the complements and the substitutes cases.

We develop several extensions of the model that are relevant for our empirical analysis. First, we map the asymmetries across inputs to differences in their inherent degree of contractibility. We show that the propensity of a firm to integrate a given stage is shaped in subtle ways by the contractibility of upstream and downstream stages. Second, we incorporate heterogeneity across final-good producers in their core productivity, while introducing fixed costs of integrating suppliers, as in Antràs and Helpman (2004). We show how such productivity differences influence the number of stages that are integrated and hence the propensity of the firm to integrate upstream relative to downstream stages. Finally, we consider a scenario in which integration is infeasible for certain segments of the value chain, for example, because of exogenous technological or regulatory factors. We show that even when integration is sparse (as is the case in our data), the model's predictions continue to describe firm boundary choices for those inputs over which integration is feasible.

To assess the validity of the model's predictions, we employ the WorldBase data set of Dun & Bradstreet, an establishment-level database covering public and private companies in many countries. For each establishment, WorldBase reports a list of up to six production activities, together with ownership information that allows us to link establishments belonging to the same firm. Our main sample consists of more than 300,000 manufacturing firms in 116 countries.

In our empirical analysis, we study the determinants of a firm's propensity to integrate upstream versus downstream inputs. To distinguish between integrated and nonintegrated inputs, we rely on the methodology of Fan and Lang (2000), combining information on firms' reported activities with input-output tables (see also Acemoglu, Johnson, and Mitton 2009; Alfaro et al. 2016). To capture the position of different inputs along the value chain, we compute a measure of the upstreamness of each input i in the production of output j using US input-output tables. This extends the measure of the upstreamness of an industry with respect to final demand from Antràs et al. (2012) and Fally (2012) to the bilateral industry-pair level. To provide a test of the model, we exploit information from WorldBase on the primary activity of each firm and use estimates of demand elasticities from Broda and Weinstein (2006), as well as measures of contractibility from Nunn (2007).

We first examine how firms' organizational choices depend on the elasticity of demand for their final good. In line with the first prediction of the model, we find that the higher the elasticity of demand faced by the parent firm, the lower the average upstreamness of its integrated inputs relative to the upstreamness of its nonintegrated inputs. This result is illustrated in a simple (unconditional) form in figure 1, based on different quintiles of the parent firm's elasticity of demand. As seen in panel A of the figure, the average upstreamness of integrated inputs is much higher when the parent company belongs to an industry with a low demand elasticity than when it belongs to one associated with a high demand elasticity. Conversely, panel B shows that the average upstreamness of nonintegrated stages is greater the higher the elasticity of demand faced by the parent's final good.[4]

The above pattern is robust in the regression analysis, even when controlling for a comprehensive list of firm characteristics (e.g., size, age, employment, sales), using different measures of the demand elasticity, as well as in different subsamples of firms (e.g., restricting to domestic

[4] Figure 1 is plotted using only inputs i that rank within the top 100 manufacturing inputs in terms of total requirements coefficients of the parent's output industry j. The average for each firm is computed weighting each input by its total requirements coefficient tr_{ij}, while excluding integrated stages belonging to the same industry j as the parent; a simple unweighted average across firms in the elasticity quintile is then illustrated. The figures obtained when considering all manufacturing inputs, when computing unweighted averages over inputs, and when considering the output industry j as an input are all qualitatively similar.

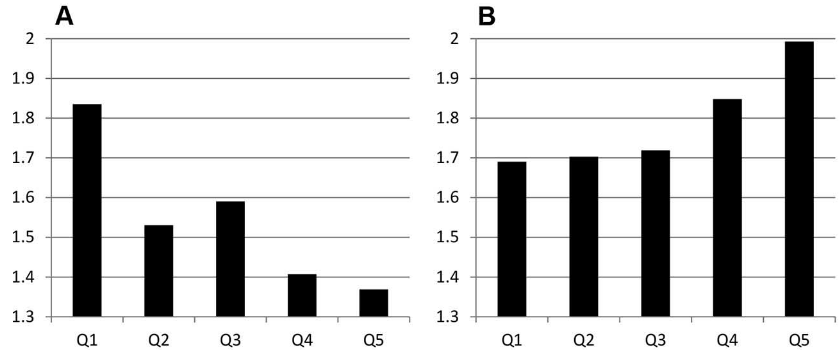

FIG. 1.—Average upstreamness of production stages, by quintile of parent's demand elasticity. *A*, Integrated stages. *B*, Nonintegrated stages.

firms or to multinationals). We also show that our results hold in specifications in which the elasticity of demand is replaced by the difference between this same elasticity and a proxy for the degree of input substitutability associated with the firm's production process. We reach a similar conclusion when we exploit within-firm variation in integration patterns. In these specifications, we find that a firm's propensity to integrate is generally lower for more upstream inputs (consistent with the smaller bars observed in panel A relative to panel B of fig. 1) and that the negative effect of upstreamness on integration is disproportionately large for firms facing high demand elasticities.

We report two further empirical regularities that are strongly consistent with the model's implications. First, we find that firms' ownership decisions are shaped by the contractibility of upstream versus downstream inputs: a greater degree of "upstream contractibility" increases the likelihood that a firm integrates upstream inputs when the firm faces a high elasticity of demand (i.e., in the complements case); conversely, it increases the propensity to outsource upstream inputs when the firm's demand elasticity is low (i.e., in the substitutes case). Intuitively, when production features a high degree of upstream contractibility, firms need to rely less on the organizational mode to counteract the distortions associated with inefficient investments upstream. Hence, high levels of upstream contractibility tend to reduce the set of outsourced stages when inputs are sequential complements, while reducing the set of integrated stages when inputs are sequential substitutes.[5] Second, we find that more

[5] The somewhat counterintuitive positive effect of contractibility on integration is a recurrent result in the property rights literature. For instance, Baker and Hubbard (2004) document that improvements in the contracting environment in the trucking industry (through the use of onboard computers) led to more integrated asset ownership. In international trade settings, Nunn and Trefler (2008), Defever and Toubal (2013), and Antràs (2015) have documented a similar positive association between contractibility and vertical integration.

productive firms integrate more inputs in industries across all the demand elasticity quintiles. This implies that more productive firms will exhibit a higher propensity to integrate relatively downstream (respectively, upstream) inputs when the elasticity of demand for their final product is low (respectively, high); this is exactly what we uncover in the data.

This set of findings suggests that contractual frictions play a key role in shaping the integration choices of firms around the world. The rich differential effects observed in the complements and substitutes cases are consistent with a view of integration choices that is rooted in the property rights approach to the theory of the firm, though we do not rule out that these could possibly be rationalized by alternative theories (as we briefly discuss in the concluding section). It is also useful to describe how our analysis relates to other recent work on vertical linkages at the firm level. In an influential study, Atalay, Hortaçsu, and Syverson (2014) find little evidence of intrafirm shipments between related plants within the United States; they instead present evidence indicating that firm boundaries are more influenced by the transfer of intangible inputs than by the transfer of physical goods. Our theory is abstract enough to allow one to interpret the sequential investments as resulting in either tangible or intangible transfers across establishments, and our empirical analysis takes into account both manufacturing and nonmanufacturing inputs (including services). That said, owing to the inherent difficulties in measuring intangible inputs, we believe that our empirical results speak more to the optimal provision of incentives along sequential value chains involving tangible inputs.[6] Relatedly, our analysis suggests that intrafirm trade flows are an imperfect proxy for the extent to which firms react to contractual insecurity by internalizing particular stages of their global value chains. As the "sparse integration" extension of our model shows, internalization decisions along value chains are consistent with an arbitrarily low level of intrafirm trade relative to the overall transaction volume in these chains. This helps reconcile our findings with those of Ramondo, Rappoport, and Ruhl (2016), who find intrafirm trade between US multinationals and their affiliates abroad to be highly concentrated among a small number of large affiliates.

Our work is closely related to two contemporaneous firm-level empirical investigations of the Antràs and Chor (2013) model. Del Prete and Rungi (2017) employ a data set of about 4,000 multinational business groups to explore the correlation between the average "downstreamness" of integrated affiliates and that of the parent firm itself (both measured relative to final demand). Luck (2019) reports corroborating evidence based on the city-level value chain position of processing export

[6] It is important to stress, however, that our findings should not be interpreted as invalidating the intangibles hypothesis. In fact, we will report some patterns in the data that are suggestive of an efficiency-enhancing role of the common ownership of proximate product lines.

activity in China. More generally, our paper is related to a recent empirical literature testing various aspects of the property rights theory of multinational firm boundaries.[7]

The remainder of the paper is organized as follows. Section II presents our model of firm boundaries with sequential production and input asymmetries. Section III describes the data. Section IV outlines our empirical methodology and presents our findings. Section V presents conclusions. The online appendix contains additional material related to both the theory and the empirical analysis.

II. Theoretical Framework

In this section, we develop our model of sequential production. We first describe a generalized version of the model in Antràs and Chor (2013) that incorporates heterogeneity across inputs beyond their position along the value chain. We then consider three extensions to derive additional theoretical results and enrich the set of predictions that can be brought to the data.

A. Benchmark Model with Heterogeneous Inputs

We focus throughout on the problem of a firm seeking to optimally organize a manufacturing process that culminates in a finished good valued by consumers. The final good is differentiated in the eyes of consumers and belongs to a monopolistically competitive industry with a continuum of active firms, each producing a differentiated variety. Consumer preferences over the industry's varieties feature a constant elasticity of substitution, so that the demand faced by the firm in question is

$$q = Ap^{-1/(1-\rho)}, \tag{1}$$

where $A > 0$ is a term that the firm takes as given, and the parameter $\rho \in (0, 1)$ is positively related to the degree of substitutability across final-good varieties. Note that A is allowed to vary across firms in the industry (perhaps reflecting differences in quality), while the demand elasticity $1/(1 - \rho)$ is common for all firms in the sector. The latter assumption is immaterial for our theoretical results but will be exploited in the empirical implementation, where we rely on sectoral estimates of demand elasticities. Given that we largely focus on the problem of a representative firm, we abstain from indexing variables by firm or sector to keep the notation tidy.

[7] This includes Antràs (2003, 2015), Yeaple (2006), Nunn and Trefler (2008, 2013), Corcos et al. (2013), Defever and Toubal (2013), and Díez (2014), among others. Our work is also related to the broader empirical literature on firm boundaries; see Lafontaine and Slade (2007) and Bresnahan and Levin (2012) for overviews.

Obtaining the finished product requires the completion of a unit measure of production stages. These stages are indexed by $i \in [0, 1]$, with a larger i corresponding to stages further downstream and thus closer to the finished product. Denote by $x(i)$ the value of the services of intermediate inputs that the supplier of stage i delivers to the firm. Final-good production is then given by

$$q = \theta \left\{ \int_0^1 [\psi(i) x(i)]^\alpha I(i)\, di \right\}^{1/\alpha}, \tag{2}$$

where θ is a productivity parameter, $\alpha \in (0, 1)$ is a parameter that captures the (symmetric) degree of substitutability among the stage inputs, the shifters $\psi(i)$ reflect asymmetries in the marginal product of different inputs' investments, and $I(i)$ is an indicator function that takes a value of one if input i is produced after all inputs $i' < i$ have been produced and a value of zero otherwise. The technology in (2) resembles a conventional constant elasticity of substitution production function with a continuum of inputs, but the indicator function $I(i)$ makes the production technology inherently sequential.

Intermediate inputs are produced by a unit measure of suppliers, with the mapping between inputs and suppliers being one-to-one. Inputs are customized to make them compatible with the needs of the firm controlling the finished product. In order to provide a compatible input, the supplier of input i must undertake a relationship-specific investment entailing a marginal cost of $c(i)$ per unit of input services $x(i)$. All agents including the firm are capable of producing subpar inputs at a negligible marginal cost, but these inputs add no value to final-good production apart from allowing the continuation of the production process in situations in which a supplier threatens not to deliver his or her input to the firm.

If the firm could discipline the behavior of suppliers via a comprehensive ex ante contract, those threats would be irrelevant. For instance, the firm could demand the delivery of a given volume $x(i)$ of input services in exchange for a fee, while including a clause in the contract that would punish the supplier severely when failing to honor this contractual obligation. In practice, however, a court of law will generally not be able to verify whether inputs are compatible or not. For the time being, we will make the stark assumption that none of the aspects of input production can be specified in a binding manner in an initial contract, except for a clause stipulating whether the different suppliers are vertically integrated into the firm or remain independent. Because the terms of exchange between the firm and the suppliers are not set in stone before production takes place, the actual payment to a supplier (say the one controlling stage i) is negotiated bilaterally only after the stage i input has been produced and the firm has had a chance to inspect it. At that point, the firm and the supplier negotiate over the division of the incremental contribution to total revenue generated by supplier i. The lack of an enforceable contract implies that suppliers can set the volume of input services $x(i)$ to maximize their payoff conditional on the value of the semifinished good they are handed by their immediate upstream supplier.

How does integration affect the game played between the firm and the unit measure of suppliers? Following the property rights theory of firm boundaries, we let the effective bargaining power of the firm vis-à-vis a supplier depend on whether the firm owns this supplier. Under integration, the firm controls the physical assets used in the production of the input, thus allowing the firm to dictate a use of these assets that tilts the division of surplus in its favor. We capture this central insight of the property rights theory in a stark manner, with the firm obtaining a share β_V of the value of supplier i's incremental contribution to total revenue when the supplier is integrated, while receiving only a share $\beta_O < \beta_V$ of that surplus when the supplier is a stand-alone entity.

This concludes the description of the setup of the model. Figure 2 summarizes the timing of events of the game played by the firm and the unit measure of suppliers.

Despite the presence of additional sources of input asymmetries, captured by the functions $\psi(i)$ and $c(i)$, the subgame perfect equilibrium of the above game can be derived in a manner similar to that of Antràs and Chor (2013). We begin by noting that, if all suppliers provide compatible inputs and the correct technological sequencing of production is followed, equations (1) and (2) imply that the total revenue obtained by the firm is given by $r(1)$, where the function $r(m)$ is defined by

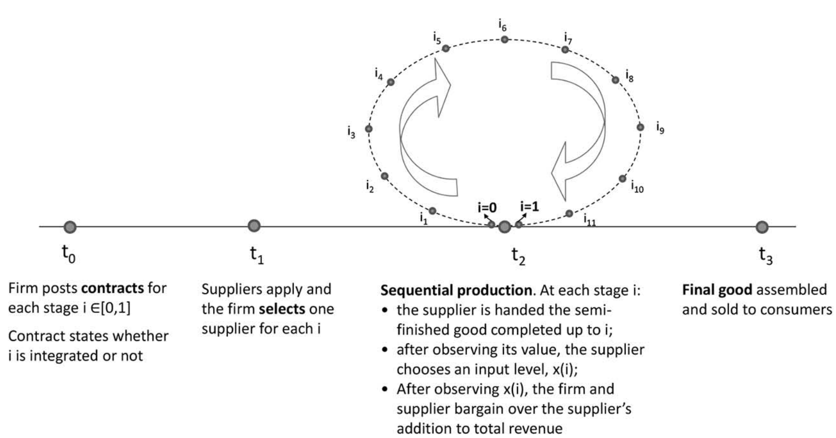

FIG. 2.—Timing of events

$$r(m) = A^{1-\rho}\theta^{\rho}\left\{\int_0^m [\psi(i)x(i)]^{\alpha} di\right\}^{\rho/\alpha}. \quad (3)$$

Because the firm can always unilaterally complete a production stage by producing a subpar input at negligible cost, one can interpret $r(m)$ as the revenue secured up to stage m.

Now consider the bargaining between the firm and the supplier at stage m. Because inputs are customized to the needs of the firm, the supplier's outside option at the bargaining stage is zero and the quasi rents over which the firm and the supplier negotiate are given by the incremental contribution to total revenue generated by supplier m at that stage.[8] Applying Leibniz's rule to (3), this is given by

$$r'(m) = \frac{\rho}{\alpha}\left(A^{1-\rho}\theta^{\rho}\right)^{\frac{\alpha}{\rho}} r(m)^{\frac{\rho-\alpha}{\rho}} \psi(m)^{\alpha} x(m)^{\alpha}. \quad (4)$$

As explained above, in the bargaining, the firm captures a share $\beta(m) \in \{\beta_V, \beta_O\}$ of $r'(m)$, while the supplier obtains the residual share $1 - \beta(m)$. It then follows that the choice of input volume $x(m)$ is characterized by the program

$$x^*(m) = \arg\max_{x(m)}\left\{[1-\beta(m)]\frac{\rho}{\alpha}\left(A^{1-\rho}\theta^{\rho}\right)^{\frac{\alpha}{\rho}} r(m)^{\frac{\rho-\alpha}{\rho}} \psi(m)^{\alpha} x(m)^{\alpha} - c(m)x(m)\right\}. \quad (5)$$

Notice that the marginal return to investing in $x(m)$ is increasing in the demand level A, while it decreases in the marginal cost $c(m)$. Furthermore, this marginal return is increasing in supplier m's bargaining share $1 - \beta(m)$, and thus, other things equal, outsourcing provides higher-powered incentives for the supplier to invest. This is a standard feature of property rights models. The more novel property of program (5) is that a supplier's marginal return to investing at stage m is shaped by all investment decisions in prior stages, that is, $\{x(i)\}_{i=0}^{m}$, as captured by the value of production secured up to stage m, that is, $r(m)$. The nature of such dependence is in turn crucially shaped by the relative size of the demand elasticity parameter ρ and the input substitutability parameter α. When $\rho > \alpha$, investment choices are *sequential complements* in the sense that higher investment levels by upstream suppliers increase the marginal return of supplier m's own investment. Conversely, when $\rho < \alpha$, investment choices are *sequential substitutes* because high values of up-

[8] Antràs and Chor (2013) provide an extensive discussion of the robustness of the key results should ex ante transfers between the firm and the suppliers be allowed and under alternative bargaining protocols that allow supplier i to lay claim over part of the revenues that are realized downstream from i.

stream investments reduce the marginal return to investing in $x(m)$. We shall refer to $\rho > \alpha$ as the *complements* case and to $\rho < \alpha$ as the *substitutes* case, as in Antràs and Chor (2013).

It is intuitively clear why low values of α will tend to render investments sequential complements. Why might a low value of ρ render investments sequential substitutes? The reason for this is that when ρ is low, the firm's revenue function is highly concave in output and thus marginal revenue falls at a relatively fast rate along the value chain. As a result, the incremental contribution to revenue associated with supplier m—which is what the firm and supplier m bargain over—might be particularly low when upstream suppliers have invested large amounts.

We now plug the first-order condition from (5) into (4) and solve the resulting separable differential equation. As shown in Section A-1 of the appendix, one can express the equilibrium volume of input m services $x^*(m)$ as a function of the whole path of bargaining shares $\{\beta(i)\}_{i\in[0,m]}$ up to stage m:

$$x^*(m) = A\theta^{\frac{\rho}{1-\rho}}\left(\frac{1-\rho}{1-\alpha}\right)^{\frac{\rho-\alpha}{\alpha(1-\rho)}}\rho^{\frac{1}{1-\rho}}\left[\frac{1-\beta(m)}{c(m)}\right]^{\frac{1}{1-\alpha}} \times \psi(m)^{\frac{\alpha}{1-\alpha}}\left(\int_0^m\left\{\frac{[1-\beta(i)]\psi(i)}{c(i)}\right\}^{\frac{\alpha}{1-\alpha}}di\right)^{\frac{\rho-\alpha}{\alpha(1-\rho)}}. \tag{6}$$

It is then straightforward to see that $x^*(m) > 0$ for all m as long as $\beta(m) < 1$. This in turn implies that the firm has every incentive to abide by the proper (or technological) sequencing of production, so that $I^*(m) = 1$ for all m (consistent with our expressions above).

Next, we roll back to the initial period prior to any production taking place, in which the firm decides whether the contract associated with a given input m is associated with integration or outsourcing. This amounts to choosing $\{\beta(i)\}_{i\in[0,1]}$ to maximize $\pi_F = \int_0^1\beta(i)r'(i)di$, with $r'(m)$ given in equation (4), $x^*(m)$ in equation (6), and $\beta(i) \in \{\beta_V, \beta_O\}$. After several manipulations, the problem of choosing the optimal organizational structure can be reduced to the following program:

$$\max_{\beta(i)} \pi_F = \Theta\int_0^1\beta(i)\left\{\frac{[1-\beta(i)]\psi(i)}{c(i)}\right\}^{\frac{\alpha}{1-\alpha}}\left(\int_0^i\left\{\frac{[1-\beta(k)]\psi(k)}{c(k)}\right\}^{\frac{\alpha}{1-\alpha}}dk\right)^{\frac{\rho-\alpha}{\alpha(1-\rho)}}di \quad \text{s.t.} \quad \beta(i) \in \{\beta_V, \beta_O\}, \tag{7}$$

where

$$\Theta = A\theta^{\frac{\rho}{1-\rho}}\frac{\rho}{\alpha}\left(\frac{1-\rho}{1-\alpha}\right)^{\frac{\rho-\alpha}{\alpha(1-\rho)}}\rho^{\frac{\rho}{1-\rho}} > 0.$$

In order to solve this problem, it will prove useful to consider a relaxed version of program (7) in which rather than constraining $\beta(i)$ to equal β_V or β_O, we allow the firm to freely choose the function $\beta(i)$ from the whole set of piecewise continuously differentiable real-valued functions. Defining

$$v(i) \equiv \int_0^i \left\{ \frac{[1-\beta(k)]\psi(k)}{c(k)} \right\}^{\frac{\alpha}{1-\alpha}} dk, \tag{8}$$

we can then turn this relaxed program into a calculus of variation problem in which the firm chooses the real-value function v that maximizes

$$\pi_F(v) = \Theta \int_0^1 \left[1 - v'(i)^{\frac{1-\alpha}{\alpha}} \frac{c(i)}{\psi(i)} \right] v'(i) v(i)^{\frac{\rho-\alpha}{\alpha(1-\rho)}} di. \tag{9}$$

In Section A-1 of the appendix, we show that imposing the necessary Euler-Lagrange and transversality conditions, and after a few cumbersome manipulations, the optimal (unrestricted) division of surplus at stage m can be expressed as

$$\beta^*(m) = 1 - \alpha \left\{ \frac{\int_0^m [\psi(k)/c(k)]^{\frac{\alpha}{1-\alpha}} dk}{\int_0^1 [\psi(k)/c(k)]^{\frac{\alpha}{1-\alpha}} dk} \right\}^{\frac{\alpha-\rho}{\alpha}}. \tag{10}$$

The term inside the braces is a monotonically increasing function of m. This confirms the claim in Antràs and Chor (2013) that whether the optimal division of surplus increases or decreases along the value chain is shaped critically by the relative size of the parameters α and ρ.[9] In the complements case ($\rho > \alpha$), the incentive to integrate suppliers increases as we move downstream in the value chain. Intuitively, given sequential complementarity, the firm is particularly concerned about incentivizing upstream suppliers to raise their investment effort in order to generate positive spillovers on the investment levels of downstream suppliers. Instead, in the substitutes case ($\rho < \alpha$), the firm is less concerned with underinvestment by upstream suppliers, while capturing rents upstream is particularly appealing when marginal revenue falls quickly with output.

A remarkable feature of equation (10) is that the slope of $\partial\beta^*(m)/\partial m$ is governed by the sign of $\rho - \alpha$ regardless of the paths of $\psi(k)$ and $c(k)$. It is worth pausing to explain why this result is not straightforward. Note that a disproportionately high value of $\psi(m)$ at a given stage m can be interpreted as that stage being relatively important in the production pro-

[9] Although Antràs and Chor (2013) considered a variant of their model with heterogeneity in $\psi(i)$ and $c(i)$, they failed to derive this explicit formula for $\beta^*(m)$ and simply noted that $\partial\beta^*(m)/\partial m$ inherited the sign of $\rho - \alpha$ (see, in particular, eq. [28] in their paper).

cess.[10] According to one of the canonical results of the property rights literature, one would then expect the incentive to outsource such a stage to be particularly large (see, in particular, proposition 1 in Antràs [2014]). Intuitively, outsourcing provides higher-powered incentives to suppliers, and minimizing underinvestment inefficiencies is particularly beneficial for inputs that are relatively important in production. One might have thus expected the optimal division of surplus $\beta^*(m)$ to be decreasing in stage m's importance $\psi(m)$. For the same reason, and given that input shares are monotonically decreasing in the marginal cost $c(m)$, one might have also expected the share $\beta^*(m)$ to be increasing in $c(m)$. One would then be led to conclude that if the path of $\psi(m)$ were sufficiently increasing in m—or the path of $c(m)$ were sufficiently decreasing in m—then $\beta^*(m)$ would tend to decrease along the value chain, particularly when the difference between ρ and α is small.

Equation (10) demonstrates, however, that this line of reasoning is flawed. No matter by how little ρ and α differ, the slope of $\beta^*(m)$ is uniquely pinned down by the sign of $\rho - \alpha$, regardless of the paths of $\psi(m)$ and $c(m)$. This result bears some resemblance to the classic result in consumption theory that an agent's dynamic utility-maximizing level of consumption should be growing or declining over time according to whether the real interest rate is greater or smaller than the rate of time preference, regardless of the agent's income path. It is important to stress, however, that the paths of $\psi(m)$ and $c(m)$ are not irrelevant for the incentive to integrate suppliers along the value chain (in the same manner in which the path of income is not irrelevant in the dynamic consumption problem). Equation (10) illustrates that the incentives to integrate a particular input will be notably shaped by the size of the ratio $\psi(k)/c(k)$ for inputs upstream from input m relative to the average size of this ratio along the whole value chain.

More specifically, in production processes featuring sequential complementarity, the higher is the value of $\psi(k)/c(k)$ for inputs upstream from m relative to its value for inputs downstream from m, the higher will be the incentive of the firm to integrate stage m. The intuition behind this result is as follows. Remember that when inputs are sequential complements, the marginal incentive of supplier m to invest will be higher, the higher are the levels of investment by suppliers upstream from m. Furthermore, fixing the ownership structure, these upstream investments will also tend to be relatively large whenever stages m' upstream from m are associated with disproportionately large values of $\psi(m')$ or low values of $c(m')$. In those situations, and because of sequential complementarity, the incentives to invest at stage m will also tend to be disproportionately

[10] Indeed, in a model with complete contracts, the share of m in the total input purchases of the firm would be a monotonically increasing function of $\psi(m)$.

large, and thus the incentive of the firm to outsource stage m will be reduced relative to a situation in which the ratio $\psi(k)/c(k)$ is common for all stages. Conversely, whenever $\rho < \alpha$, investments are sequential substitutes, and thus high upstream investments related to disproportionately high upstream values of $\psi(m')/c(m')$ for $m' < m$ will instead increase the likelihood that stage m is outsourced.

So far, we have focused on a characterization of the optimal bargaining share $\beta^*(m)$, but the above results can easily be turned into statements regarding the propensity of firms to integrate ($\beta^*(m) = \beta_V$) or outsource ($\beta^*(m) = \beta_O$) the different stages along the value chain. In particular, in Section A-1 of the appendix, we prove the following proposition:

Proposition 1. In the complements case ($\rho > \alpha$), there exists a unique $m_C^* \in (0, 1]$ such that (i) all production stages $m \in [0, m_C^*)$ are outsourced, and (ii) all stages $m \in [m_C^*, 1]$ are integrated within firm boundaries. In the substitutes case ($\rho < \alpha$), there exists a unique $m_S^* \in (0, 1]$ such that (i) all production stages $m \in [0, m_S^*)$ are integrated within firm boundaries, and (ii) all stages $m \in [m_S^*, 1]$ are outsourced. Furthermore, both m_C^* and m_S^* are lower, the higher is the ratio $\psi(m)/c(m)$ for upstream inputs relative to downstream inputs.

Figure 3 illustrates the main result in proposition 1 concerning the optimal pattern of ownership along the value chain. When the demand faced by the final-good producer is sufficiently elastic, then there exists a unique cutoff stage such that all inputs prior to that cutoff are outsourced, and all inputs (if any) downstream of it are integrated. The converse prediction holds when demand is sufficiently inelastic (i.e., in the sequential substitutes case): the firm would instead integrate relatively upstream inputs, while outsourcing would take place relatively downstream.

Although the last statement in proposition 1 follows pretty immediately from our discussion of the properties of the solution $\beta^*(m)$ to the relaxed problem, it can also be shown more directly by explicitly characterizing the thresholds m_C^* and m_S^*. For the sequential complements case, we show in Section A-1 of the appendix that, provided that integration and outsourcing coexist along the value chain, the threshold m_C^* is given by

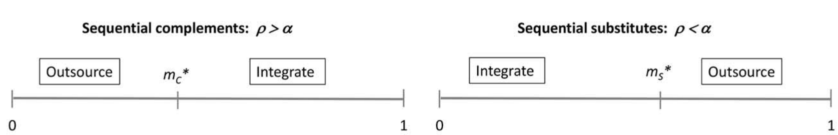

Fig. 3.—Firm boundary choices along the value chain

$$\frac{\int_0^{m_C^*}[\psi(k)/c(k)]^{\frac{\alpha}{1-\alpha}}dk}{\int_0^1[\psi(k)/c(k)]^{\frac{\alpha}{1-\alpha}}dk} = \left(1+\left(\frac{1-\beta_O}{1-\beta_V}\right)^{\frac{\alpha}{1-\alpha}}\left\{\left[\frac{1-\frac{\beta_O}{\beta_V}}{1-\left(\frac{1-\beta_O}{1-\beta_V}\right)^{-\frac{\alpha}{1-\alpha}}}\right]^{\frac{\alpha(1-\rho)}{\rho-\alpha}}-1\right\}\right)^{-1}. \quad (11)$$

Notice then that the larger the value of $\psi(k)/c(k)$ in upstream production stages (in the numerator of the left-hand side) relative to downstream production stages, the lower will be the value of m_C^*; the set of integrated stages will thus be larger.[11] (The analogous expression for m_S^* in the substitutes case is reported in Sec. A-1 of the appendix.)

B. Extensions

1. Heterogeneous Contractibility of Inputs

In order to develop empirical tests of proposition 1—and especially its last statement—it is important to map variation in the ratio $\psi(m)/c(m)$ along the value chain to certain observables. With that in mind, in this section we explore the link between $\psi(m)$ and the degree of contractibility of different stage inputs. In Section A-1 of the appendix, we also briefly relate marginal cost variation in $c(m)$ along the value chain to the sourcing location decisions of the firm.[12]

Remember that in our benchmark model, $x(m)$ captures the services related to the noncontractible aspects of input production, in the sense that the volume $x(m)$ cannot be disciplined via an initial contract and is chosen unilaterally by suppliers. Conversely, we shall now assume that $\psi(m)$ encapsulates investments and other aspects of production that are specified in the initial contract in a way that precludes any deviation from that agreed level. In light of equation (2), our assumptions imply that input production is a symmetric Cobb-Douglas function of contractible and noncontractible aspects of production. To capture differential

[11] In the complements case, integration and outsourcing coexist along the value chain when $\beta_V(1-\beta_V)^{\alpha/(1-\alpha)} > \beta_O(1-\beta_O)^{\alpha/(1-\alpha)}$, which ensures $m_C^* < 1$. When instead $\beta_V(1-\beta_V)^{\alpha/(1-\alpha)} < \beta_O(1-\beta_O)^{\alpha/(1-\alpha)}$, the firm finds it optimal to outsource all stages, i.e., $m_C^* = 1$.

[12] In the absence of contractual frictions, $\psi(m)/c(m)$ would be positively related to the relative use of input m in the production of the firm's good, and one could presumably use information from input-output tables to construct empirical proxies for this ratio. Unfortunately, such a mapping between $\psi(m)/c(m)$ and input m's share in the total input purchases of firms is blurred by incomplete contracting and sequential production.

contractibility along the value chain, we let stages differ in the (legal) costs associated with specifying these contractible aspects of production. More specifically, we denote these contracting costs by $[\psi(m)]^{\phi}/\mu(m)$ per unit of $\psi(m)$. We shall refer to $\mu(m)$ as the level of *contractibility* of stage m.[13] The parameter $\phi > 1$ captures the intuitive notion that it becomes increasingly costly to render additional aspects of production contractible. We shall assume that the firm bears the full cost of these contractible investments (perhaps by compensating suppliers for them up-front), but our results would not be affected if the firm bore only a fraction of these costs. To simplify matters, we let the marginal cost $c(m)$ of noncontractible investments be constant along the value chain, that is, $c(m) = c$ for all m.

In terms of the timing of events summarized in figure 2, notice that nothing has changed except for the fact that the initial contract also specifies the profit-maximizing choice of $\psi(m)$ along the value chain. Furthermore, once the levels of $\psi(m)$ have been set at stage t_0, the subgame perfect equilibrium is identical to that in our previous model in which $\psi(m)$ was assumed exogenous. This implies that the firm's optimal ownership structure along the value chain will seek to maximize the program in (7), and the solution of this problem will be characterized by proposition 1.

As shown in Section A-1 of the appendix, after solving for the optimal choice of $\beta(m) \in \{\beta_V, \beta_O\}$, one can express firm profits net of contracting costs as

$$\tilde{\pi}_F = \Theta \frac{\alpha(1-\rho)}{\rho(1-\alpha)} c^{\frac{-\rho}{1-\rho}} \Gamma(\beta_O, \beta_V) \left[\int_0^1 \psi(i)^{\frac{\alpha}{1-\alpha}} di \right]^{\frac{\rho(1-\alpha)}{\alpha(1-\rho)}} - \int_0^1 \frac{[\psi(i)]^{\phi}}{\mu(i)} di, \qquad (12)$$

where remember that

$$\Theta = A\theta^{\frac{\rho}{1-\rho}} \frac{\rho}{\alpha} \left(\frac{1-\rho}{1-\alpha} \right)^{\frac{\rho-\alpha}{\alpha(1-\rho)}} \rho^{\frac{\rho}{1-\rho}} > 0,$$

and where $\Gamma(\beta_O, \beta_V) > 0$ is a function of β_O and β_V, as well as of α and ρ (see Sec. A-1 of the appendix for the full expression). The choice of the profit-maximizing path of $\psi(i)$ will thus seek to maximize $\tilde{\pi}_F$ in (12).

A notable feature of equation (12) is that, leaving aside variation in the contracting costs $\mu(i)$, the marginal incentive to invest in the contractible components of input production is independent of the input's position in the value chain. This result is not entirely intuitive because, relative to a complete contracting benchmark, the degree of under-

[13] Acemoglu, Antràs, and Helpman (2007) also model input production as involving a Cobb-Douglas function of contractible and noncontractible inputs, but they capture the degree of contractibility by the elasticity of input production to the contractible components of production. In our setup with sequential production, however, such an approach precludes an analytical solution of the differential equations characterizing the equilibrium.

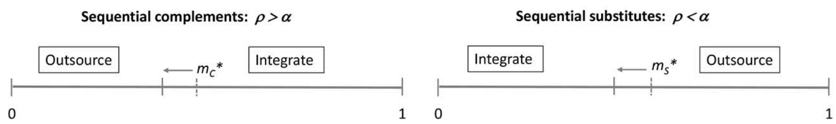

FIG. 4.—The effect of an increase in upstream contractibility

investment in noncontractible inputs varies along the value chain and the endogenous (but coarse) choice of ownership structure does not fully correct these distortions. One might have then imagined that the choice of $\psi(i)$ would have partly sought to remedy these remaining inefficiencies. Instead, variation in the firm's choice of contractible investments $\psi(i)$ is solely shaped by variation in contractibility $\mu(i)$. More precisely, the first-order conditions associated with problem (12) imply that for any two inputs at stages m and m', we have

$$[\psi(m)/\psi(m')]^{\phi-\frac{\alpha}{1-\alpha}} = \mu(m)/\mu(m').$$

For the second-order conditions of problem (12) to be satisfied, we need to assume that $\phi > \alpha/(1-\alpha)$, and thus the path of $\psi(m)$ along the value chain is inversely related to the path of the exogenous contracting costs $1/\mu(m)$.[14] In light of our discussion in the last section, this implies the following proposition:

PROPOSITION 2. There exist thresholds $m_C^* \in (0,1]$ and $m_S^* \in (0,1]$ such that, in the complements case, all production stages $m \in [0, m_C^*)$ are outsourced and all stages $m \in [m_C^*, 1]$ are integrated; in the substitutes case, all production stages $m \in [0, m_S^*)$ are integrated, while all stages $m \in [m_S^*, 1]$ are outsourced. Furthermore, both m_C^* and m_S^* are lower, the higher is the contractibility $\mu(m)$ for upstream inputs relative to downstream inputs.

Figure 4 illustrates the key result of proposition 2. Intuitively, the higher the contractibility of upstream inputs, the less firms need to rely on upstream organizational decisions as a way to counteract the distortions associated with inefficient investments by upstream suppliers. Consequently, high levels of upstream contractibility tend to reduce the set of outsourced stages whenever final-good demand is elastic or inputs are not too substitutable, while they tend to reduce the set of integrated stages whenever final-good demand is inelastic or inputs are highly substitutable.

By mapping variation in $\psi(m)$ to the degree of input contractibility, proposition 2 helps operationalize our previous proposition 1. In our empirical analysis, we will employ proxies for input contractibility to develop a sector-level measure of the extent to which noncontractibilities

[14] The inequality $\phi > \alpha/(1-\alpha)$ is necessary but not sufficient for the second-order conditions to be satisfied (see Sec. A-1 of the appendix).

feature in upstream relative to downstream stages in the production of the output. We will then study how firm-level ownership decisions are shaped by this relative importance of upstream versus downstream contractibilities in both the complements and substitutes cases.

2. Heterogeneous Productivity of Final-Good Producers

Our model incorporates heterogeneity across final-good producers in terms of their demand level A and their core productivity θ. In this section, we show how such heterogeneity shapes firm boundary choices along the value chain, in the presence of fixed organizational costs associated with vertically integrating production stages. More specifically, we shall now assume that if a firm wants to integrate a given stage $i \in [0, 1]$, it needs to pay a fixed cost equal to $f_V > 0$.[15]

In order to facilitate a swifter transition to the empirical analysis, we shall revert to our benchmark model with exogenous paths of $\psi(i)$ and $c(i)$. We will relegate most mathematical details to Section A-1 of the appendix, in which we show that proposition 1 continues to apply in this environment with fixed costs of integration. More precisely, there continue to exist thresholds $m_C^* \in (0, 1]$ and $m_S^* \in (0, 1]$ such that all production stages $m \in [0, m_C^*)$ are outsourced and all stages $m \in [m_C^*, 1]$ are integrated in the complements case; all production stages $m \in [0, m_S^*)$ are integrated and all stages $m \in [m_S^*, 1]$ are outsourced in the substitutes case. Furthermore, one can still show that both m_C^* and m_S^* are lower, the higher is the ratio $\psi(m)/c(m)$ for upstream inputs relative to downstream inputs. These characterization results can be obtained even though the equations determining the cutoffs m_C^* and m_S^* are now significantly more involved.

More relevant for the purposes of this section, the equilibrium conditions defining m_C^* and m_S^* can also be used to study how these thresholds are affected by changes in A and θ. In Section A-1 of the appendix, we show that m_C^* is necessarily a decreasing function of the level of firm demand A or firm productivity θ. By contrast, m_S^* is increasing in both A and θ. In words, this implies that regardless of the sign of $\rho - \alpha$, relatively more productive firms will tend to integrate a larger interval of production stages. The intuition behind this is simple: more productive firms find it easier to amortize the fixed cost associated with integrating more stages.

In our empirical analysis, we will explore whether the observed intraindustry heterogeneity in integration choices is in accordance with these predictions, which we summarize in the following proposition:

[15] Our results below would continue to hold in the presence of fixed costs f_O associated with outsourcing stages, as long as those fixed costs are lower than f_V.

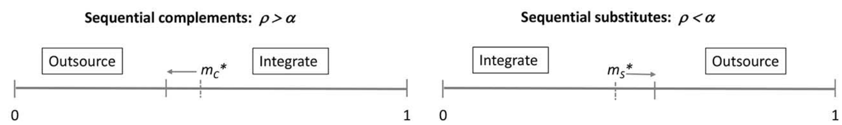

FIG. 5.—The effect of an increase in productivity of the final-good producer

PROPOSITION 3. In the presence of fixed costs of integration, the statements in proposition 1 continue to hold. Furthermore, the cutoff m_C^* is decreasing in firm-level demand A and firm-level productivity θ, while m_S^* is increasing in A and θ.

Figure 5 illustrates how an increase in the productivity θ of the final-good producer (or an increase in firm-level demand A) affects integration choices along the value chain. The interval of integrated stages expands in both cases, but in a manner that would lead us to observe relatively more internalization of upstream stages when inputs are sequential complements and, conversely, relatively more internalization of downstream stages in the substitutes case.

3. Sparse Integration and Intrafirm Trade

Our framework has the strong implication that the sets of integrated and outsourced stages are both connected and jointly constitute a partition of [0, 1]. As might have been expected, this strong prediction of the model is not borne out in the data. In fact, integrated stages are very sparse in our data set, and the overwhelming majority of them "border" with outsourced stages immediately upstream and downstream from them.[16] This paucity of integration might be due to technological or regulatory factors that make vertical integration infeasible for certain production stages. We next briefly outline a third extension of our model that accommodates such sparsity, and we demonstrate that it does not undermine the validity of the key predictions of the model that we will take to the data.

A simple way to render integration infeasible for certain segments of the value chain is to assume that the fixed cost of integrating those segments is arbitrarily large. In terms of our second extension above, we thus now have that the fixed cost of integration is stage-specific and takes

[16] For our full sample of firms, the median number of integrated stages is two, while the median number of nonintegrated stages—i.e., all inputs with positive total requirements coefficients—is 906. When restricting the sample to the top 100 manufacturing inputs ranked by the total requirements coefficients of the associated output industry, 0.11 percent of all integrated stages are immediately preceded or succeeded by another integrated stage. The next section discusses in detail how we identify integrated and nonintegrated stages and their position in the value chain.

a value of $f_V(m) = +\infty$ for any $m \in \Upsilon$, where Υ is the set of stages that cannot possibly be integrated. For simplicity, we assume that the fixed costs of integration are finite and identical for all remaining stages, so $f_V(m) = f_V$ for $m \in \Omega$, where Ω is the set of integrable stages (i.e., $\Omega = [0, 1]\backslash\Upsilon$). Clearly, by making the set Υ larger and larger, one can make integration decisions arbitrarily sparse in our model. As we show in Section A-1 of the appendix, despite the presence of the exogenously nonintegrable stages, we can establish the following proposition:

Proposition 4. If $\rho > \alpha$, the firm cannot possibly find it optimal to integrate a positive measure of stages located upstream from a positive measure of outsourced stages $(\tilde{m}, \tilde{m} + \varepsilon) \in \Omega$ that could have been integrated. If $\rho < \alpha$, the firm cannot possibly find it optimal to integrate a positive measure of stages located downstream from a positive measure of outsourced stages $(\tilde{m}, \tilde{m} + \varepsilon) \in \Omega$ that could have been integrated.

Naturally, proposition 4 provides a much weaker characterization of the integration decisions of firms along their value chain than our previous propositions 1–3. Yet, a corollary of proposition 4 is that, holding constant the set Υ of stages that cannot possibly be integrated, the average upstreamness of integrated stages relative to the average upstreamness of outsourced stages should be lower when $\rho > \alpha$ than when $\rho < \alpha$. This relative upstreamness of integrated and nonintegrated stages is what we refer to as "ratio-upstreamness" in our regression analysis and will be one of the key metrics employed to assess the empirical validity of the model.

An interesting implication of the sparsity of integrated stages in the value chain is that, as the set Υ expands, the volume of intrafirm trade in the value chain becomes smaller and smaller. Intuitively, in such a case, each interval of integrated stages becomes increasingly isolated and necessarily trades at arm's length with their immediate "neighbors" in the value chain. This confirms our claim in the introduction that in sequential production processes in which physical goods flow through both integrated and nonintegrated plants, and in which the former are largely outnumbered by the latter, the volume of intrafirm trade flows may be a poor proxy of the extent to which firms' integration decisions are shaped by contractual incompleteness.

III. Data Set and Key Variables

We turn now to our empirical analysis. To assess the validity of our model, we need firm-specific information on integrated and outsourced inputs, as well as a measure of the upstreamness of these various inputs. We also require proxies for whether a final-good industry falls into the complements or substitutes case and a measure of input contractibility. In this section, we describe the data set that we employ, together with the construction of these key variables.

A. *The Worldbase Data Set*

Our core firm-level data set is Dun & Bradstreet's (D&B) WorldBase, which provides comprehensive coverage of public and private companies across more than 100 countries and territories.[17] WorldBase has been used extensively in the literature, in particular, to explore research questions related to the organizational practices of firms around the world.[18]

A key advantage of WorldBase is that the unit of observation is the establishment, namely, a single physical location where industrial operations or services are performed or business is conducted. Each establishment in WorldBase is assigned a unique identifier, called a DUNS number.[19] Where applicable, the DUNS number of the global ultimate owner is also reported, which allows us to keep track of ownership linkages within the data set. In addition, WorldBase provides information on (i) the location (address) of each establishment; (ii) the four-digit SIC code (1987 version) of its primary industry and the SIC codes of up to five secondary industries; (iii) the year it was started or in which current ownership took control; and (iv) basic data on employment and sales.

Note that each firm in the data either (i) is a single establishment or (ii) is identified in WorldBase as a "global ultimate." The former refers to a business entity whose entire activity is in one location and that does not report ownership links with other establishments in WorldBase. For the latter, D&B WorldBase defines a "global ultimate" to be the top, most important, responsible entity within a corporate family tree that has more than 50 percent ownership of other establishments. We link each global ultimate to all its identified majority-owned subsidiaries, in both manufacturing and nonmanufacturing, by using the DUNS number of the global ultimate that is reported for establishments. The set of integrated SIC activities for a single establishment is simply the list of up to six SIC codes associated with it. The set of integrated SIC codes for a global ultimate is the complete list of SIC activities that are performed in either its headquarters or one of its subsidiaries. Moving forward, we will refer simply to each observation as a "parent" firm, indexed by p.

For our analysis, we use the 2004/5 WorldBase vintage and focus on parent firms in the manufacturing sector—that is, whose primary SIC

[17] The data in WorldBase are compiled from a large number of sources, including business registers, company websites, and self-registration. See Alfaro and Charlton (2009) for a detailed discussion and comparisons with other data sets.

[18] Recent uses include Acemoglu et al. (2009), Alfaro and Charlton (2009), Alfaro and Chen (2014), Fajgelbaum, Grossman, and Helpman (2015), and Alfaro et al. (2016).

[19] D&B uses the US Standard Industrial Classification (SIC) Manual, 1987 edition, to classify business establishments. The Data Universal Numbering System—the D&B DUNS number—supports the linking of plants and firms across countries and tracking of plants' histories including name changes.

code lies between 2000 and 3999—with a minimum total employment (across all establishments) of 20. To be clear, while each parent firm in our sample has a primary SIC code in manufacturing, we nevertheless include all the parent firm's integrated SIC activities (in both manufacturing and nonmanufacturing) in the exercise that follows. In all, our sample contains 320,254 parent firms from 116 countries; 259,312 of these are single-establishment firms, while 60,942 are global ultimates. Among the global ultimates, 6,370 observations have subsidiaries in more than one country and are thus multinational firms. Panel A of table A-1 in the appendix provides descriptive statistics for our full sample, as well as for the subset of multinationals. Not surprisingly, multinationals are, on average, larger in terms of employment, sales, and number of integrated SIC codes, as compared to the typical firm in our data. We will show nevertheless that our core findings concerning the relationship between upstreamness and integration patterns are stable when we look at different subsamples.

B. Key Variables

We describe below the dependent variable and the key industry controls used in our analysis. Descriptive statistics for these controls are provided in table A-2 in the appendix.

1. Integrated and Outsourced Inputs

For each parent, WorldBase provides us with information on the inputs that are integrated within the firm's ownership boundaries. In order to further identify which inputs are outsourced, we combine the above with information from US input-output (I-O) tables, following the methodology of Fan and Lang (2000).

Consider an economy with $N > 1$ industries. We refer to *output* industries by j and *input* industries by i. For each industry pair, the I-O tables report the dollar value of i used directly as an input in the production of \$1 of j, also known as the direct requirements coefficient, dr_{ij}; denote with D the square matrix that has dr_{ij} as its (i, j)th entry. In practice, each input i not only can be used directly but could also enter further upstream, that is, more than one stage prior to the actual production of j. The total dollar value of i used either directly or indirectly to produce \$1 of j is the total requirements coefficient, tr_{ij}. As is well known, tr_{ij} is given by the (i, j)th entry of $[I - D]^{-1}D$, where I is the identity matrix and $[I - D]^{-1}$ is the Leontief inverse matrix.

In our baseline analysis, we designate the primary SIC code reported in WorldBase for each parent p as its output industry j. We first use the I-O tables to deduce the set of four-digit SIC inputs $S(j)$—including both manufacturing and nonmanufacturing inputs—that are used either directly or indirectly in the production of j, namely, $S(j) = \{i : tr_{ij} > 0\}$. We identify which inputs are integrated and which are outsourced as follows. Define $I(p) \subseteq S(j)$ to be the set of integrated inputs of parent p. The elements of $I(p)$ are the primary and secondary SIC codes of p and all its subsidiaries (if any) as reported in WorldBase, these being inputs that the parent can in principle obtain within its ownership boundaries. We then define the complement set, $NI(p) = S(j) \setminus I(p)$, to be the set of nonintegrated SICs for parent p, these being the inputs required in the production of j that have not been identified as integrated in $I(p)$. Note that with this construction, the primary SIC activity j of the parent is automatically classified as an element of $I(p)$, so we will later explore the robustness of our results to dropping this "self-SIC" code. (We will also consider several alternative treatments of what constitutes the output industry j for those parent firms that feature multiple manufacturing SIC codes.)

To implement the above, we turn to the 1992 US Benchmark I-O Tables from the Bureau of Economic Analysis (BEA). The US tables are one of the few publicly available I-O accounts that provide a level of industry detail close to the four-digit SIC codes used in WorldBase, while the 1992 vintage is the most recent year for which the BEA provides a concordance from its I-O industry classification to the 1987 SIC system.[20] Readers familiar with these tables will be aware that the concordance is not a one-to-one key. This is not a major problem given our focus on parents whose primary output j is in manufacturing, as the key assigns a unique six-digit I-O industry to each four-digit SIC code between 2000 and 3999. Outside these sectors, in those inputs i whose six-digit I-O industry code maps to multiple four-digit SIC codes, we split the total requirements value tr_{ij} equally across the multiple SIC codes that i maps to.

Panel A of table A-1 in the appendix shows that the mean tr_{ij} value associated with the inputs integrated by firms in WorldBase is 0.019241 (or 0.006774 when the I-O diagonal entries are dropped); this is larger than the average tr_{ij} value across the 416,349 (i, j) pairs in the I-O tables that are relevant to our study (0.001311). In other words, firms tend to integrate stages that are more important in terms of total requirements usage.[21] Moreover, 98.0 percent of the (i, j) pairs in our WorldBase sample, namely, inputs i that are integrated by a parent firm with output indus-

[20] This concordance is available from http://www.bea.gov/industry/exe/ndn0017.exe.

[21] In the 1992 US I-O tables, there are 416,349 I-O pairs that are relevant to our study, namely, that involve a SIC manufacturing output j and a SIC input i (in either manufacturing or nonmanufacturing), with $tr_{ij} > 0$. Of these, 57,057 or 13.7 percent can be found in our sample of integrated input by parent primary industry pairs. The share is very similar if the input-output pairs along the diagonal are excluded from consideration (13.6 percent = 56,612/415,904).

try j, are relevant for production in the sense that $tr_{ij} > 0$.[22] As mentioned before, firms tend to integrate very few of the inputs necessary to produce their final good. The median number of integrated stages is two, compared to a median number of nonintegrated stages equal to 906. There is considerable skewness, as the corresponding 90th, 95th, and 99th percentiles of the number of integrated stages are three, four, and six, while the maximum number is 254.[23] As discussed below, however, integrated inputs tend to be "bunched" together along the value chain, consistent with our model.

2. Upstreamness

We make further use of the information on production linkages contained in I-O tables, to obtain a measure of the upstreamness of an input i in the production of output j. To capture this, we build on the methodology in Antràs et al. (2012) and Fally (2012) and define

$$\text{Upstreamness}_{ij} = \frac{dr_{ij} + 2\sum_{k=1}^{N} dr_{ik}dr_{kj} + 3\sum_{k=1}^{N}\sum_{l=1}^{N} dr_{ik}dr_{kl}dr_{lj} + \cdots}{dr_{ij} + \sum_{k=1}^{N} dr_{ik}dr_{kj} + \sum_{k=1}^{N}\sum_{l=1}^{N} dr_{ik}dr_{kl}dr_{lj} + \cdots}. \quad (13)$$

Observe that dr_{ij} is the value of i that enters exactly one stage prior to the production of j, that $\sum_{k=1}^{N} dr_{ik}dr_{kj}$ is the value of i that enters two stages prior to production of j, and so on and so forth. The denominator in (13) is therefore equal to tr_{ij}, written as an infinite sum over the value of i's use that enters exactly n stages removed from the production of j (where $n = 1, 2, \ldots, \infty$). The numerator is similarly an infinite sum, but there each input use term is multiplied by an integer equal to the number of stages upstream at which the input value enters the production process. Looking then at (13), Upstreamness_{ij} is a weighted average of how many stages removed from j the use of i is, where the weights correspond to the share of tr_{ij} that enters at that corresponding upstream stage. In particular, a larger Upstreamness_{ij} means that a greater share of the total input use value of i is accrued further upstream in the production process for j.

Note that $\text{Upstreamness}_{ij} \geq 1$ by construction, with equality if and only if $tr_{ij} = dr_{ij}$, namely, when the entirety of the input use of i goes directly into the production of j via one stage. With some matrix algebra, one can

[22] Of these pairs, 85.6 percent actually exceed the median tr_{ij} value of 0.000163 (where this median is taken over the same 416,349 I-O pairs from n. 21). We obtain similarly high relevance rates when restricting the count to manufacturing inputs only or if we drop the self-SIC of the parent firm (i.e., pairs in which $i = j$).

[23] The median number of integrated inputs is very similar when computed industry by industry, varying between one and three. On the other hand, the maximum number of integrated inputs exhibits more variation across industries, ranging from three to 254 (with a median value of 26).

see that the numerator of (13) is equal to the (i, j)th entry of $[I - D]^{-2}D$. Together with the formula for tr_{ij} noted earlier (i.e., the (i, j)th entry of $[I - D]^{-1}D$), one can then calculate Upstreamness$_{ij}$ when provided with the direct requirements matrix. We should stress the distinction between Upstreamness$_{ij}$ and the measure put forward in Antràs et al. (2012) and Fally (2012). The measure in this earlier work captured the average production line position of each industry i with respect to final demand (i.e., consumption and investment), whereas our current Upstreamness$_{ij}$ instead reflects the position of input i with respect to output industry j and is therefore a measure of production staging specific to each input-output industry pair.[24]

We use the direct requirements matrix derived from the 1992 US I-O tables to calculate Upstreamness$_{ij}$.[25] We first obtain Upstreamness$_{ij}$ for each six-digit I-O industry pair, before mapping these to four-digit SIC codes. As mentioned earlier, each four-digit manufacturing SIC code is mapped to a single six-digit I-O code; this means that we can uniquely assign an Upstreamness$_{ij}$ value to SIC code pairs in which both the input i and output j are in manufacturing. The complications arise only when we have a nonmanufacturing input i that maps to multiple six-digit I-O codes. For such cases, we take a simple mean of Upstreamness$_{ij}$ over the constituent I-O codes of the SIC input industry.[26] To be clear, what this yields is a measure of the average number of production stages based on the I-O classification system that are traversed between a given pair of SIC industries. Panel B of table A-1 in the appendix presents some basic information on Upstreamness$_{ij}$ after the mapping to SIC codes. There, we also illustrate in figure A-1 the rich variation in this measure, using one particular input industry, tires and inner tubes (SIC 3011).

As noted before, firms tend to integrate few inputs. This is a key feature of the data that our model can accommodate, as explained in the discussion on "sparse integration" in Section II.B.3. Our upstreamness measure allows us to examine the extent to which—though sparse—integrated inputs nevertheless tend to be "bunched" together, consistent

[24] The Upstreamness$_{ij}$ measure also has the interpretation of an "average propagation length," this being a concept introduced in Dietzenbacher, Luna, and Bosma (2005) to capture the average number of stages taken by a shock in i to spread to industry j. Dietzenbacher et al. show that this average propagation length has the appealing property that it is invariant to whether one adopts a forward or backward linkage perspective when computing the average number of stages between a pair of industries.

[25] We apply an open-economy and net-inventories correction to the direct requirements matrix D before calculating tr_{ij} and Upstreamness$_{ij}$. This involves a simple adjustment to each dr_{ij} to take into account input flows across borders, as well as into and out of inventories, on the assumption that these flows occur in proportion to what is observed in domestic input-output transactions; see Antràs et al. (2012) for details.

[26] We have obtained very similar results under alternative approaches, including using the median value, taking a random pick, or using the tr_{ij}-weighted average value.

with the environment described in this earlier extension on sparse integration. To do so, we focus on firms that report at least two secondary manufacturing SIC codes (on top of their primary output industry j). Table A-3 in the appendix computes the probability that a pair of randomly drawn integrated manufacturing SICs of a given firm would belong to any two quintiles of Upstreamness_{ij}, where the quintiles are taken over all SIC manufacturing inputs i in the value chain for producing j; the reported probability is an average across all firms under consideration. From table A-3, one can see that firms are clearly more likely to integrate inputs in the first quintile of upstreamness than in the other quintiles. Leaving aside this first quintile, note that the probability that a firm integrates an input is significantly higher when it already owns an input in the same quintile, and furthermore, these probabilities fall for quintiles that are further apart. These patterns are suggestive of the existence of bunching along the value chain in the integration decisions of firms.

3. Ratio-Upstreamness

To test whether the variation across parent firms in integration decisions is consistent with our theory, we first explore specifications with a dependent variable that summarizes the extent to which a firm's integrated inputs tend to be more upstream compared to its nonintegrated inputs. For this purpose, we construct the following measure for each parent:

$$\text{Ratio-Upstreamness}_{jp} = \frac{\sum_{i\in I(p)} \theta^{I}_{ijp}\text{Upstreamness}_{ij}}{\sum_{i\in NI(p)} \theta^{NI}_{ijp}\text{Upstreamness}_{ij}}, \tag{14}$$

where $\theta^{I}_{ijp} = tr_{ij}/\Sigma_{i\in I(p)} tr_{ij}$ and $\theta^{NI}_{ijp} = tr_{ij}/\Sigma_{i\in NI(p)} tr_{ij}$. This takes the ratio of a weighted-average upstreamness of p's integrated inputs relative to that of its nonintegrated inputs; the weights are proportional to the total requirements coefficients to capture the relative importance of each input in the production of j. $\text{Ratio-Upstreamness}_{jp}$ is thus larger, the greater the propensity of p to integrate relatively upstream inputs, while outsourcing more downstream inputs.

We will consider several alternative constructions of $\text{Ratio-Upstreamness}_{jp}$ to assess the robustness of our results. These include (i) restricting $S(j)$ to the set of "ever-integrated" inputs, namely, inputs i for which we actually observe at least one parent in industry j that integrates i within its boundaries; (ii) restricting $S(j)$ to the set of manufacturing inputs; and (iii) excluding the self-SIC from $S(j)$. The first alternative measure of $\text{Ratio-Upstreamness}_{jp}$ is of particular importance. The restriction to the set of ever-integrated inputs is a plausible criterion for removing input-output industry pairs for which the fixed costs of integration are prohibitively high. By constructing $\text{Ratio-Upstreamness}_{jp}$ using only the subset of inputs for which integration is seen in our data set to be feasible, we are able to test more closely the predictions of the model that arise in the empirically relevant case in which integrated inputs are sparse (i.e., proposition 4). Panel C of table A-1 in the appendix presents summary statistics for the different ratio-upstreamness measures.

Our first set of regression specifications will use Ratio-Upstreamness$_{jp}$ as the dependent variable and thus seek to exploit the variation across firms in this measure. Our theory has predictions at the input level as well, so we will also present evidence based on variation within firms in integration decisions across inputs. For this second set of specifications, we adopt as the dependent variable a 0-1 indicator for whether the input in question is integrated within the parent's ownership structure, that is, whether $i \in I(p)$. In both the cross- and within-firm exercises, we will present evidence based on a broad set of inputs used in production by the firms, as well as when restricting to the subset of ever-integrated inputs to account for the sparsity of integrated stages.

Our data set does not allow us to directly observe whether plants that are related in an ownership sense actually contribute inputs and components to a common production process. It is important to stress that any potential misclassification of integrated versus nonintegrated inputs (in the sets $I(p)$ and $NI(p)$) would give rise to measurement error in the dependent variable in our regressions. To the extent that this is classical measurement error, it would make our coefficient estimates less precise, making it harder to find empirical support for the model's predictions.

4. Demand Elasticity

As highlighted in our theory, the incentives to integrate upstream or downstream suppliers are crucially affected by whether the elasticity of demand faced by the firm (ρ_j) is higher or lower than the elasticity of technological substitution across its inputs (α_j). For practical reasons, we focus on variation in the former in most of the regressions, since detailed estimates of demand elasticities are available from standard sources. To capture ρ_j, we use the US import demand elasticities from Broda and Weinstein (2006). The original estimates are for Harmonized System (HS10) products, and we average these up to the SIC industry level using US import trade values as weights (see Sec. A-2 of the appendix for further details). Since the HS10 codes are highly disaggregated, this should in principle provide a good proxy for ρ_j in the model, short of having actual firm-level elasticities. We will also pursue several refinements of ρ_j by using only elasticities for those HS10 codes deemed as consumption and capital goods in the United Nations' Classification by Broad Economic Categories (BEC). (The omitted category is goods classified as intermediates.) As the model arguably applies better to final goods, a demand elasticity constructed on the basis of such products should yield a cleaner proxy for ρ_j. Note that when refining the construction in this manner, about half of the 459 SIC manufacturing industries are dropped, namely, those industries composed entirely of intermediate goods.

The UN BEC classification also provides a basis for constructing a proxy for α_j. From the model, α_j is closely related to the elasticity of demand for each intermediate input by firms in industry j. We therefore begin by computing the average demand elasticity for each four-digit SIC code using now only those HS10 elasticities that correspond to products classified as intermediates, in an analogous fashion to the construction of the ρ_j refinements above. We construct our proxy for α_j as the weighted average of the intermediate-good demand elasticities across inputs i used in j's production, with weights proportional to the total requirements coefficients, tr_{ij}.

In principle, the value of $\rho_j - \alpha_j$ could then be used to distinguish whether a given industry j falls in the complements or substitutes case. Nevertheless, since our proxies of ρ_j and especially α_j are imperfect, in our baseline regressions we will associate the sequential complements case with high values of ρ_j and the substitutes case with low values of ρ_j. This approach is valid insofar as the demand elasticity and input substitutability parameters are relatively uncorrelated across industries.[27] For corroboration, we will also report specifications in which the complements and substitutes cases are related to the size of the difference $\rho_j - \alpha_j$.

5. Input Contractibility

The model further predicts that patterns of integration will depend on the extent to which contractible inputs tend to be "front-loaded" or located in the early stages of the production process. We therefore construct the variable Upstream-Contractibility$_j$, which reflects the tendency for high-contractibility inputs to enter the production of output j at relatively upstream stages, for use in the cross-firm regressions.

We follow Nunn (2007) in first constructing a measure of input contractibility for each SIC industry. The basis for this measure is the Rauch (1999) classification of products into whether they are (i) homogeneous, (ii) reference-priced, or (iii) differentiated in nature. The "contract intensity" of an industry is then the share of the constituent HS product codes in the composition of the industry's input use that is classified as differentiated (i.e., neither homogeneous nor reference-priced), on the

[27] Indeed, the pairwise correlation between the constructed proxy for α_j and the measures of ρ_j (both the baseline measure and its refinements) is low, ranging between $-.026$ and .083. As reported in table A-2 in the appendix, our proxies for α_j are on average higher than those for ρ_j.

premise that it is inherently more difficult to specify and enforce the terms of contractual agreements for such products. As our interest is in the converse concept of contractibility, we use instead one minus the Nunn measure of contract intensity.[28] Denote this metric of input contractibility for industry i by cont_i. Then, for each output industry j, we calculate Upstream-Contractibility$_j$ as a weighted covariance between the upstreamness of its manufacturing inputs (defined in eq. [13] and abbreviated here with upst_{ij}) and the contractibility of these inputs (cont_i):

$$\text{Upstream-Contractibility}_j = \sum_{i \in S^m(j)} \theta_{ij}^m (\text{upst}_{ij} - \overline{\text{upst}}_{ij})(\text{cont}_i - \overline{\text{cont}}_i), \quad (15)$$

where $S^m(j)$ is the set of all manufacturing inputs used in the production of j (i.e., with $tr_{ij} > 0$). The weights are given by $\theta_{ij}^m = tr_{ij} / \sum_{k \in S^m(j)} tr_{kj}$, while $\overline{\text{upst}}_{ij} = \sum_{i \in S^m(j)} \theta_{ij}^m \text{upst}_{ij}$ and $\overline{\text{cont}}_i = \sum_{i \in S^m(j)} \theta_{ij}^m \text{cont}_i$ are total requirements weighted averages of the upstreamness and contractibility variables, respectively. Therefore, if high-contractibility inputs tend to be located at earlier production stages, this will lead to a larger (more positive) covariance and hence a higher Upstream-Contractibility$_j$.[29]

In the within-firm regressions, we can perform a more detailed test of the role of contractibility in explaining the propensity to integrate particular inputs. Motivated by the theory, we construct the variable Contractibility-up-to-i_{ij}, which is an input-output industry pair–specific measure of the contractibility up to input i in the production of j. This is computed as

$$\text{Contractibility-up-to-}i_{ij} = \frac{\sum_{k \in S_i^m(j)} tr_{kj} \text{cont}_k}{\sum_{k \in S^m(j)} tr_{kj} \text{cont}_k}, \quad (16)$$

where the relevant set of inputs, $S_i^m(j)$, for the sum in the numerator is those manufacturing inputs that are located upstream of and including i itself in the production of j, that is, $S_i^m(j) = \{k \in S^m(j) : \text{Upstreamness}_{kj} \geq \text{Upstreamness}_{ij}\}$. The denominator thus sums up the product of the total requirements and contractibility values across all manufacturing inputs used in the production of j, with the numerator being the partial sum excluding all inputs downstream of i. The construction of (16) is intended to approximate the $\int_0^i [\psi(k)]^{\alpha/(1-\alpha)} dk / \int_0^1 [\psi(k)]^{\alpha/(1-\alpha)} dk$ term, which appears

[28] In Nunn's (2007) notation, the measure of input contractibility that we use is equal to $1 - z^{rs1}$. The results reported are based on the "conservative" Rauch (1999) classification but are robust when using the alternative "liberal" classification instead.

[29] We have obtained similar results when experimenting with alternative measures of Upstream-Contractibility$_j$ that take a ratio of the tr_{ij}-weighted upstreamness of inputs classified as being of high contractibility relative to those classified as low contractibility, in a manner analogous to the construction of the ratio-upstreamness measure in (14). To distinguish high- versus low-contractibility inputs, we have adopted either the first-tercile, median, or second-tercile values of cont_i across the 459 SIC manufacturing industries as cutoffs (results available on request).

in equation (10) in the theory. There, it was shown that "contractibility up to i" plays a central role in the expression for the optimal β^* and, hence, the propensity toward integration of each input.

IV. Empirical Methodology and Results

We next translate the key results of our model into a series of empirical predictions that can be taken to the data. According to proposition 1, integration patterns along the value chain should vary systematically for industries that fall under the sequential complements versus substitutes cases. Our approach to distinguish between these two cases focuses on variation in ρ_j (or, alternatively, $\rho_j - \alpha_j$). However, the limitations inherent in how ρ_j and α_j are constructed mean that we cannot use them to precisely delineate where the cutoff between the two cases lies.[30] Consequently, what we test is a weaker version of proposition 1 that examines whether the propensity to integrate upstream stages falls as ρ_j (alternatively, $\rho_j - \alpha_j$) increases, and we more confidently move toward the complements case. We thus formulate the first cross-firm prediction of our model as follows:

P.1 (Cross). A firm's propensity to integrate upstream (as opposed to downstream) inputs should fall with ρ_j (alternatively, $\rho_j - \alpha_j$), where j is the final-good industry of the firm.

Our data also allow us to explore integration decisions made across different inputs at the firm level, through specifications in which the unit of observation is a parent firm by input SIC pair. In this within-firm setting, we can restate the first prediction as follows:

P.1 (Within). The upstreamness of an input should have a more negative effect on the propensity of a firm to integrate that input, the larger is ρ_j (alternatively, $\rho_j - \alpha_j$).

The first extension of the model developed in Section II.B.1 provides us with further predictions that emerge from considering heterogeneity in the contractibility of inputs. In particular, proposition 2 suggests that the relative propensity to integrate upstream inputs depends on the extent to which contractible inputs tend to be located in the early stages of production. Moreover, the effect of upstream contractibility varies subtly across the sequential complements and substitutes cases. The second cross-firm prediction of our model, and the corresponding prediction at the firm-input pair level, can thus be summarized as follows:

P.2 (Cross). A greater degree of contractibility of upstream inputs should decrease a firm's propensity to integrate upstream (as opposed

[30] The theory would suggest running separate regressions for industries in which $\rho_j < \alpha_j$ vs. $\rho_j > \alpha_j$. However, given the limitations of our proxies for ρ_j and α_j, we will use the quintiles of $\rho_j - \alpha_j$ to distinguish empirically between the complements and substitutes cases. We report some within-firm results based on whether $\rho_j > \alpha_j$ or $\rho_j < \alpha_j$ in Sec. A-3 of the appendix.

to downstream) inputs when the firm is in a final-good industry with low ρ_j (alternatively, $\rho_j - \alpha_j$). Conversely, it should increase that propensity when the firm is in a final-good industry with a high ρ_j (alternatively, $\rho_j - \alpha_j$).

P.2 (Within). The degree of contractibility of inputs upstream of a given input (relative to the inputs downstream of it) should have a more positive effect on the propensity of a firm to integrate that input, the larger is ρ_j (alternatively, $\rho_j - \alpha_j$).

From the second extension of the model developed in Section II.B.2, we can derive predictions concerning the role of the productivity of final-good producers. The results in proposition 3 can be stated in testable form as follows:

P.3. More productive firms should integrate more inputs, irrespective of ρ_j (or $\rho_j - \alpha_j$). Relative to less productive firms, they should have a higher propensity to integrate downstream (relative to upstream inputs) when ρ_j (alternatively, $\rho_j - \alpha_j$) is low and a higher propensity to integrate upstream (relative to downstream inputs) when ρ_j (alternatively, $\rho_j - \alpha_j$) is high.

A. *Cross-Firm Results*

We first exploit variation in integration choices across firms to assess the validity of our model's predictions. To examine prediction P.1 (Cross), we estimate the following regression:

$$\log \text{Ratio-Upstreamness}_{jpc} = \beta_0 + \sum_{n=2}^{5} \beta_n \mathbf{1}(\rho_j \in \text{Quint}_n(\rho)) + \beta_X X_j + \beta_W W_p + D_c + \epsilon_{jpc}. \tag{17}$$

The dependent variable is the log ratio-upstreamness measure, defined in equation (14), which captures the propensity of each parent p with primary SIC industry j to integrate relatively upstream inputs. The subscript c is introduced to index the country where the parent is located, as we will include a full set of country fixed effects, D_c, among the controls. We report standard errors clustered at the level of the SIC output industry j.

The key regressors of interest are the $\mathbf{1}(\rho_j \in \text{Quint}_n(\rho))$ terms, these being indicator variables for whether the demand elasticity for industry j belongs in the nth quintile of that variable; the first quintile is the omitted category. Prediction P.1 (Cross) suggests that β_n should be negative for higher n: As we transition to industries that feature a higher demand elasticity and thus are more likely to fall under the complements case, the propensity to integrate upstream relative to downstream inputs should fall. The use of the quintile dummies allows us to estimate a relatively flexible relationship between our proxy for ρ_j and the ratio-upstreamness dependent variable. In the appendix, we have verified that our findings hold strongly when using a simpler median cutoff specification to distinguish between the complements and substitutes cases (see table A-5).

We include a list of auxiliary industry and firm controls in the above specification. The vector X_j includes measures of factor intensity, R&D intensity, and a value-added to shipments ratio (see Sec. A-2 of the appendix for a more detailed description, as well as table A-2 in that same appendix for basic summary statistics). The vector W_p contains parent firm characteristics obtained from WorldBase. This includes several variables that reflect the size of the parent, namely, the number of establishments, whether it is a multinational, as well as log total employment and log total sales.[31] We also account for the age of the parent by including the year of its establishment (or in which current ownership took control).

Table 1 reports the results of estimating (17). Column 1 presents a basic specification in which only the elasticity quintile dummies (excluding the first quintile) and parent country fixed effects are included; to this, column 2 adds the industry controls in X_j, and column 3 adds the firm controls in W_p. A clear pattern emerges particularly from column 2 onward: the estimated coefficients on each of the quintile dummies are negative, with the magnitude of these coefficients increasing steadily as we move from the second to the fifth elasticity quintile. The negative effect is moreover significant at the 1 percent level for the highest-elasticity quintiles, consistent with prediction P.1 (Cross), confirming that the propensity to integrate upstream stages is lower in industries that correspond more closely to the complements case. Concerning the auxiliary controls, the estimates indicate that there is a tendency toward upstream integration in more equipment capital-intensive industries, as well as in firms with more establishments, younger firms, and multinationals.

The remaining columns in table 1 explore alternative elasticity measures to capture industries in the complements case. Column 4 restricts the construction of ρ_j to the use of product-level elasticities classified by the UN BEC as either consumption or capital goods (dropping the intermediate-use products), while column 5 further limits this to just consumption goods elasticities; these in principle yield elasticities that pertain more directly to final-goods demand. Reassuringly, this does not change the key finding of a negative and highly significant coefficient for the high-elasticity quintiles, even though the SIC industries that are composed entirely of intermediate-use goods are dropped from the sample. Finally, column 6 brings in information related to the demand elasticity for intermediate inputs, through the proxy for α_j. The key right-hand-side variables are now dummies for

[31] For employment and sales, we also include dummy variables for whether the respective variables were based on actual data or were otherwise estimated/approximated by WorldBase.

the quintiles of $\rho_j - \alpha_j$, where ρ_j is the demand elasticity from column 5 based on consumption goods only and the construction of α_j was described earlier (in Sec. III). We continue to find that the propensity to integrate upstream stages is lower for industries that more likely correspond to the complements case on the basis of $\rho_j - \alpha_j$. Note that the implied magnitudes of these effects are fairly sizable: looking at columns 5 and 6, the fifth-quintile point estimates of −0.1849 and −0.1026 correspond to a range of between a half and a full standard deviation decrease (relative to the first quintile) in the propensity to integrate upstream inputs. For an illustration of these patterns of integration along the value chain based on examples of firms from our sample, please see figures A-2 and A-3 in Section A-3 of the appendix.

We turn next to assess the validity of prediction P.2 (Cross). For this, we augment the specifications in (17) in order to uncover the effects of upstream contractibility on integration:

$$\log \text{Ratio-Upstreamness}_{jpc} =$$

$$\beta_0 + \sum_{n=1}^{5} \beta_{Un} \mathbf{1}(\rho_j \in \text{Quint}_n(\rho)) \times \text{Upstream-Contractibility}_j \tag{18}$$

$$+ \sum_{n=2}^{5} \beta_n \mathbf{1}(\rho_j \in \text{Quint}_n(\rho)) + \beta_X X_j + \beta_W W_p + D_c + \epsilon_{jpc}.$$

Relative to (17), we now further interact each of the quintile dummies with Upstream-Contractibility$_j$; on the basis of prediction P.2 (Cross), we would expect $\beta_{U1} < 0$ and $\beta_{U5} > 0$ in this regression.

The results from estimating (18) are reported in table 2. The main effects of the quintile elasticity dummies exhibit a pattern similar to that in the more parsimonious regressions in table 1, with negative and significant coefficients especially as we transition to the higher quintiles.[32] Of note, we find that in the complements case, a higher degree of upstream contractibility does counteract the above tendency to outsource upstream inputs, as the coefficient on the fifth elasticity quintile interacted with Upstream-Contractibility$_j$ is positive and statistically significant (at the 1 percent level) across all columns. Conversely, the interaction between the first elasticity quintile dummy and Upstream-Contractibility$_j$ bears the opposite sign, indicating that upstream contractibility instead

[32] We perform a test for whether the effect of being in the fifth quintile, evaluated at the median in-sample value of Upstream-Contractibility$_j$ in that fifth demand elasticity quintile, is in fact significantly different from zero. The p-values reported in each column confirm that this is indeed the case, so that the propensity to integrate upstream inputs is lower in the fifth relative to the first elasticity quintile; this holds true regardless of the variant of the elasticity proxy used across the columns. The role of upstream contractibility is also confirmed when using a median cutoff specification to distinguish between the complements and substitutes cases (see table A-6 in the appendix).

TABLE 1
UPSTREAMNESS OF INTEGRATED VERSUS NONINTEGRATED INPUTS

	Dependent Variable: Log Ratio-Upstreamness$_{jpc}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Ind.(Quintile 2 Elas$_j$)	−.0209	−.0290	−.0278	−.0590	−.0802*	.0634
	[.0345]	[.0319]	[.0314]	[.0447]	[.0474]	[.0550]
Ind.(Quintile 3 Elas$_j$)	−.0742**	−.0802**	−.0782**	−.0569	−.0982**	−.0379*
	[.0336]	[.0316]	[.0309]	[.0454]	[.0429]	[.0224]
Ind.(Quintile 4 Elas$_j$)	−.0480	−.0893***	−.0881***	−.1068**	−.1685***	−.0942***
	[.0365]	[.0337]	[.0331]	[.0459]	[.0457]	[.0259]
Ind.(Quintile 5 Elas$_j$)	−.0588	−.0955***	−.0947***	−.1156***	−.1849***	−.1026***
	[.0377]	[.0325]	[.0318]	[.0420]	[.0459]	[.0317]
Log (Skilled Emp./Workers)$_j$		.0080	.0069	.0073	−.0290	−.0215
		[.0238]	[.0239]	[.0290]	[.0379]	[.0386]
Log (Equip. Capital/Workers)$_j$		.1127***	.1112***	.0731***	.0768***	.0949***
		[.0195]	[.0192]	[.0183]	[.0205]	[.0257]
Log (Plant Capital/Workers)$_j$		−.0331	−.0325	−.0087	−.0240	−.0316
		[.0210]	[.0207]	[.0228]	[.0276]	[.0290]
Log (Materials/Workers)$_j$		−.0311	−.0322	−.0397*	−.0099	−.0190
		[.0222]	[.0222]	[.0237]	[.0290]	[.0317]
R&D Intensity$_j$		.0053	.0044	.0113	.0048	.0017
		[.0058]	[.0057]	[.0070]	[.0086]	[.0103]
(Value-Added/Shipments)$_j$		−.1270	−.1356	−.0840	.1725	.1453
		[.1295]	[.1301]	[.1323]	[.1699]	[.1665]

	(1)	(2)	(3)	(4)	(5)	(6)
Log (No. of Establishments)$_p$			.0570***	.0612***	.0661***	.0640***
			[.0031]	[.0037]	[.0047]	[.0052]
Year Started$_p$			.0001	.0001*	.0002**	.0003***
			[.0001]	[.0001]	[.0001]	[.0001]
Multinational$_p$			.0105**	.0125**	.0192**	.0304***
			[.0048]	[.0060]	[.0079]	[.0085]
Log (Total Employment)$_p$			−.0003	.0004	.0005	−.0005
			[.0016]	[.0017]	[.0019]	[.0019]
Log (Total USD Sales)$_p$			.0003	−.0004	−.0003	−.0001
			[.0008]	[.0009]	[.0011]	[.0012]
Elasticity based on	All goods	All goods	All goods	BEC cons. & cap. goods	BEC cons. goods	BEC cons. & α proxy
Parent country dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	316,977	316,977	286,072	206,490	144,107	144,107
No. of industries	459	459	459	305	219	219
R^2	.0449	.1504	.1580	.1770	.2333	.2268

NOTE.—The sample comprises all firms with primary SIC in manufacturing and at least 20 employees in the 2004/5 vintage of D&B WorldBase. The dependent variable is the log ratio-upstreamness measure described in Sec. III. Quintile dummies are used to distinguish firms with primary SIC output that are in high- vs. low-demand elasticity industries. Cols. 1–3 use a measure based on all available HS10 elasticities from Broda and Weinstein (2006); col. 4 restricts this construction to HS codes classified as consumption or capital goods in the UN BEC; col. 5 further restricts this to consumption goods; col. 6 uses the consumption-goods-only demand elasticity minus a proxy for α to distinguish between the complements and substitutes cases. All columns include parent country fixed effects. Cols. 3–6 also include indicator variables for whether the reported employment and sales data, respectively, are estimated/missing/from the low end of a range, as opposed to being from actual data (coefficients not reported). Standard errors are clustered by parent primary SIC industry.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

TABLE 2
Effect of Upstream Contractibility

	Dependent Variable: Log Ratio-Upstreamness$_{jpc}$			
	(1)	(2)	(3)	(4)
Ind.(Quintile 2 Elas$_j$)	−.0350	−.0611	−.0490	.0763**
	[.0300]	[.0396]	[.0429]	[.0323]
Ind.(Quintile 3 Elas$_j$)	−.1104***	−.0566	−.0683**	−.0476**
	[.0288]	[.0405]	[.0328]	[.0223]
Ind.(Quintile 4 Elas$_j$)	−.1207***	−.1605***	−.1611***	−.1185***
	[.0304]	[.0292]	[.0277]	[.0236]
Ind.(Quintile 5 Elas$_j$)	−.1409***	−.1760***	−.1643***	−.1108***
	[.0297]	[.0306]	[.0292]	[.0260]
Upstream-Contractibility$_j$				
× Ind.(Quintile 1 Elas$_j$)	−1.5540***	−1.5492***	−1.8562***	−.8114
	[.4934]	[.4177]	[.4446]	[.5369]
× Ind.(Quintile 2 Elas$_j$)	−.9810***	−.5723	−.6886	−2.0195***
	[.3165]	[.5973]	[.7621]	[.6896]
× Ind.(Quintile 3 Elas$_j$)	.3271	−.3234	−.4171	.1796
	[.2408]	[.3742]	[.3855]	[.1727]
× Ind.(Quintile 4 Elas$_j$)	.3849	1.0662***	.6855***	.9811***
	[.2867]	[.2319]	[.2106]	[.2565]
× Ind.(Quintile 5 Elas$_j$)	.7106***	1.0530***	1.1171***	1.0419***
	[.2148]	[.2149]	[.2273]	[.2275]
p-value: Q5 at median Upst.-Cont.$_j$	[.0002]	[.0001]	[.0000]	[.0000]
Elasticity based on	All goods	BEC cons. & cap. goods	BEC cons. goods	BEC cons. & α proxy
Industry controls	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes
Parent country dummies	Yes	Yes	Yes	Yes
Observations	286,072	206,490	144,107	144,107
No. of industries	459	305	219	219
R^2	.2204	.2792	.3064	.3191

Note.—The sample comprises all firms with primary SIC in manufacturing and at least 20 employees in the 2004/5 vintage of D&B WorldBase. The dependent variable is the log ratio-upstreamness measure described in Sec. III. Upstream-Contractibility$_j$ is the total requirements weighted covariance between the contractibility and upstreamness of the manufacturing inputs used to produce good *j*. Quintile dummies are used to distinguish firms with primary SIC output in high- vs. low-demand elasticity industries. Col. 1 uses a measure based on all available HS10 elasticities from Broda and Weinstein (2006); col. 2 restricts this construction to HS codes classified as consumption or capital goods in the UN BEC; col. 3 further restricts this to consumption goods; col. 4 uses the consumption-goods-only demand elasticity minus a proxy for α to distinguish between the complements and substitutes cases. All columns include the full list of SIC output industry controls, firm-level variables, and parent country dummies used in the specifications in table 1, cols. 3–6. Standard errors are clustered by parent primary SIC industry.

* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

acts to raise the propensity to integrate downstream inputs in this latter case. This last pattern appears most strongly in columns 1–3, where a demand elasticity associated with the output industry ρ_j is used to separate the complements from the substitutes cases. In column 4, where $\rho_j - \alpha_j$

is used instead, the largest negative effect appears to be concentrated in the second elasticity quintile. The overall message we obtain is nevertheless in line with prediction P.2 (Cross), which relates integration decisions to the sequencing of high- versus low-contractibility inputs.

As discussed earlier, a key feature of the data is that integration is sparse. Proposition 4 shows that this does not affect the qualitative predictions of our model, if we limit attention to the subset of inputs over which integration is feasible. This suggests that a sharper test of our theory would seek to drop inputs for which integration is prohibitively costly. In table A-7 in Section A-3 of the appendix, we implement one such test by constructing the ratio-upstreamness measure on the set of ever-integrated inputs only (as previously defined in Sec. III) and rerunning the specifications from table 2. Once again, the patterns line up with our model's predictions: regardless of the elasticity proxy used, the propensity to integrate upstream stages is lower for firms in higher-elasticity quintiles, but this effect is moderated in industries in which production features a greater degree of Upstream-Contractibility$_j$.

We have subjected the cross-firm regressions to an extensive series of robustness checks. Because of space constraints, we refer the reader to tables A-8–A-12 in the appendix, which elaborate on these checks.

We next move to test prediction P.3 of our model concerning the role of heterogeneity in firm productivity. For this purpose, we are limited to using a simple measure of log sales per worker, computed using total sales and employment across all establishments of the parent, to proxy for the firm-level parameter θ in the model, as WorldBase contains little information on the operations of firms beyond this.[33] Moreover, when available, these variables are often based on estimates rather than on administrative data. To reduce the possible influence of such measurement error, we use a dummy variable, $\mathbf{1}(\theta_p > \theta_{j,\text{med}})$, which identifies highly productive firms as those with log sales per worker above the median value within each output industry j.

According to the first part of prediction P.3, more productive firms should integrate more inputs, in both the complements and substitutes cases. To verify this, we estimate the following:

$$\log\,(\text{No. of Integrated Inputs})_{jpc} =$$

$$\beta_0 + \sum_{n=1}^{5} \beta_n \mathbf{1}(\theta_p > \theta_{j,\text{med}}) \times \mathbf{1}(\rho_j \in \text{Quint}_n(\rho)) \tag{19}$$

$$+\ \beta_W W_p + D_{jc} + \epsilon_{jpc}.$$

[33] Because log sales per worker is a measure of revenue-based productivity, it captures variation in both θ and A. Proposition 3 shows, however, that our comparative statics results hold regardless of whether one varies θ or A.

Note that the appropriate source of variation that we focus on here is that across firms within a given industry, so the above regression is estimated with country-industry fixed effects, D_{jc}.[34]

The results from running (19) are reported in the first two columns of table 3. We use a measure of ρ_j constructed using consumption goods only demand elasticities in column 1, before using the alternative proxy for $\rho_j - \alpha_j$ in column 2. The estimated coefficients of the $\mathbf{1}(\theta_p > \theta_{j,\mathrm{med}}) \times \mathbf{1}(\rho_j \in \mathrm{Quint}_n(\rho))$ interaction terms are almost all positive and significant, confirming that more productive firms tend to integrate more SIC activities, regardless of whether the industry in question falls closer to being in the substitutes or complements case.

According to the second part of prediction P.3, more productive firms should exhibit a higher ratio-upstreamness in the complements case. The underlying intuition is that more productive firms would be able to bear the higher fixed costs of integrating a larger set of stages within firm boundaries and so would engage in integrating some upstream inputs when compared against smaller, less productive firms in the same industry. Conversely, the opposite would hold in the substitutes case, with more productive firms instead featuring a lower ratio-upstreamness. To test for such a pattern in the data, we therefore replace the dependent variable in (19) with log Ratio-Upstreamness$_{jpc}$ and reestimate the regression. The results are reported in columns 3 and 4 of table 3, these being based, respectively, on the ρ_j and $\rho_j - \alpha_j$ proxies used in the first two columns of the same table. The patterns that emerge are entirely in line with prediction P.3: the estimated coefficient of the interaction term between $\mathbf{1}(\theta_p > \theta_{j,\mathrm{med}})$ and the first quintile of ρ_j is negative and significant, while the corresponding coefficient for the fifth quintile of ρ_j is positive and significant. We obtain a very similar set of estimates in columns 5 and 6, where we use the version of the ratio-upstreamness measure that is based on ever-integrated inputs. Thus, more productive firms have a lower (respectively, higher) relative propensity to integrate upstream inputs when the elasticity of demand for their final product is low (respectively, high).[35]

Summing up, the cross-firm regressions provide strong evidence that the propensity for a firm to integrate relatively upstream inputs is weakest when the demand elasticity faced by that industry is largest, in line with prediction P.1 (Cross). Predictions P.2 (Cross) and P.3 concerning the role of upstream contractibility and the productivity of final-good producers also receive strong support.

[34] We can thus include the firm-level variables, W_p, in (19), but not the vector of industry controls, X_j.

[35] The alert reader may wonder why we do not explore triple interactions between the demand elasticity quintiles, the high-productivity dummy, and the upstream contractibility variable. However, as discussed in the proof of proposition 3 in Sec. A-1 of the appendix, it is in general not possible to sign this effect in the theory.

TABLE 3

WITHIN-SECTOR, CROSS-FIRM HETEROGENEITY IN EFFECTS

	Dependent Variable					
	Log (No. of Int. Inputs)$_{jpc}$		Log Ratio-Upstreamness$_{jpc}$			
	All Inputs (1)	All Inputs (2)	All Inputs (3)	All Inputs (4)	Ever-Int. Inputs (5)	Ever-Int. Inputs (6)
Ind.(Log(Sales/Emp)$_p$ > median)						
× Ind.(Quintile 1 Elas$_j$)	.0195***	.0123	−.0026**	−.0023**	−.0029**	−.0023**
	[.0066]	[.0081]	[.0013]	[.0010]	[.0014]	[.0010]
× Ind.(Quintile 2 Elas$_j$)	.0190	.0216***	−.0002	−.0035*	−.0001	−.0036*
	[.0117]	[.0066]	[.0018]	[.0020]	[.0018]	[.0020]
× Ind.(Quintile 3 Elas$_j$)	.0342***	.0373**	.0039	.0064**	.0041	.0065**
	[.0120]	[.0171]	[.0033]	[.0027]	[.0033]	[.0027]
× Ind.(Quintile 4 Elas$_j$)	.0334***	.0286***	.0061***	.0060***	.0061***	.0059***
	[.0095]	[.0092]	[.0014]	[.0014]	[.0014]	[.0014]
× Ind.(Quintile 5 Elas$_j$)	.0212*	.0204*	.0082***	.0078***	.0082***	.0078***
	[.0109]	[.0106]	[.0024]	[.0024]	[.0024]	[.0024]
Elasticity based on	BEC cons.	BEC cons. & α proxy	BEC cons.	BEC cons. & α proxy	BEC cons.	BEC cons. & α proxy
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Parent country-industry dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142,135	142,135	142,135	142,135	142,135	142,135
No. of industries	219	219	219	219	219	219
R^2	.3809	.3809	.7665	.7666	.7631	.7632

NOTE.—The sample comprises all firms with primary SIC in manufacturing and at least 20 employees in the 2004/5 vintage of D&B WorldBase. The dependent variable in cols. 1 and 2 is the log number of four-digit SIC codes integrated by the firm, while that in cols. 3–6 is the log ratio-upstreamness measure described in Sec. III. In cols. 3 and 4, the dependent variable is constructed on the basis of all inputs, while in cols. 5 and 6 it is constructed on the basis of the set of ever-integrated inputs. Quintile dummies are used to distinguish firms with primary SIC output in high- vs. low-demand elasticity industries; cols. 1, 3, and 5 use the elasticity measure based only on HS10 codes classified as consumption goods in the UN BEC, while cols. 2, 4, and 6 use the consumption-goods-only demand elasticity minus the proxy for α to distinguish between the complements and substitutes cases. All columns include parent country by parent primary SIC industry pair dummies and the full list of firm-level variables used in the specifications in table 1, cols. 3–6. Standard errors are clustered by parent primary SIC industry.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

B. *Within-Firm Results*

We next exploit our data in more detail by examining whether the patterns of integration within firms are consistent with our model's predictions. To study within-firm integration decisions, we restructure the data so that an observation is now an input i by parent p pair.

To assess the validity of prediction P.1 (Within), we run the following specification:

$$\text{Integration}_{ijp} = \gamma_0 + \sum_{n=1}^{5} \gamma_n \mathbf{1}(\rho_j \in \text{Quint}_n(\rho)) \times \text{Upstreamness}_{ij} + \gamma_X X_{ij} + D_i + D_p + \epsilon_{ijp}. \tag{20}$$

The dependent variable is a 0-1 indicator for whether the firm p with primary output j has integrated the input i within firm boundaries. The key explanatory variables are the terms involving Upstreamness_{ij} and its interactions with the different quintiles of the elasticity variable. We include a full set of parent fixed effects, D_p, thus focusing on within-firm variation in Integration_{ijp}; these fixed effects also absorb any systematic differences arising from the identity of the output industry or country of incorporation of the parent firm. When examining within-firm integration patterns in this manner, our theory would suggest that $\gamma_1 > 0$ and $\gamma_5 < 0$.

We estimate (20) as a linear probability model, with standard errors clustered by an i-j pair. To avoid including firms for which occurrences of integration are exceedingly rare, we restrict the sample to parent firms that have integrated at least one manufacturing input other than the parent's output industry code. To keep the regressions tractable, we limit the sample to the top 100 manufacturing inputs i used by each industry j as ranked by the total requirements coefficient, tr_{ij}.[36] Among the top 100 inputs, we further retain only those inputs i that are ever-integrated by a parent firm in output j (as defined previously in Sec. A-7 in the appendix). This is done bearing in mind the extension on sparse integration from Section II.B.3: Including in the regression inputs for which integration is not feasible could obscure our ability to test proposition 4 cleanly, particularly in this within-firm, cross-input specification.[37]

The regression in (20) includes a vector X_{ij} to capture other industry pair characteristics that might be correlated with the propensity of a parent firm in industry j to integrate input i. It includes three sets of variables. First, we control for the dummy variable Self-SIC_{ij}, which is equal to one if and only if $i = j$. The dependent variable in (20) always takes

[36] The top 100 manufacturing inputs cover between 88 and 98 percent of the total requirements value of each output industry.

[37] We report broadly similar results in tables A-16 and A-17 in the appendix when using all top 100 inputs.

on a value of one when $i = j$, as $j \in I(j)$ by definition. Including this dummy thus allows us to focus on the effects of Upstreamness$_{ij}$ for manufacturing inputs other than j.[38] Second, we control for the overall importance of input i in the production of j, as reflected in the log of the total requirements coefficient, tr_{ij}.

Third, we include a series of variables to capture the proximity between two industries i and j, which have been explored elsewhere in the empirical literature on the determinants of firm ownership.[39] Using the 1992 US I-O tables, we have constructed a measure of Upstream-Complementarity$_{ij}$ for each pair of industries, as the correlation between the direct requirements coefficients of inputs $k \neq i, j$ used in the production of i and j, respectively. Similarly, we have constructed Downstream-Complementarity$_{ij}$ as the correlation in the direct use of i and j (expressed as a share of gross output in i and j, respectively) across buying industries $k \neq i, j$. As argued by Fan and Lang (2000), these measures capture the extent to which two industries enjoy economies of scale in jointly procuring inputs or in sharing marketing and distribution costs.[40] We have also constructed several measures of the relatedness of industries based on their factor intensities, as the absolute difference between industries i and j in their skill, equipment capital, plant capital, and R&D intensities, respectively. As pointed out by Atalay et al. (2014), empirical studies testing the resource-based view of the firm show that when firms expand, they enter industries for which the resource (e.g., capital, skill, or R&D) requirements match the requirements of the industries in which the firm had already been producing (see Montgomery and Hariharan 1991; Neffke and Henning 2013). Last but not least, the dummy variables Same-SIC2$_{ij}$ and Same-SIC3$_{ij}$ respectively identify industries that share the first two and the first three digits in their SIC codes. Similar indicators have been widely used in the literature to capture the proximity between two industries (e.g., Alfaro and Charlton 2009). (Summary statistics for these industry-pair variables are reported in table A-4 in the appendix.)

Rounding off the description of (20), in our most stringent specifications, we will introduce a full set of input dummies, D_i, to control for characteristics of each input that might affect a firm's propensity to integrate it. When these input fixed effects are used, only covariates that vary at the input-output (i-j) pair level can be identified in the estimation.

Table 4 reports the results of the estimation of (20). Column 1 reports a parsimonious specification, in which we include the interactions between

[38] The findings are very similar if we drop the self-SIC inputs entirely from the sample (see tables A-16 and A-17 in the appendix).

[39] We are grateful to an anonymous referee for suggesting the inclusion of such variables.

[40] While Fan and Lang (2000) take the average of these two complementarity measures in their study, we use each of them as separate variables in our regressions.

Upstreamness$_{ij}$ and the demand elasticity dummies (constructed from consumption goods elasticities only), the Self-SIC$_{ij}$ dummy, and log tr_{ij}. The negative coefficients obtained on Upstreamness$_{ij}$ point to a lower propensity to integrate upstream inputs across all output industries in general. However, in line with the weaker statement in prediction P.1 (Within), firms are significantly less likely to integrate upstream inputs in the complements case compared to the substitutes case: the γ_1 coefficient for the first elasticity quintile interaction is significantly larger than the γ_5 coefficient for the fifth-quintile interaction. The test for the equality of these coefficients is rejected (see the p-values near the bottom of the table).

In the columns that follow, we include the different measures of proximity between industries i and j. Controlling for Upstream-Complementarity$_{ij}$ and Downstream-Complementarity$_{ij}$ in column 2, we now find that firms in the lowest demand elasticity quintile are more likely to integrate upstream inputs ($\gamma_1 > 0$ and significant at the 10 percent level), while those in the highest-elasticity quintile are more likely to integrate downstream inputs ($\gamma_5 < 0$ and significant at the 1 percent level). Thus, including proxies of the scope for cost savings in input procurement and in marketing and distribution leads us to find support for the stronger version of our model's predictions.[41] This pattern persists when we add the measures of factor intensity differences (col. 3), the dummies for sharing the same first two or first three SIC digits (col. 4), as well as input fixed effects (col. 5). When instead we use the $\rho_j - \alpha_j$ proxy to distinguish between the complements and substitutes cases (col. 6), we lose the positive sign on the γ_1 coefficient, but the propensity to integrate upstream remains significantly weaker in the fifth relative to the first elasticity quintile.

It is worth noting that the estimated coefficients for the variables capturing the proximity between two industries are broadly consistent with theories that emphasize the importance of intangibles in firm boundary choices (Atalay et al. 2014). In particular, one interpretation of the positive and significant effects of the upstream- and downstream-complementarity measures is that firms are more likely to engage in integration when it is easier to share intangible knowledge related to common input procurement or marketing and distribution practices. Likewise, the regressions indicate that firms are more likely to integrate inputs with skill intensity

[41] The correlation between Upstreamness$_{ij}$ and Upstream-Complementarity$_{ij}$ is $-.413$, while that with Downstream-Complementarity$_{ij}$ is $-.406$; these are computed over the restricted subset of ever-integrated top 100 manufacturing inputs, but the correlations are similar if all top 100 manufacturing inputs are included. There is thus a tendency for inputs that exhibit weaker complementarities in either procurement or marketing/distribution to be located more upstream relative to the final-good industry. This accounts for why the Upstreamness$_{ij}$ interaction coefficients move into either less negative or more positive terrain once the effects of upstream- and downstream-complementarities are directly controlled for in col. 2 of table 4.

requirements similar to those of the parent's output industry, possibly because similarity of skills is important for facilitating the transfer of intangible assets from parents to subsidiaries. It is thus reassuring that despite controlling (albeit imperfectly) for these additional motives behind firm boundary choices, we continue to find evidence supporting the subtle predictions of our model on how upstreamness affects integration patterns.

As a final exercise, we empirically assess prediction P.2 (Within). For this, we include interactions between the elasticity quintiles ρ_j and Contractibility-up-to-i_{ij}, where the latter variable captures the contractibility of all inputs up to i in the production of j:

$$\text{Integration}_{ijp} = \gamma_0 + \sum_{n=1}^{5} \gamma_n \mathbf{1}(\rho_j \in \text{Quint}_n(\rho)) \times \text{Contractibility-up-to-}i_{ij} + \gamma_X X_{ij} + D_i + D_p + \epsilon_{ijp}. \tag{21}$$

Recall that Contractibility-up-to-i_{ij} was constructed in (16) as an empirical proxy for $\int_0^i [\psi(k)]^{\alpha/(1-\alpha)} dk / \int_0^1 [\psi(k)]^{\alpha/(1-\alpha)} dk$ from the model. Looking back at the expression for the optimal bargaining share, $\beta^*(m)$, in equation (10), one would then expect that Contractibility-up-to-i_{ij} would raise the propensity to integrate input i if industry j came under the complements case, while having the opposite effect in the substitutes case. This would lead us to expect that $\gamma_1 < 0$ and $\gamma_5 > 0$, although finding that $\gamma_5 > \gamma_1 > 0$ would be consistent with the weaker statement in prediction P.2 (Within).

The results from estimating (21) are reported in table 5. As in table 4, we begin by reporting a parsimonious specification in which we include only the interactions between Contractibility-up-to-i_{ij} and the demand elasticity quintiles, the self-SIC dummy, and log tr_{ij} (col. 1). While the interactions with Contractibility-up-to-i_{ij} all yield positive coefficients, the magnitude of these coefficients is largest in the highest-elasticity quintile. (The difference between the first- and fifth-quintile coefficients is statistically significant; see the p-value at the bottom of the table.) The results obtained are similar when controlling for the additional industry-pair variables related to the proximity of industries (cols. 2–4), controlling for input industry fixed effects (col. 5), as well as when using the proxy of α_j to refine the demand elasticity quintiles (col. 6). Consistent with prediction P.2 (Within) of our model, the findings of table 5 thus show that a greater contractibility of inputs upstream of i increases the propensity to integrate input i more for firms facing a higher elasticity of demand for their final product.

We have performed a series of additional estimations to verify the robustness of the within-firm results (see Sec. A-3 of the appendix). Tables A-14

TABLE 4
INTEGRATION DECISIONS WITHIN FIRMS: THE ROLE OF UPSTREAMNESS

	Dependent Variable: Integration$_{ijp}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Upstreamness$_{ij}$						
× Ind.(Quintile 1 Elas$_j$)	−.0043***	.0032*	.0048***	.0054***	.0036*	−.0005
	[.0014]	[.0018]	[.0018]	[.0019]	[.0020]	[.0021]
× Ind.(Quintile 2 Elas$_j$)	−.0111***	−.0042**	−.0022	−.0030	−.0044	.0035
	[.0027]	[.0020]	[.0019]	[.0019]	[.0034]	[.0023]
× Ind.(Quintile 3 Elas$_j$)	−.0102***	−.0023	.0001	−.0002	−.0028	−.0054
	[.0017]	[.0021]	[.0022]	[.0021]	[.0027]	[.0039]
× Ind.(Quintile 4 Elas$_j$)	−.0129***	.0023	.0043	.0034	.0012	.0016
	[.0033]	[.0033]	[.0030]	[.0028]	[.0023]	[.0025]
× Ind.(Quintile 5 Elas$_j$)	−.0229***	−.0169***	−.0153***	−.0146***	−.0077**	−.0079**
	[.0047]	[.0056]	[.0055]	[.0052]	[.0034]	[.0033]
Self-SIC$_{ij}$	.9664***	.9207***	.9134***	.8823***	.8517***	.8517***
	[.0033]	[.0085]	[.0091]	[.0164]	[.0177]	[.0176]
Log (Total Requirements$_{ij}$)	.0016**	.0022***	.0034***	.0028***	.0035***	.0038***
	[.0008]	[.0008]	[.0008]	[.0008]	[.0012]	[.0012]
Upstream-Complementarity$_{ij}$		.0403***	.0367***	.0174***	.0200***	.0200***
		[.0039]	[.0038]	[.0037]	[.0037]	[.0037]
Downstream-Complementarity$_{ij}$		.0284***	.0260***	.0129**	.0171***	.0163***
		[.0065]	[.0064]	[.0052]	[.0059]	[.0057]
Diff. Log (Skilled Emp./Workers)$_{ij}$			−.0170***	−.0156***	−.0213***	−.0217***
			[.0039]	[.0037]	[.0044]	[.0045]

	(1)	(2)	(3)	(4)	(5)	(6)
Diff. Log (Equip. Capital/Workers)$_{ij}$			−.0034	−.0038*	−.0089***	−.0089***
			[.0024]	[.0023]	[.0030]	[.0030]
Diff. Log (Plant Capital/Workers)$_{ij}$			−.0015	−.0008	.0041	.0041
			[.0023]	[.0023]	[.0026]	[.0026]
Diff. R&D Intensity$_{ij}$			−.0010	.0004	.0004	.0004
			[.0006]	[.0007]	[.0006]	[.0006]
Same-SIC2$_{ij}$				.0204***	.0166***	.0160***
				[.0041]	[.0028]	[.0028]
Same-SIC3$_{ij}$				.0457***	.0416***	.0419***
				[.0149]	[.0126]	[.0127]
p-value: Upstreamness$_{ij}$, quintile 1 − quintile 5	[.0000]	[.0003]	[.0002]	[.0001]	[.0005]	[.0161]
Elasticity based on	BEC cons.	BEC cons.	BEC cons.	BEC cons.	BEC cons.	BEC cons. & α proxy
Observations	2,648,348	2,467,486	2,467,486	2,467,486	2,467,486	2,467,486
R^2	.5376	.5398	.5407	.5440	.5646	.5646
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Input industry i fixed effects	No	No	No	No	Yes	Yes
No. of i-j pairs	8,548	7,225	7,225	7,225	7,225	7,225
No. of parent firms	46,992	41,931	41,931	41,931	41,931	41,931

Note.—The dependent variable is a 0-1 indicator for whether the SIC input is integrated. Each observation is a SIC input by parent firm pair, where the set of parent firms comprises those with primary SIC industry in manufacturing and employment of at least 20, which have integrated at least one manufacturing input apart from the output self-SIC. The sample is restricted to the set of the top 100 ever-integrated manufacturing inputs, as ranked by the total requirements coefficients of the SIC output industry. The quintile dummies in cols. 1–5 are based on the elasticity measure constructed using only those HS10 elasticities from Broda and Weinstein (2006) classified as consumption goods in the UN BEC; col. 6 uses the consumption-goods-only demand elasticity minus a proxy for α to distinguish between the complements and substitutes cases. All columns include parent firm fixed effects, while cols. 5 and 6 also include SIC input industry fixed effects. Standard errors are clustered by input-output industry pair.

* Significant at the 10 percent level.

** Significant at the 5 percent level.

*** Significant at the 1 percent level.

TABLE 5
INTEGRATION DECISIONS WITHIN FIRMS: THE ROLE OF CONTRACTIBILITY

	Dependent Variable: Integration$_{ijp}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Contractibility-up-to-i_{ij}						
× Ind.(Quintile 1 Elas$_j$)	.0216***	−.0017	−.0065	−.0105	.0014	.0148**
	[.0050]	[.0061]	[.0064]	[.0066]	[.0063]	[.0058]
× Ind.(Quintile 2 Elas$_j$)	.0388***	.0158*	.0097	.0120	.0232***	.0020
	[.0084]	[.0084]	[.0080]	[.0074]	[.0070]	[.0067]
× Ind.(Quintile 3 Elas$_j$)	.0356***	.0093	.0035	.0032	.0221***	.0267***
	[.0053]	[.0072]	[.0075]	[.0068]	[.0073]	[.0086]
× Ind.(Quintile 4 Elas$_j$)	.0497***	−.0036	−.0085	−.0058	.0122	.0127
	[.0119]	[.0126]	[.0120]	[.0108]	[.0084]	[.0083]
× Ind.(Quintile 5 Elas$_j$)	.0822***	.0514***	.0470***	.0445***	.0418***	.0411***
	[.0144]	[.0163]	[.0161]	[.0153]	[.0108]	[.0103]
Self-SIC$_{ij}$	.9601***	.9204***	.9140***	.8827***	.8513***	.8512***
	[.0039]	[.0083]	[.0089]	[.0163]	[.0177]	[.0178]
Log (Total Requirements$_{ij}$)	.0003	.0016	.0028***	.0023**	.0013	.0015
	[.0009]	[.0010]	[.0010]	[.0009]	[.0011]	[.0011]
Upstream-Complementarity$_{ij}$		.0393***	.0360***	.0167***	.0205***	.0207***
		[.0041]	[.0039]	[.0037]	[.0036]	[.0037]
Downstream-Complementarity$_{ij}$		.0278***	.0255***	.0124**	.0172***	.0159***
		[.0069]	[.0067]	[.0054]	[.0058]	[.0056]
Diff. Log (Skilled Emp. Workers)$_{ij}$			−.0169***	−.0154***	−.0210***	−.0209***
			[.0039]	[.0036]	[.0044]	[.0044]

TABLE 5 (*Continued*)

	Dependent Variable: Integration$_{ijp}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Diff. Log (Equip. Capital/Workers)$_{ij}$			−.0029	−.0034	−.0087***	−.0087***
			[.0021]	[.0021]	[.0030]	[.0030]
Diff. Log (Plant Capital/Workers)$_{ij}$			−.0015	−.0008	.0042	.0041
			[.0023]	[.0022]	[.0027]	[.0027]
Diff. R&D Intensity$_{ij}$			−.0011*	.0003	.0003	.0003
			[.0006]	[.0007]	[.0006]	[.0006]
Same-SIC2$_{ij}$				.0203***	.0160***	.0153***
				[.0040]	[.0028]	[.0028]
Same-SIC3$_{ij}$				.0461***	.0422***	.0429***
				[.0148]	[.0126]	[.0127]
p-value: Contractibility-up-to-i_{ij}, quintile 1 − quintile 5	[.0000]	[.0007]	[.0005]	[.0002]	[.0001]	[.0068]
Elasticity based on	BEC cons.	BEC cons	BEC cons.	BEC cons.	BEC cons.	BEC cons. & α proxy
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Input industry *i* fixed effects	No	No	No	No	Yes	Yes
Observations	2,648,348	2,467,486	2,467,486	2,467,486	2,467,486	2,467,486
No. of parent firms	46,992	41,931	41,931	41,931	41,931	41,931
No. of *i*-*j* pairs	8,548	7,225	7,225	7,225	7,225	7,225
R^2	.5383	.5397	.5406	.5438	.5647	.5647

Note.—The dependent variable is a 0-1 indicator for whether the SIC input is integrated. Each observation is a SIC input by parent firm pair, where the set of parent firms comprises those with primary SIC industry in manufacturing and employment of at least 20, which have integrated at least one manufacturing input apart from the output self-SIC. The sample is restricted to the set of the top 100 ever-integrated manufacturing inputs, as ranked by the total requirements coefficients of the SIC output industry. The Contractibility-up-to-i_{ij} measure is the share of the total-requirements weighted contractibility of inputs that has been accrued in production upstream of and including input *i* in the production of output *j*. The quintile dummies in cols. 1–5 are based on the elasticity measure constructed using only those HS10 elasticities from Broda and Weinstein (2006) classified as consumption goods in the UN BEC; col. 6 uses the consumption-goods-only demand elasticity minus a proxy for α to distinguish between the complements and substitutes cases. All columns include parent firm fixed effects, while cols. 5 and 6 also include SIC input industry fixed effects. Standard errors are clustered by input-output industry pair.

* Significant at the 10 percent level.
** Significant at the 5 percent level.
*** Significant at the 1 percent level.

and A-15 confirm the robustness of our results concerning the role of upstreamness and contractibility in shaping integration decisions along the value chain, when we restrict the sample to different subsets of firms (single-establishment firms, domestic firms, and multinationals). Tables A-16 and A-17 show that our results are similar if we (i) drop parent firms that do not have an integrated input (apart from the self-SIC) among the top 100 manufacturing inputs as ranked by total requirements value; (ii) focus on parents that have integrated at least three of their top 100 manufacturing inputs; (iii) drop the self-SIC from the estimation; and (iv) include all top 100 manufacturing inputs (instead of focusing on the subset of ever-integrated inputs). In table A-17, we show that the estimated effects of Contractibility-up-to-i_{ij} are robust to controlling for a measure of the contractibility of input i itself.

V. Conclusion

In this paper, we show how detailed data on the activities of firms around the world can be combined with information from standard input-output tables to study integration choices along value chains. Building on Antràs and Chor (2013), we first describe a property rights model in which a firm's boundaries are shaped by characteristics of the different stages of production and their position along the value chain. As available theoretical frameworks of sequential production are highly stylized, a key contribution here is to develop a richer model of firm behavior that can guide an empirical analysis using firm-level data.

To assess the evidence, we use the WorldBase data set, which contains establishment-level information on the activities of firms located in a large set of countries. The richness of our data allows us to run specifications that exploit variation in organizational features across firms, as well as within firms and across their various manufacturing stages. In line with our model's predictions, we find that whether a firm integrates suppliers located upstream or downstream depends crucially on the elasticity of demand faced by the firm. Moreover, the propensity to integrate upstream (as opposed to downstream) inputs depends on the extent to which contractible inputs tend to be located in the early or late stages of the value chain, as well as on the productivity of final-good producers. The patterns that we uncover provide strong evidence that considerations driven by contractual frictions critically shape firms' ownership decisions along their value chains.

Although we have interpreted our empirical findings as being supportive of the relevance of a property rights model of firm boundaries in a sequential production environment, they could in principle be consistent with alternative theories. The key features of our model that generate predictions in line with the patterns observed in the data are as follows: (i) relative to integration, nonintegration is associated with higher-powered incentives for suppliers; (ii) variation in the demand elasticity affects the relative importance of eliciting high effort or investments in upstream versus downstream stages; and (iii) higher contractibility is associated with less inefficient investments. As argued by Tadelis and Williamson (2013), one could envision transaction cost models of firm boundaries satisfying properties i and iii, which coupled with our model of sequential production would also produce feature ii. In addition, when discussing our empirical results (specifically, the within-firm regressions), we have highlighted some patterns that are consistent with alternative theories (e.g., Atalay et al. 2014) advocating that common ownership allows firms to efficiently move intangible inputs across their production units.

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