Vertical Integration, Supplier Behavior, and Quality Upgrading among Exporters*

Christopher Hansman
Columbia University

Jonas Hjort
Columbia University
& BREAD & NBER

Gianmarco León
Universitat Pompeu Fabra
and Barcelona GSE

Matthieu Teachout
Columbia University

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Abstract

This paper studies the relationship between backward vertical integration and output quality. The setting is a large manufacturing sector in Peru where plants produce a vertically differentiated but otherwise homogeneous product for export: fishmeal. We link customs data on each shipment's value and quality grade to plant level production data, transaction level data on supplies from integrated and independent suppliers (fishing boats), and GPS measures of supplier behavior. We first document a highly robust correlation between the quality grade of a firm's exports and the share of its inputs that comes from vertically integrated suppliers at the time of production. We then show that firms adopt a strategy of sourcing more of their inputs from integrated suppliers when faced with firm-specific high-quality demand shocks. Guided by a conceptual framework in which the worse outside option of supplier managers that are integrated with downstream buyers lowers their incentive to "shirk" on input quality, we explore *why* output quality is higher when inputs come from integrated suppliers. Exploiting changes in supplier status and exogenous variation in production conditions, we show that a given supplier supplying a given plant on average delivers smaller batches of higher quality inputs (i.e., fresher fish) when integrated, and does so comparatively more (i) when there is a need for the downstream firm to produce high quality output, and (ii) when plankton conditions makes it difficult to produce high quality inputs.

*cjh2182@columbia.edu, hjort@columbia.edu, gianmarco.leon@upf.edu, mrt2138@columbia.edu. We thank Charles Angelucci, Pol Antràs, David Atkin, Amit Khandelwal, Eric Verhoogen, Xiao Yu Wang, and seminar participants at Columbia University and Stanford SCID-IGC for helpful comments and suggestions, and Patrick Kennedy and Leonor Lamas for great research assistance and field work. The Peruvian Ministry of Production and Cesar Casahuamán kindly shared access to data.

1 Introduction

Why does so much of world trade occur within firm boundaries?[1] Research on this classical question goes back to Coase (1937)'s seminal contributions, and a vast range of theories has since explored the reasons why firms may prefer their suppliers (or clients) to be integrated. Many emphasize the role of property rights (Grossman & Hart, 1986; Hart & Moore, 1990) and/or incomplete contracts (Williamson, 1971; Lafontaine & Slade, 2007), which are common in developing countries (Nunn, 2007).[2] But theories of vertical integration have rarely been tested empirically as the datasets available to researchers generally include, at best, information on between-firm transactions (Lafontaine & Slade, 2007; Bresnahan & Levin, 2012). An initial take-away from recent analyses of within-firm transaction data is that vertical integration helps downstream firms influence their suppliers when contracting is imperfect (Atalay *et al.* , 2014; Macchiavello & Miquel-Florensa, 2016). Combined with evidence that high quality inputs can enable downstream firms to increase the quality of their output and export to rich countries (Schott, 2004; Hummels & Klenow, 2005; Verhoogen, 2008; Goldberg *et al.* , 2010; Kugler & Verhoogen, 2012; Halpern *et al.* , 2015), this suggests that an economically consequential motivation for integrating – quality upgrading – may have been overlooked.

We investigate the hypothesis that vertical integration represent a strategy potential exporters in settings where contracts are incomplete use to control their suppliers' behavior and the resulting quality of inputs in order to produce goods that can be sold to richer consumers. We do so in the context of one of Latin America's biggest industries: fishmeal manufacturing in Peru. Fishmeal is a vertically differentiated but otherwise homogeneous product whose intermediate input is non-contractible because fish quality is difficult to observe at the time of purchase (Natividad, 2014, 2016; Hansman *et al.* , 2016).[3] We first explore how the quality grade and price of a firm's exports differ when more of its suppliers are integrated, and when more of its supply is coming from integrated suppliers. We then construct an instrument for the demand for quality a firm faces in a given production season to investigate if firms choose to vertically integrate in order to produce higher quality grade goods. In the last part of the paper we explore *why* firms may be better able to control integrated suppliers. We present a simple framework in which a worse outside option for the owner/manager of a supplier if she is vertically integrated with the downstream firm lowers her incentive to "shirk" on input quality. Guided by the framework, we use "switchers" to test how a supplier's quantity-versus-quality relevant behaviors change once integrated, focusing both on average behavior and the behavioral response to the supplied plant producing higher quality output and exogenous variation in production conditions.

Peru's fishmeal manufacturing sector is an ideal setting to explore the relationship between vertical integration and output quality for several reasons. First, we directly observe quality. Public inspectors verify manufacturing firms' monthly reports of each plant's output of both the traditional "fair average quality" (FAQ) and "prime" quality fishmeal. While the FAQ versus prime classification of a batch of fishmeal is binary and governed by a cut-off on the protein content (quality) ladder, the horizontally non-differentiated nature of the product allows us to infer a continuous measure of quality for each export shipment. To do

[1] The observations that one third of world trade occurs within firm boundaries and within-firm transactions account for half of U.S. value added are well-known (Antràs, 2003; Lafontaine & Slade, 2007).

[2] The incompleteness of contracts in developing countries might be part of the reason why vertical integration is more common there (Acemoglu *et al.* , 2005).

[3] Fishmeal is a brown powder made by burning or steaming fish, and often used as animal feed. Peru's fishmeal industry – the biggest in the world – accounts for around 3 percent of the country's GDP and 10 percent of global fish capture (Paredes & Gutierrez, 2008; De La Puente *et al.* , 2011). Some of the countries that import comparatively high quality grades of fishmeal are rich – for example Japan – while others are middle-income. We refer to countries that import high quality fishmeal collectively as "rich" for simplicity.

so we use detailed data from a fishmeal consulting firm on the prevailing price across the range of protein content levels in a given week×export port, in combination with the quantity, price, and date information available in customs data.[4] We thus avoid relying on purely unit price-based quality measurement procedures that risk conflating quality with mark-ups and horizontal differentiation (see e.g. Khandelwal, 2010).

Second, for the universe of transactions between manufacturing plants and suppliers (boats), we observe the date, quantity, and parties involved in administrative data from Peru's regulatory authorities. Domestic transactions data is rare, especially when reported at the daily level, for an entire industry, and including within-firm transactions. In combination with production and customs data, observing supply transactions allows us to track the flow of products across three different stages of a global value chain – from input supply to processing in manufacturing plants to international customers – and to observe who trades with whom at each stage and the outcome of the transaction.

Finally, the setting allows us to observe the behavior of suppliers hour by hour. The fishing boats that supply the fishmeal plants are required to transmit GPS signals to the regulatory authorities in real time while at sea. The regulatory authorities gave us access to the stored GPS data. We use GPS-based proxies for quality-conducive behaviors to explore how a supplier's quantity and quality choices differ when integrated, using "switchers" for identification. We also use measures of plankton concentration across space constructed from NASA satellite images to test how suppliers' behavioral response to exogenous variation in production conditions differs when integrated.

Our results are as follows. Firms produce higher quality output and achieve higher export prices when they own more of their suppliers. This "ownership" effect could in itself have several possible explanations, but we find the same at plant level, and when controlling for fixed supplier and downstream firm characteristics. We also find that it is not ownership per se but the share of a plant's supplies coming from integrated suppliers at a given point in time that matter for output quality. If our estimates reflect a causal relationship, they imply that a plant increasing the share of its inputs that comes from vertically integrated suppliers from 0 to 100 percent would increase the share of its output that is of high quality by 7 percent, controlling for the plant's technological capacity.

We also find that downstream manufacturers significantly increase the share of supply that is obtained from vertically integrated suppliers when they face greater relative demand for high quality, as instrumented by firm-specific demand shocks. It thus appear that exporters strategically "act on" the apparent quality benefits of vertical integration.

We then present a simple framework in which input quality is unobservable at the time of delivery, and the outside option of a manager depends on who owns her productive assets. If the downstream firm she delivers to purchases the assets from her, she goes from being an independent supplier paid on quantity to becoming an employee. The threat of being fired increases the manager's incentive to deliver high quality input.

Finally, we show that, as predicted by the framework, integrated suppliers adopt a behavior that is consistent with the objective of delivering higher quality inputs. Inputs *in a given supplier-plant relationship* on average come in smaller batches of higher quality (i.e., fresher fish) when the supplier is owned by the plant, and the difference is greater (i) when the downstream firm is producing high quality output, and (ii) when plankton conditions make the trade-off between producing quantity and quality more pressing.

In sum, our results show that exporters in settings with imperfect contracting strategically source more

[4]The customs data also contains information on the export destination country.

of their input from vertically integrated suppliers when demand for quality is high, and that the reason appears to be that a greater ability to influence the behavior of integrated suppliers makes it possible to produce higher quality output when inputs are sourced internally. In addition to documenting an overlooked motivation for vertical integration, these results represent some of the first evidence on the *effectiveness* of strategies used by exporters in developing countries to upgrade the quality of their products.

This paper bridges and advances the vertical integration and quality upgrading literatures. Economic research on the boundaries of the firm and input-output structures goes back to Coase (1937)'s seminal contributions.[5] We follow Atalay *et al.* (2014), Hong & Li (2016), and Macchiavello & Miquel-Florensa (2016) in using domestic transactions data to study vertical integration: like Atalay *et al.* (2014) we observe the same supplier-plant pair transacting both as independent entities and once integrated,[6] and like Macchiavello & Miquel-Florensa (2016) we can link the downstream firms to their export transactions. In settings where contracts are complete, the behaviors conducive to downstream output quality we show to be lacking among independent suppliers could be achieved through contracts. In this sense our paper stands on the shoulders of the strand of the literature focusing on incomplete contracting that was started by Williamson (1971). While the conceptual framework we present most closely follows Shapiro & Stiglitz (1984)'s idea of outside options disciplining worker behavior, the logic of the framework and our hypothesized explanation for why suppliers behave "better" when integrated follows Grossman & Hart (1986) and Baker *et al.* (2002). In our framework and the setting we study, however, relational contracts do not restore the first best.

We are not aware of previous studies of the relationship between vertical integration and downstream output quality. The evidence we present on how firms strategically source more of their input from vertically integrated suppliers when demand for quality is high resonates with recent findings from Alfaro *et al.* (forthcoming). They show – focusing on homogeneous products and using changes in trade policy for identification – that higher prices in product markets lead to more vertical integration due to the associated productivity gains.[7] We instead show that vertical integration enables manufacturing plants to incentivize upstream suppliers to deliver high quality inputs, which in turn makes it possible for the downstream firm to produce a product of higher quality.

The quality upgrading literature is newer, but it is now well-documented that producers of high quality goods use high quality inputs (Kugler & Verhoogen, 2012), more skilled workers (Verhoogen, 2008; Frías *et al.* , 2009), and export to richer destination countries (Bastos *et al.* , 2016; Manova & Zhang, 2012).[8] While Peru's fishmeal manufacturing sector shares most features with other manufacturing sectors in poor and middle- income countries,[9] studying the universe of downstream firms and suppliers in a particular industry allows us to fully observe the market's structure.[10] The unusual collection of datasets we use makes

[5]Other than incomplete contracts (Williamson, 1971), theories of vertical integration focus on the risk of hold-up (Williamson, 1975), property rights and relationship-specific investments (Grossman & Hart, 1986; Hart & Moore, 1990), technological motivations such as economies of scale (Tirole, 1988), span-of-control (Simon, 1981; Geanakoplos & Milgrom, 1991), and productivity-based selection (Antràs & Helpman, 2004). See Gibbons (2005) and Lafontaine & Slade (2007); Bresnahan & Levin (2012) for great overviews of respectively the theoretical and empirical vertical integration literatures.

[6]Our evidence on how vertically integrated suppliers do their work differently than independent suppliers resonates with Atalay *et al.* (2014)'s findings on the transfer of "intangible inputs" within firms.

[7]Aghion *et al.* (2006) instead explore how the extent of competition in the product market affects firm's propensity to vertically integrate.

[8]Our use of the "demand pull" methodology – instrumenting for the demand a firm faces at a given point in time by interacting its initial export destinations with importer countries' total imports (or changes in exchange rates) – follows many fruitful applications of this Bartik approach in the trade literature, including Park *et al.* (2009); Brambilla *et al.* (2012); Bastos *et al.* (2016).

[9]In the fishmeal sector, as in many manufacturing sectors, natural resources constitute a large part of inputs and technology is an important determinant of quality. However, fishmeal is not a horizontally differentiated good.

[10]Our focus on a particular industry follows many prominent papers in the empirical vertical integration literature, including

it possible to unpeel an additional layer and "look inside the firm". We document how and why a new dimension of the organization of production – a *firm's* structure – affects the quality produced, and show that firms use vertical integration strategically in response to high quality demand shocks.

The rest of the paper is organized as follows. In Section 2 we provide background on the context and lay out the various datasets we use, and in Section 3 we explore the association between output quality and vertical integration. In Section 4 we investigate how firms' use of integrated suppliers changes when demand for quality is high. In Section 5 we present the conceptual framework and show how the behavior of integrated suppliers differs from independent suppliers. Section 6 concludes.

2 Background and data

2.1 Peru's fishmeal manufacturing sector

Peru's fishmeal plants buy fish from industrial fishing boats and export most of their production to foreign buyers. The sector is large: Peru is the world largest exporter of fishmeal,[11] and the anchovy fishery that supplies the manufacturing plants account for approximately 10 percent of global fish capture (Paredes & Gutierrez, 2008). Fishmeal plants are present in around 22 towns along the coast that have a suitable port. In 2009, the first year in our sample, there were about 89 fishmeal plants. They were owned by 37 companies and supplied by around 1,000 active industrial fishing boats.

The regulatory authorities allow the wooden ("viking") and steel boats that supply the plants to fish anchovies during two fishing seasons each year.[12] Only steel boats can be owned by downstream fishmeal firms. The majority of steel boats are owned by either boat firms ("armadores") or fishmeal firms, while wooden boats are generally owned by individuals or families. Boats offload fish at the plant's docking station. The fish is then transported into the plant through a conveyor belt. Inside the plant, the fish is weighed and cleaned. After cleaning, the fish is dried and converted into fishmeal. The fish is processed as soon as possible after being offloaded as fishmeal is more valuable the fresher the fish, and for the same reason fishing boats go out for at most one day at a time. Negotiations between independent boats and plants take place over the radio while the boats are at sea.

Two different technologies are available for the wet reduction process necessary to turn fish into fishmeal: steam drying, wherein the fish is indirectly dried with steam (hereinafter "High technology"), and exposing the fish directly to heat (hereinafter the "Low technology").[13] In the 1990s and early 2000s, almost all plants used the Low technology, but most plants in Peru's fishmeal sector upgraded to the new High technology in the 2000s or early 2010s.

The quality grade of a batch of fishmeal is denoted by its origin country and protein content,[14] which in Peru typically ranges from 63 to 68 percent. In addition to the exact protein content, a binary indicator in which batches with protein content above a given level are labeled "prime" quality and batches below that

Woodruff (2002); Baker & Hubbard (2003, 2004); Forbes & Lederman (2009); Macchiavello & Miquel-Florensa (2016).

[11] Peru accounts for around 30 percent of the world's exports. Source: COMTRADE data.

[12] The exact start and end dates of the seasons vary from year to year, and differ for the North/Central and South regions. The marine ecosystem differs in the South – below the $-16\,^{\circ}\mathrm{S}$ parallel – which represents around 8 percent of total fishmeal production.

[13] Confusingly, the term "fair average quality (FAQ)" is in Peru's fishmeal sector often used to denote *both* the Low technology and fishmeal of low quality (discussed below), although the correlation between use of the Low technology and producing output of low quality is far from one. We use the term FAQ only to describe output quality.

[14] The type of fish used as input and other features of the production environment differ across countries.

cut-off are labeled "fair average quality" is sometimes used for Peruvian fishmeal. Price differentials across transactions for Peruvian fishmeal of a given quality grade in a given time period are minor.

As seen in Figure 1, firms and plants that use the High technology produce higher average quality fishmeal (we discuss the data used in Sub-section 2.2). This is because the High technology preserves the protein content of the fish through the production process better.[15] Another important determinant of fishmeal quality is input quality. Fresher anchovies yield a final product with higher protein content on average. We interviewed fishmeal industry associations and captains to gain a qualitative understanding of the conditions under which contracting takes place. They informed us that the quality of Peruvian anchovies cannot easily be observed when a negotiation takes place. Captains' superior knowledge of the quality of the catch creates an information asymmetry that makes input quality hard to contract on.

During our data period, around 95 percent of Peru's total fishmeal production was exported. The three largest buyers are China (55 percent of exports), Germany (14 percent), and Japan (7 percent), but many other countries also import Peruvian fishmeal. The product is primarily used as feed in aquaculture, and for pigs and chickens. In theory fishmeal can be stored for up to six or even 12 months, but we find that most of the production is sold before the next fishing season begins, as seen in Appendix Figure A2.

Our period of analysis is 2009 to 2015, or the first 11 fishing and fishmeal production seasons after the introduction of "individual, transferable quotas" (ITQs) in the Peruvian anchovy fishing sector.[16] Before the ITQ system, the sector operated under a "total allowable catch" (TAC) – or "race for the resource"[17] – system wherein there was little scope for incentives generated by vertical integration or other features of the economic environment to influence a boat's behavior, other than possibly how fast it could/would fish (see Natividad, 2014). Under the ITQ system, Peru's anchovy fishery is similar in many dimensions to other natural resource sectors that supply downstream factories, including the fact that the suppliers own the assets from which the resource is extracted.

2.2 Data

Starting downstream and moving upstream, we use the following sources of data:

Export transactions. Almost all Peruvian fishmeal is exported. We have detailed data on the universe of fishmeal exports at the transaction level from Peru's customs authority.[18] We observe the date of the transaction, the port of transaction, the destination country, the weight of the fishmeal shipment, the value of the transaction, and the exporting firm (though not the specific plant that made the fishmeal).

While we do not observe quality grade directly in the customs data, we can approximate quality unusually well. We take advantage of fishmeal's vertically differentiated but horizontally homogeneous nature, which means that a higher per-unit price should imply a higher protein content rather than for example

[15] As very few firms in our sample only have the Low technology, we define a High technology firm as one for which the High technology share of total processing capacity is higher than the median (0.67).

[16] The ITQ law came into effect in the North/Central region on April 20th, 2009 and in the South on July 7th, 2009. The quotas can be transferred between boats, subject to certain rules. Firms or individuals that own several boats/quotas are free to allocate their total quota to a subset of those boats. Quota-owners can also rent their quota out to others, for up to three years at a time.

[17] In a TAC system a total, national quota is set before the fishing season starts. The introduction of the ITQ system in Peru was motivated by the well-documented and unsurprising fact that under TAC, fishing became a "race" for the resource in which boats caught as much fish as they could until, shortly after the season began, the total quota was reached (see e.g. Hansman *et al.* , 2016).

[18] While total fishmeal exported is approximately 95 percent of total fishmeal produced, which confirms that we see the universe of Peruvian fishmeal exports, the smallest firms use intermediaries to export. We cannot link intermediated exports to a specific firm's production.

mark-ups. Aggregate data from the International Fishmeal and Fish Oil organization (IFFO), who obtain their information directly from fishmeal companies, confirms that the price of Peruvian fishmeal with protein content in the highest range ("super prime") is on average 13 percent higher than that of fishmeal with protein content in the low range (FAQ). We start with exports' unit values. Using the date and port of transaction, we map these to price data at the week×port×protein content level recorded by a fishmeal consulting company in order to infer a given shipment's quality grade.The inferred protein content of a firm's exports at a point in time is highly correlated with the "high quality share of production" directly observed for the firm's plants in production data (discussed below), and also with the exports' unit values. Unit values are uncorrelated with the size of the shipment, indicating that fishmeal firms do not offer bulk discounts.

Plant production. We also have access to administrative data from Peru's Ministry of Production (which regulates the fishmeal industry) on all plants' production. Plants are required to submit information to the authorities on their production of high and low quality (protein content) fishmeal every month. Quality is thus directly reported in the plant production data using a binary measure. As discussed in Sub-section 2.1, the distinction between high quality (prime) and low quality (FAQ) fishmeal as reported by plants is based on a protein content level cut-off. The production data reported by plants is subject to auditing by government inspectors.

Plant registry. We link the production data with an administrative plant registry that contains information at the monthly level on each plant's technological production capacity (expressed in metric tons that can be produced per hour with respectively the installed Low and High technology) and which firm owns the plant. We also use this registry to link the export and production data. We can do so for almost all firms.

Supply transactions. The Ministry of Production also records all transactions between the fishmeal plants and their suppliers of raw materials, i.e. fishing boats. Information on the date of the transaction, and the boat, plant, and amount of fish involved (though not the price), is included. Datasets that record the universe of transactions between a downstream industry and their suppliers of materials are unusual. The Supply transactions registry for the Peruvian fishmeal industry is especially unique in that it includes information on within-firm transactions.

Boat registry. We merge the supply transactions data with an administrative boat registry that provides information on a boat's owner, the material the boat is made of (wood versus steel), its storage capacity and engine power, and whether it has a cooling system installed.[19]

Boat GPS data. Peruvian fishing boats that supply fishmeal plants are required to have a GPS tracking system installed, and to continuously transmit their GPS signal to the Ministry of Production while at sea. The ministry stores the transmitted information – the boat's ID, latitude, longitude, speed, and direction – each hour on average, and shared the resulting dataset with us.

Since we do not directly observe where a boat fishes, we construct an algorithm to infer the fishing

[19]Unfortunately, information on engine power is only available for 2004-2006 and so we do not observe any improvements in engine power from one year to another during our period of analysis. However, changes in engine power are very rare from 2004 to 2006 so we consider this boat characteristic to be fixed.

location and -time. The algorithm exploits the fact that a boat's speed is a lot lower when searching for fish or actively fishing than when traveling back to port.[20]

It is important to note that only about half of the observations in the Supply transactions dataset can be matched to a GPS recording, and the missing GPS observations are not "missing at random". Some boat owners, for example, disappear from the GPS data for a complete calendar year. However, such missingness is unlikely to be of concern for regressions at the boat level, the level at which we analyze the GPS data.

Internal data from a large firm. One of the largest fishmeal firms in Peru shared its internal records on sales and payments to suppliers with us.[21] The firm has been operating for more than a decade, and owns many plants distributed throughout the coast. The sales records are detailed and include information on the shipment's type of packing, its free-on-board value, the price per metric ton, the buyer, destination country, date of the contract, and the terms. Most importantly for our purposes, the sales records include information on the specific plant that produced a given shipment of fishmeal.

Phytoplankton data. We use NASA chlorophyll concentration data to predict fish abundance. This data allows scientists to measure how much phytoplankton is growing in the ocean by observing the color of the light reflected from the shallow depths of the water. Phytoplankton contain a photosynthetic pigment called chlorophyll that lends them a greenish color. In the rest of this paper, we use the term "plankton concentration" when referring to chlorophyll concentration. The data is available for each date and each $0.1°$-latitude$\times 0.1°$-longitude (roughly 10 kilometer$\times$10 kilometer) grid-cell.[22]

Table 1 shows summary statistics on the fishmeal industry for our sample period. There are approximately 766 active boats per fishing season. About 28 percent of them are owned by a fishmeal firm. There is significant heterogeneity in boat characteristics such as storage capacity, engine power, and average offload weight. Fishing trips last about 21 hours on average and boats travel in average up to 76 kms from their delivery port, highlighting that finding fish requires a lot of effort.

There is also some heterogeneity in the processing capacity, installed high technology, and high quality grade share of production of the 89 plants we observe. Monthly average production is about 3000 metric tons. These plants are owned by 37 firms, but the seven largest companies account for approximately 78 percent of total production. Firms differ considerably in their average number of export transactions per season, and the size and value of shipments.

[20] Specifically, we follow Natividad (2014) and assume that a boat is throwing its nets if speed is below 2.9 kilometers/hour. The industry association IFFO confirmed to us that the method should provide fairly accurate results. We have also used two alternative algorithms for inferring fishing location and -time; these yield similar results.

[21] We do not make use of the supply records because almost all information they contain is available to us for the entire sample of firms and suppliers through the Supply transactions and Boat registry datasets.

[22] The data is no longer available at the day level on the NASA website (only at the week or month level), but was still available in late 2015 when we scraped the data. See `http://neo.sci.gsfc.nasa.gov/view.php?datasetId=MY1DMM_CHLORA`. Because some points are missing, we interpolate the missing data by taking the average of a date and geographical interpolations.

3 Vertical Integration and Output Quality

In this section, we document a series of correlations between vertical integration (hereinafter "VI") and output quality that collectively point towards a causal relationship. We estimate

$$\text{Quality}_{it} = \alpha + \beta_1 \text{VI}_{it} + \beta_2 \text{HighTech}_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{1}$$

where Quality_{it} is a measure of the quality of the output produced by firm or plant i during production season or month t. As discussed in Section 2.2, at the firm level we measure output quality using log export unit prices and protein content. (For the firm that provided internal data, we can use these two measures also at the plant level). As our regressions are at the production season level, we average these across specific export transactions, weighting by quantity. These two measures are complementary. Unit prices – the measure of output quality typically used in the existing literature – are important outcomes in and of themselves, but could partially reflect mark-ups and/or within-season fluctuations in the world price of fishmeal. Protein content instead provides a direct measure of output quality. At plant level, we measure output quality as the share of fishmeal produced that is of high quality (as measured by a binary categorization).

Our interest is in β_1 , which measures the correlation between output quality and VI. The type of technology the firm or plant uses to convert fish into fishmeal is an important determinant of output quality, and one that could plausibly correlate with VI (if e.g. both respond to constraints such as access to credit). We thus control for HighTech_{it}, i.e., steam drying (High) technology. At the firm level, HighTech_{it} is equal to the share of installed capacity that is of the high type, while at the plant level, where we observe whether any high technology is installed, HighTech_{it} is instead a dummy variable. We include production season and firm or plant fixed effects and thus analyze changes in output quality for those firms or plants that see a change in VI within a given season, relative to other firms/plants that do not see a change in VI in the same season. Finally, ε_{it} is a heteroskedasticity robust standard error.

A possible concern when matching export transactions to input transactions is that fishmeal can be stored for several months so that firms might attempt to strategically time their export transactions based on time variation in the prevailing prices. In practice inventories are small – between +10 and -10 percent of total production – as seen in Appendix Figure A2, however.[23] This is likely because many contracts are entered into before the production season starts, and because firms' ability to "time" their sales is in actuality limited. Another possible concern is that firms that are about to end operations and close down might sell off their fishmeal, in which case a lower unit price might not reflect lower quality but rather a "going-out-business" discount. To deal with this possibility we remove firm-season pairs that produce and export for the last time from our sample, but the results are robust to including these observations.

We begin by exploring the relationship between the number of suppliers owned and output quality at the firm level.[24] In Table 2 we see that owning one more supplier is associated with the fishmeal exported commanding a 0.3 percent higher unit price, and having a protein content that is 0.027 percent higher.

[23] Firms usually produce for two-three months at a time, that is, during the period when fishing is allowed. They ramp up exporting towards the end of the production season, and have typically sold all fishmeal before the next production season begins. Figure A2 shows the density of inventories defined as the difference between seasonal production and exports (during the production season and the months right after the production season) divided by total production (over the production season). As the graph illustrates, for the vast majority of observations in our sample, inventories are between +10 and -10 percent of total production, which confirms that storage of output is limited.

[24] Some boats owned by a fishmeal firm are not operating as quotas can be transferred across boats owned by the same fishmeal firm.

While vertical integration affecting output quality is one possible explanation for these patterns, it may also be that firms for example are able to purchase suppliers during periods when output quality is high for other reasons.

In the analysis in Panel A of Table 3 we continue to focus on the export unit prices and quality grade achieved by firms. However, we now measure VI as the share of inputs coming from VI suppliers, rather than as the number of suppliers owned. We find that firms obtain 13 percent higher prices for their fishmeal when they buy all of their input from VI suppliers, relative to when they buy all their input from independent suppliers. This price differential is roughly equal to the difference between the average unit price of the lowest quality category and highest quality category fishmeal as defined by a five-step quality category ladder used by industry associations that report average prices. We also find that firms produce fishmeal with 1.3 percent higher protein content when they buy all their input from VI suppliers; a quality grade differential about one-third of the difference between the average protein content of lowest and highest quality category fishmeal. We conclude that it is not so much ownership of suppliers per se that matter for output quality but the share of a firm's supplies coming from integrated suppliers at a given point in time.

In Panel B of Table 3 we repeat the same analysis as in Panel B, but now at the plant rather than the firm level. This is possible for the sample of plants belonging to the fishmeal firm that shared data enabling us to link export transactions with the plant that produced the fishmeal.[25] We include plant fixed effects and thus focus on changes in share of supply coming from VI suppliers over time within a given plant. The magnitude and significance of the estimates are very similar to those in the firm level analysis.

In Panel C of Table 3 we remain at the plant level, but now include all 89 plants observed in our full sample. With the full sample we can use the binary measure of quality discussed in Section 2.2. Our outcome variable is thus the share of the plant's production in a given month that is of the high quality type. We find that the share of plants' output that is of high quality is seven percent higher when they obtain all of their input from VI suppliers, relative to when they obtain all their input from independent suppliers. The magnitude of the association between VI and output quality we find when focusing on binary output quality measured at the plant level, is thus in line with the association we find with a continuous measure of quality grade at the firm level and for the plants belonging to a specific firm.[26] The findings in Panel B and C help rule out a story in which an exogenous shock to a fishmeal firm's output quality make it easier to cover the fixed (acquisition) cost or variable cost (for example the cost of gas) of using owned suppliers.

In Table 4 we return to the firm level analysis. We repeat the regressions shown in Panel A of Table 3, but now include a series of controls for characteristics of the firm's suppliers in addition to our regressor of interest. Controlling for the share of inputs coming from steel boats; high capacity boats;[27] and boats with a cooling system leaves the magnitude and significance of the coefficient on share of inputs coming from VI suppliers essentially unchanged.[28] These findings indicate that it is the integrated-versus-independent status itself rather than other characteristics of the boats supplying a fishmeal firm at a given point in time that predicts the production of high quality grade fishmeal.[29]

[25] Another difference between the plant level analysis in Panel B and C relative to the firm level analysis in Panel A is that for plants we use whether the plant has (any) high technology installed, not the share of total capacity that is high technology.

[26] For completeness we also run regressions at the firm level, using our binary measure of quality available at the plant level. The results are in Table A1 of the Appendix

[27] We define "high capacity" as greater than the 75th percentile.

[28] Note that two of the supplier characteristics variables included – Share of inputs from high capacity boats and Share of inputs from boats with cooling system – are significantly correlated with output quality in the cross-section of firms. One reason why the coefficients on these characteristics are not significant in Table 4 is that we observe little change in these boat characteristics over time.

[29] In Table 3 we focus on the protein content as the measure of output quality; the corresponding results for unit prices are shown in

Another concern might be that an unobservable shock to a firm's productivity could induce the firm to both acquire suppliers and increase output quality (without the former affecting the latter), as in Kugler & Verhoogen (2012). We thus add a control for the firm's share of total industry production; this has very little effects on the estimated VI supply coefficient. This finding also suggests that a "foreclosure" story in which buying suppliers helps downstream firms increase their mark-ups by excluding competitors from the market cannot explain our results (Ordover *et al.* , 1990).

While other mechanisms may also contribute to the association between VI and output quality we first saw in Table 2, in sum, the evidence discussed in this section strongly suggest that at least part of the explanation is that VI supply directly affects output quality. In the next section, we explore how demand for high quality fishmeal affects VI.

4 Demand for Quality and Vertical Integration

If VI enables the production of higher quality output then profit maximizing firms should make use of VI to a greater extent when demand for quality is high. To test this hypothesis, we now use quality-differentiated demand shocks from specific destinations as an instrument for the observed quality of exports at the firm level.

Our approach relies on two important facts about the fishmeal sector. First, firms export different qualities to different destinations. This is apparent in the export transactions data, where some destination countries (e.g. Chile and Japan) consistently buy higher unit price and protein content fishmeal than other countries.[30] It is also clear in the sales records of the large firm that shared its data with us, where the quality column for exports to some destination countries is simply filled in with the name of the country (e.g. "Thailand" quality). An increase in demand from high quality importers should thus increase the quality content of Peruvian fishmeal exports.

The second important fact about the Peruvian fishmeal sector is that the timing of contract negotiations relative to production is such that firms can change the supply strategy followed in a given production season in response to high or low demand from particular importer countries. The industry association informed us that almost all contracts for a given season's production are negotiated either before the season starts, or early in the season.[31]

To construct our demand shocks, we follow a "Bartik instrument" approach similar to Bastos *et al.* (2016) (see also Park *et al.* (2009); Brambilla *et al.* (2012)). In the second stage, we investigate whether quality has a positive impact on our measures of VI:

$$\text{VI}_{it} = \alpha + \beta_1 \text{Quality}_{it} + \gamma_i + \delta_t + \varepsilon_{it} \tag{2}$$

We control for firm and production season fixed effects as in Section 3. In the first stage quality is instrumented by demand shocks from specific destinations as follows:

$$\text{Quality}_{it} = \gamma_i + \delta_t + \sum_j \beta_j \, (\text{I}^j_{i2008} \, S^j_{-it}) + \varepsilon_{it} \tag{3}$$

Appendix Table A2.

[30] See Appendix Table A3 for a list of the main importers of Peruvian fishmeal and the average quality imported.

[31] In our primary approach we focus on contemporaneous (same season) demand shocks. In Appendix Table A4 we show results for demand shocks that occur in the $t-1$ season.

where j is an export destination country, and $\mathrm{I}^{j}_{i2008}\ S^{j}_{-it}$ are our excluded instruments. I^{j}_{i2008} is a dummy variable equal to one if firm i exported to destination j in 2008, the year prior to our analysis period. S^{j}_{-it} is the leave-firm-i-out share of total exports to destination j in season t. S^{j}_{-it} is therefore a proxy for demand from destination j at a given point in time. Changes in j's demand should matter more for firms that previously exported to j, which we capture in the interaction between S^{j}_{-it} and I^{j}_{i2008}. We denote this "leave-firm-i-out" approach Method 1 henceforth.

In our second approach to instrumenting for high quality demand shocks, we replace S^{j}_{-it} by $S^{j}_{-Peru,t}$, the leave-Peru-out share of world fishmeal imports from country j in season t. Peru only accounts 30 percent of the world production of fishmeal and many other countries export fishmeal. We construct this variable from BACI data.[32] BACI data is only available at the year level while our measures of quality produced are at the season level, with some seasons spanning two years. We thus match a production season to the year in the BACI data that spans most of the season. We denote this "leave-Peru-out" approach Method 2 henceforth.

Rather than select a set of high quality importer countries of arbitrary size, we take an agnostic approach and allow the data to inform us which countries' demand has the biggest impact on quality exported. To do so we use LASSO regressions to select the countries to be included in the first stage.[33] LASSO selects Japan and Australia to be our excluded instruments for Method 1 and Japan and Canada for Method 2. Reassuringly, the high quality importers selected by the LASSO method are also ones that we can see by inspection of our quality measures are ones that import high average unit prices and protein content fishmeal.

The existing literature that uses destination country demand shocks for identification often struggles with weak instruments. We compute the Kleibergen-Paap Wald test statistic for weak instruments. Comparing the statistics reported in Table 5 to the Stock-Yogo critical values,[34] we cannot reject the null hypothesis that our instruments are weak. However, we can reject the hypothesis that the coefficients on the excluded instruments are jointly zero when they are included in place of quality itself in the second stage regression using the Anderson-Rubin Wald test.

Another potential concern is that the liquidity that comes along with increased demand (rather demand for quality itself) may affect firms' ability to integrate. That is, if firms' seasonal revenues are expected to be higher when demand for quality is high, they may be better able to access the capital necessary to vertically integrate, and do so for other reasons than to satisfy the demand for high quality. While this possibility is a priori unlikely since we focus on *use* of integrated suppliers rather than acquisitions, we address it by including controls for total seasonal sales. This has very little effect on the estimated coefficients.

The OLS and the second stage IV results are reported in Table 5. We find that firms respond to high quality demand shocks by sourcing a higher share of their inputs from VI suppliers. We conclude that obtaining more of their inputs from VI suppliers is a *strategy* that firms use in order to produce higher quality fishmeal when demand for quality is high.

[32] BACI data is a consolidated version of COMTRADE data. A precise description of how the data is constructed can be found in Gaulier & Zignago (2010). The 6-digit product code for fishmeal is **230120**

[33] LASSO (least absolute shrinkage and selection operator) is a regression analysis method that performs both variable selection and regularization in order to enhance the prediction accuracy and interpretability of the statistical model it produces.

[34] Though Stock-Yogo's critical values are computed for the homoskedastic case, it is standard practice to compare the Kleibergen-Paap Wald test statistics to these critical values even when one reports standard errors that allow for heteroskedasticity.

5 Supplier Status and Behavior (TBC)

In the two previous sections, we have seen that downstream firms produce higher quality output when they source more of their inputs from VI suppliers, and that firms source more of their inputs from VI suppliers when they face greater demand for high quality output. In this section, we study *how* the use of VI suppliers benefits downstream firms.

When the quality of inputs is unobservable to downstream firms and thus cannot be contracted upon, whether suppliers are owned or independent may be important. In our setting, input quality depends on the behavior of the boat while at sea, which can be observed by the fishmeal plant only imperfectly. We thus hypothesize that fishmeal firms can use VI to induce their suppliers to adopt a behavior that improves the quality of the inputs they deliver.

What kind of supplier behavior is likely to improve the quality of inputs delivered? The industry associations and Peruvian fishmeal firms we talked to all stated that the main determinant of fishmeal quality, apart from the technology used by the plant, is the freshness of the fish at the time of processing. The freshness of the fish depends on several factors. The first one is how the fish is stored while the boat is at sea. Some boats have an integrated cooling system on board, but the majority use ice to keep the fish fresh while traveling back to port. Fish that has been too heavily weighed down ("crushed") while stored on the boat will also be of lower quality when processed. The second factor that matters for freshness is how much time passes in between when the fish is brought out of the water and when it is processed by the fishmeal plant. While boats can thus achieve higher fish quality by fishing close to port and bringing the catch to shore quickly, they face a quantity-quality trade-off. For example, spending more time at sea fishing is likely to result in a bigger catch per trip.

[THE FOLLOWING IS AN INFORMAL DESCRIPTION OF THE LOGIC OF OUR FRAMEWORK, WHICH IS TBC SOON] While downstream firms can observe suppliers' effort to produce quantity, they cannot observe the effort to produce high quality inputs perfectly. We make an assumption similar to Shapiro & Stiglitz (1984)'s labor discipline model, in that there is a small probability that the downstream firm finds out that a supplier did not put in effort to produce quality. Downstream firms can then incentivize supplier managers to put in effort to produce quality with the threat that their loss if caught shirking would be high enough. Under integration, because downstream firms own the production assets, they can threaten to fire supplier managers if they do not put in effort to produce quality. In that case the supplier managers would be left unemployed.[35] However, if the supplier managers own the assets, the downstream firms can punish them only weakly if caught shirking, as they will be able to sell their supplies to other downstream firms.

The intuition developed here is similar to the one developed in Grossman & Hart (1986) and Baker *et al.* (2002), in that the outside option is the key to determining whether the supplier makes a relationship-specific investment (in our case, puts in effort). But unlike Baker *et al.* (2002), relational contracts are not equivalent to integration here. Because different downstream firms stand at different points on the demand for quality ladder (see Section 4), different firms should have different objectives on the quality-quantity trade-off. Firms with a low value for high quality inputs should therefore compete to buy as much fish as possible on the spot market. Therefore, even if suppliers were paid a premium for bringing quality repeatedly, the outside option for independent suppliers might high enough that there would be little incentive for

[35] This assumption is especially realistic in our setting because the total number of boats allowed to fish in Peru is fixed (new boats cannot be introduced because of the quota system).

the supplier manager to put in quality-effort. In equilibrium, knowing that independent suppliers would find it optimal to shirk, the downstream firm would not implement a relational contract with independent suppliers and would only buy from them on the spot market.

In our data we observe payments to suppliers in the internal data a large firm shared with us.[36] We see that at a given point in time all independent suppliers are paid a fixed price per metric ton delivered, and port-day fixed effects explain 99% of the price variation across transactions, confirming that downstream plants pay market prices when buying from independent suppliers.[37]

With this framework in mind, we now study how a supplier's status matters for its behavior. We use the boat GPS data discussed in Section 2.2 to measure supplier behavior. We focus our analysis on "switchers" – suppliers that are bought (or sold) by a fishmeal firm during our data period – as differences in the behavior of integrated and VI suppliers could otherwise be explained by differential characteristics. Note, however, that we do not see any significant changes in boats' observable characteristics (e.g. cooling systems or storage capacity) when switchers become integrated. Any change in behavior post-integration should thus be due to the VI status itself.[38]

We proceed in three steps. In Sub-section 5.1 we show how a supplier's *average* behavior changes when it is integrated with a downstream firm. In Sub-section 5.2 we show how a supplier's behavioral response to the quality produced by the plant supplied changes once integrated. Finally, in Sub-section 5.3, we show how a supplier's response to exogenous variation in production conditions differs once integrated.

5.1 Vertical integration and supplier average behavior

We first explore how the average behavior of a supplier changes with integration. We estimate:

$$\mathrm{B}_{ijt} = \alpha + \beta \mathrm{VI}_{ijt} + \gamma_{ij} + \delta_t + \varepsilon_{ijt} \tag{4}$$

where B_{ijt} is a measure of the behavior of supplier i, delivering to plant j, on day t. VI_{ijt} is an indicator for whether the boat is integrated and delivers to its parent firm on the date in question. We use date fixed effects (δ_t) to control for potential time trends in behaviors and include Boat×Plant fixed effects (γ_{ij}) so that we focus on how integration affects supplier behavior in a specific supplier-downstream firm relationship.

We report results for four different behaviors: (i) Total quantity fished per trip, (ii) Maximum distance from port at which we observe the boat during a trip, (iii) Total time at sea per trip, and (iv) Time spent traveling back from the last fishing location to port.[39]

The results are in Table 6. Column 1 shows that, when integrated and supplying a parent plant, a boat delivers on average about six percent less per trip compared to when it supplies the same plant while independent. We interpret this result as indicative that boats dedicate more of their storage capacity to ice in order to keep the catch fresher and less crushed under other fish, when they are integrated. Several industry actors we interviewed reported that most fishmeal firms provide trainings on how best to store the fish on board to integrated boats.

[36] The administrative Supply transactions registry does not provide information on the price paid by downstream firms.

[37] Relational contracts may exist in the fishmeal industry, but if so, they likely address other problems, e.g. supply assurance as in Macchiavello & Miquel-Florensa (2016).

[38] Appendix Table XX shows that switchers' characteristics differ from the average supplier characteristics, but they do not change with integration.

[39] As discussed in Section 2.2, we proxy for fishing location using the boat's speed.

Column 2 shows that boats fish approximately four percent closer to port when integrated, again consistent with the hypothesis that fishmeal firms use VI to induce supplier behaviors that improve the quality of their inputs. In column 3, we see that boats spend on average three percent less time at sea when integrated; however, we do not find a significant decrease in the time spent between the last fishing location and port, as seen in column 4. A potential concern arising when looking at these results is that suppliers just put less effort while at sea when they become integrated and that increases in quality are just an upside effect of integration. The results in column 5, however, do not suggest this. Boats are more likely to go out at sea to fish when integrated, perhaps to compensate for the fact that they bring less per trip post-integration.

We conclude that suppliers, when integrated, behave on average in ways that are likely to increase the quality of downstream firms' inputs.

5.2 Vertical integration, quality upgrading, and supplier behavior

In the previous sub-section we analyzed how supplier *average* behavior changes with integration. In this sub-section we explore how a VI supplier *changes* its behavior when the plant it supplies produces higher quality fishmeal, relative to when the supplier is independent. We estimate the following equation:

$$\mathrm{B}_{ijt} = \alpha + \beta_1 \mathrm{VI}_{ijt} \times \mathrm{I}[\text{Low Quality}_{jt}] + \beta_2 \mathrm{VI}_{ijt} \times \mathrm{I}[\text{High Quality}_{jt}] + \gamma_{ij} \times \mathrm{I}[\text{High Quality}_{jt}] + \delta_t + \varepsilon_{ijt} \quad (5)$$

where $\mathrm{I}[\text{Low Quality}_{jt}]$ is a dummy equal to 1 when plant j – i.e. the plant supplier i supplies at t – produces comparatively low quality fishmeal (and conversely for $\mathrm{I}[\text{High Quality}_{jt}]$),[40]. In this setting, we include Boat×Plant×Quality fixed effects($\gamma_{ij} \times \mathrm{I}[\text{High Quality}_{jt}]$) to control for potentially already different behaviors when the plant produces high or low quality, before integration. The other variables are as defined in equation (4).

This specification allows us to estimate how the difference between how the supplier behaves in a given supplier-plant relationship when it is integrated with the plant versus independent depends on whether the plant is producing low or high quality at the time. Because we estimate this difference out of switchers, the marginal impact of the behavior of a given boat on the quality produced by the plant is likely to be small. We thus interpret β_2 as the boat's response to the plant's intention to produce higher quality.

The results are presented in Table 7. Column 1 shows that VI boats tend to fish a lower quantity per trip regardless of whether the plant they deliver to produces low or high quality at the time. However, columns 2, 3 and 4 show that, when integrated, boats adjust their behavior, so as to supply fresher fish when the plant they are supplying is producing high quality. When integrated with the plant being supplied, boats fish about seven percent closer to port, spend about six percent less time at sea and five percent less time to bring the fish back to the port, when the plant is producing high quality. These results suggest that integrated suppliers adapt their behavior to the current needs of the downstream plant being supplied. The last row of Table 7 shows that, with the exception of the first column, the behavior of integrated suppliers is significantly diffrent when the downstream plant produces higher quality.

[40] We define this dummy variable using the measure of quality we observe at the plant level, namely the share of the plant's production that is of the high quality type of fishmeal. The dummy is equal to 1 if the share of the plant's production that is of high quality is higher than the median in our sample.

5.3 Vertical integration, variation in production conditions, and supplier behavior

We have seen that when the supplier-buyer pair is vertically integrated, suppliers behave in ways more conducive to producing high quality inputs on average and, especially, at times when the downstream buyer is in need of high quality inputs. We now explore how a supplier's response to exogenous variation in production conditions depends on its status. To do so, we take advantage of variation across space and time in the ocean along the coast of Peru in plankton concentration. Plankton is the primary food source of small pelagic fish, including Peruvian anchovies. Phytoplankton concentration can thus be used to predict the abundance of fish in a specific location.[41] We use data on phytoplankton concentrations constructed from NASA satellige images as described in Section 2.2.

To identify the exact conditions that lead to availability of more and better fish, we use 2015 data and for the rest of this paper exclude 2015 data from our regressions of interest. We first define good fishing conditions for a specific location. The NASA phytoplankton data is at the level of 0.1°-latitude×0.1°-longitude (roughly 10 kilometer×10 kilometer) grid-cells. We match the plankton data with the fishing locations of boats that we obtained from the GPS data. We first look at the likelihood that at least one boat fishes in a specific grid-cell as a function of the log(Plankton concentration).[42] The top panel of Figure 2 shows that the higher the log(Plankton concentration), the higher the likelihood that the location is chosen by at least one boat. The bottom panel of Figure 2 shows the residualized quantity fished by boats (i.e., we "take out" boat fixed effects) as a function of log(Plankton concentration). The graph shows a positive and approximately linear relationship between log(Plankton concentration) and quantity fished. Overall, the two panels of the figure show that a higher plankton concentration is associated with better fishing conditions. For the rest of this section, we define a location as *good for fishing* if the log(Plankton concentration) is greater than the median defined over all locations where at least one boat fishes at some point in 2015.

Our objective is to define how good the fishing conditions in the area outside of a specific fishmeal port are on a specific day.[43] We first construct the share of fishing locations around the port that are *good for fishing* on the day in question.[44] (Figure 3 shows a map of plankton concentrations on a randomly picked day around the fishmeal port of Chimbote, which is indicated by the square symbol. The blue dots correspond to locations that are *bad (not good) for fishing* and the red dots to locations that are *good for fishing*). We then define the conditions for a port-day to be *difficult* if the share of its fishing locations that are *good for fishing* is lower than the 20th percentile in the distribution of port-days in our sample.[45]. In this sense, our definition of *difficult conditions* corresponds to days when it is challenging to find fish around the port. Figure 4 shows that on the days when the conditions are *difficult*, supply of fish to plants at the port is on average 90 percent lower.

With this measure in hand, we explore whether VI differentially benefits downstream firms' output

[41] See Axbard (2016) and Fluckiger & Ludwig (2015) for economic papers using plankton data to predict abundance of fish.

[42] We take logs because the distribution of Plankton concentration is fat-tailed.

[43] We do not focus on the conditions facing a specific boat at a specific location because the boat's choice of where to fish is likely to be endogenous to its characteristics and objectives.

[44] We use only the locations that are within 145 kilometers of the port, the 95th percentile of the maximum distance from the port of delivery at which a boat is observed during a fishing trip.

[45] The distribution of the share of locations that are *good for fishing* is shown in Figure 3 (b).

quality when upstream production conditions are difficult. We estimate the following equation:

$$\begin{aligned}\text{Quality}_{jt} = \alpha + \beta_1 \text{VI}_{jt} + \beta_2 \text{Difficult conditions}_{jt} \\ + \beta_3 \text{VI}_{jt} \times \text{Difficult conditions}_{jt} + \beta_4 \text{HighTech}_{jt} + \gamma_j + \delta_t + \varepsilon_{jt}\end{aligned} \tag{6}$$

where $\text{Difficult conditions}_{jt}$ is a continuous variable defined as the firm-season level average of *Difficult conditions* defined at the port-day level.

The results are presented in Table 8. The second row shows that if a firm is subject to more *difficult conditions* during a production season, the quality of its fishmeal is significantly lower. We interpret this finding as evidence that when conditions are *difficult* according to our measure, it is more challenging not only to fish quantity, but also quality.[46]

Row 3 of Table 8 shows that firms can reduce the impact of such *difficult conditions* on the quality of their output by sourcing more of their inputs from VI boats. Since we normalize the *difficult conditions* variable to a mean of 0, the first row can be interpreted as the total correlation between the VI share of inputs and output quality. Comparing the first row of columns 1 and 2, and columns 3 and 4, we see that when we control for *difficult conditions* and its interaction with the VI share of inputs, the correlation between VI and output quality falls by about 20 percent.[47] Using integrated suppliers thus allows firms to partially overcome the challenges to producing high quality output that arise when upstream production conditions are difficult, a fact that accounts for part of the correlation between VI and quality we saw in Section 3.

We next explore whether the ability of VI suppliers to mitigate *difficult conditions* is explained by their behavior at such times. We estimate the folowing equation:

$$\begin{aligned}B_{ijt} = \alpha + \beta_1 \text{VI}_{ijt} \times \text{I}[\text{Difficult conditions}_{ijt} = 0] + \beta_2 \text{VI}_{ijt} \times \text{I}[\text{Difficult conditions}_{ijt} = 1] \\ + \gamma_{ij} \times \text{Difficult conditions}_{ijt} + \delta_t + \varepsilon_{ijt}\end{aligned} \tag{7}$$

where $\text{Difficult conditions}_{ijt}$ is a dummy equal to 1 when the conditions around the port where plant j operates are *difficult* as defined above. As in the previous section, we include Boat×Plant×*Difficult conditions* ($\gamma_{ij} \times \text{Difficult conditions}_{ijt}$) to control for potentially already different behaviors when the production conditions change before integration. The other variables are defined as previously. We thus estimate how a boat changes its behavior on days when conditions are *difficult* when it is integrated relative to when it is independent.

The results are in Table 9. Column 1 shows that boats tend to fish less on days when conditions are *difficult* when they are VI (though the coefficient is not significant). More importantly, they fish about 25 percent closer to the port, spend 19 percent less time at sea, and bring the fish back to port in 21 percent less time. Such changes in supplier behavior are likely to have a significant impact on the quality of the inputs supplied to the downstream firm, helping to explain why it appears important for output quality to use VI suppliers when conditions are *difficult*. The last row of Table Table 9 shows that the behavior of integrated boats is significantly different when conditions are *difficult*.

As detailed in the previous paragraphs, the boats that supply fishmeal plants face a trade-off between

[46] ADD BIOLOGY REFS

[47] In Appendix Table A5, we present similar regressions at the plant (as opposed to firm) level (using the binary measure of quality available at plant level), and also when restricting the sample to a big fishmeal firm that shared its transaction data with us. The results are qualitatively very similar to those in Table 8, but less precisely estimated.

quantity and quality fished because of the technology they operate under. This trade-off is likely to be particularly pressing during *difficult* production conditions, when both fishing quantity and quality requires greater effort. Because it is not possible to contract on quality, independent boats are paid based on quantity. Instead, integration allows downstream firms to incentivize suppliers to put in the right type of effort, and so particularly when the production conditions make the quantity-quality trade-off more critical.

6 Conclusion

This paper identifies an overlooked motivation for vertical integration in incomplete contracts settings: downstream firms strategically integrate in order to produce high quality products. Acquiring their inputs from integrated suppliers allows manufacturing plants to better control their suppliers and incentivize upstream firms to supply high quality inputs

Using within- and across-firm transaction level data between buyers and suppliers and various direct measures of quality produced by downstream plants and firms in the Peruvian fishmeal manufacturing industry, we first show that an increase in the share of inputs coming from integrated suppliers is robustly associated with higher output quality. We then instrument for output quality with firm-specific, export destination demand shocks. We find that when firms face higher demand from importers of high quality, they source more of their inputs from VI suppliers.

In the second part of this paper, we investigate *why* output quality is higher when plants and their suppliers are vertically integrated, using GPS based measures of supplier behavior. In the context we study, input quality is difficult to assess and therefore cannot be contracted upon. Our results show that vertical integration enables manufacturing firms to induce upstream suppliers to allocate effort towards tasks that increase input quality. Specifically, fishing boats change their behavior consistently with the objective of delivering fresher fish – which allows their clients to produce higher quality fishmeal – once integrated. They do so more when the downstream plant produces high quality, and when the fishing conditions make the trade-off between quantity and quality more pressing.

These results demonstrate a specific strategy that firms in developing countries can and do adopt in order to upgrade the quality of their products and achieve export-driven growth. They resonate with other recent work starting to address how specific changes in organizational structure or contracts help firms, for example, deal with unforeseen contingencies (Forbes & Lederman, 2010; Novak & Stern, 2008) or change the technology of production (Atkin *et al.* , 2015). Given how different the network structure of the economy looks across sectors and countries, it is clear that much remains to be done.

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TABLE 1: SUMMARY STATISTICS

		Mean	Sd
Firms	Total number of firms	37	
	Export shipment (metric tons)	384	(360)
	Export Price ($/metric ton)	1443	(312)
	Number of destinations per season	7.57	(5.45)
	Number of export transactions per season	89	(101)
Plants	Total number of plants	89	
	Has high technology	0.82	(0.38)
	High quality share of production	0.82	(0.37)
	Monthly production (metric tons)	3092	(3288)
	Processing capacity (metric tons/hour)	102	(56)
Boats	Number of boats operating over a season	766	240
	Owned by a downstream firm	0.28	(0.45)
	Steel	0.44	(0.50)
	Storage capacity (m3)	187	(164)
	Power engine (hp)	430	(342)
	Number of fishing trips	24	(13)
	Number of delivery ports	3.47	(1.95)
	Offload weight (metric tons)	114	(113)
	Time at sea per trip (hours)	20.84	(9.97)
	Maximum distance to Port on a trip (kms)	76	(46)

Notes: Plants' capacity measure the total weight of fish that can be processed in an hour. *Steel* is a binary variable equal to 1 if a boat is a steel boat (in general bigger than the wooden boats). *Offload* is the amount fished on a fishing trip. *Time at sea per trip* is the total time spent at sea on a fishing trip. *Maximum distance to Port on a trip* is the maximum distance at which a boat is from the port on a fishing trip.

TABLE 2: QUALITY EXPORTED AND VERTICALLY INTEGRATED SUPPLIERS

	Dep. var: Log(unit price)		Dep. var: Protein content	
	(1)	(2)	(3)	(4)
Number of suppliers owned	0.003^{**}	0.003^{**}	0.025^{**}	0.027^{**}
	(0.001)	(0.001)	(0.012)	(0.013)
High technology share of used capacity		0.059^{**}		0.756^{**}
		(0.025)		(0.300)
Season FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Mean of Dep. Var.	7.21	7.21	65.5	65.5
N	190	190	190	190

Notes: *Log(unit price)* is the log of the quantity weighted average unit price of exports during a season. *Protein content* is the quantity weighted average of a measure of quality infered with a database that provides weekly prices by quality. *High technology share of capacity* is the share of the total processing capacity (measured in metric tons per hour) that is of the high technology. One observation is a firm during a fishing season. Robust Standard Errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

TABLE 3: QUALITY AND VERTICALLY INTEGRATED SHARE OF INPUTS

	Panel A: Firm level			
	Dep. var: Log(unit price)		Dep. var: Protein content	
	(1)	(2)	(3)	(4)
Share of inputs from VI suppliers	0.129**	0.129**	1.335***	1.336***
	(0.056)	(0.056)	(0.450)	(0.445)
High technology share of capacity		0.057**		0.737**
		(0.024)		(0.296)
Season FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Mean of Dep. Var.	7.21	7.21	65.5	65.5
N	190	190	190	190
	Panel B: Plant level for a major firm			
	Dep. var: Log(unit price)		Dep. var: Protein content	
	(1)	(2)	(3)	(4)
Share of inputs from VI suppliers	0.115***	0.107**	1.372**	1.340**
	(0.042)	(0.044)	(0.654)	(0.656)
Has high technology		0.031		0.124
		(0.027)		(0.378)
Season FEs	Yes	Yes	Yes	Yes
Plant FEs	Yes	Yes	Yes	Yes
Mean of Dep. Var.	7.23	7.23	65.8	65.8
N	66	66	66	66

	Panel C: Plant level	
	Dep. var: High quality share of production	
	(1)	(2)
Share of inputs from VI suppliers	0.119***	0.068***
	(0.022)	(0.020)
Has high technology		0.535***
		(0.036)
Season FEs	Yes	Yes
PlantFEs	Yes	Yes
Mean of Dep. Var.	0.82	0.82
N	2149	2146

Notes: *Log(unit price)* is the log of the quantity weighted average unit price of exports during a season. *Protein content* is the quantity weighted average of a measure of quality infered with a database that provides weekly prices by quality. *High technology share of capacity* is the share of the total processing capacity (measured in metric tons per hour) that is of the high technology. *Share of inputs from VI suppliers* is the share of a firm's (or plant's) inputs that come from VI suppliers during a season (or month). Panel A looks at the correlation between the VI share of inputs and quality exported at the firm-season level. Panel B focuses on one major firm in the Peruvian fishmeal industry and looks at the correlation between quality produced and VI inputs across the set of plants within that firm. Panel C uses data from all plants, at the month level, but uses a binary variable for quality. Robust Standard Errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4: QUALITY EXPORTED, VERTICALLY INTEGRATED SHARE OF INPUTS AND VARIOUS CONTROLS

	Dep. var: Protein content				
	(1)	(2)	(3)	(4)	(5)
Share of inputs from VI suppliers	1.336***	1.378***	1.308***	1.321***	1.376***
	(0.445)	(0.504)	(0.449)	(0.439)	(0.451)
Share of inputs from steel boats		−0.098			
		(0.539)			
Share of inputs from high capacity boats			0.184		
			(0.920)		
Share of inputs from boats with cooling system				0.754	
				(0.904)	
Share of Industry's total production					2.472
					(3.612)
High technology share of used capacity	0.737**	0.736**	0.746**	0.765**	0.735**
	(0.296)	(0.297)	(0.302)	(0.298)	(0.298)
Season FEs	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes
Mean of Dep. Var.	65.5	65.5	65.5	65.5	65.5
N	190	190	190	190	190

Notes: Steel boats are different from wooden boats in that they are bigger and more suited from industrial fishing. They are also subject to a different regulation. High capacity boats are boats from which the capacity is in the upper quartile of the distribution. Some boats have an integrated cooling system; the others boats use ice to keep the fish fresh. Robust Standard Errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 5: QUALITY EXPORTED AND VERTICALLY INTEGRATED SHARE OF INPUTS - IV REGRESSIONS

	Dep. var: Share of inputs from VI suppliers					
	OLS	OLS	IV - Method 1 *Leave-firm-i-out*	IV - Method 1 *Leave-firm-i-out*	IV - Method 2 *Leave-Peru-out*	IV - Method 2 *Leave-Peru-out*
	(1)	(2)	(3)	(4)	(5)	(6)
Protein content	0.022^{**}	0.020^{*}	0.075^{*}	0.076	0.080^{**}	0.082^{*}
	(0.010)	(0.010)	(0.042)	(0.050)	(0.037)	(0.045)
Log(Sales)		0.007		-0.025		-0.029
		(0.013)		(0.030)		(0.028)
Season FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dep. Var.	0.42	0.42	0.42	0.42	0.42	0.42
N	179	179	179	179	179	179
First stage			Dep. var: Protein content			
	(1)	(2)	(3)	(4)	(5)	(6)
Japan			4.699^{*}	3.277	5.163^{**}	2.828
			(2.698)	(2.831)	(2.341)	(2.559)
Australia			-5.446^{***}	-4.753^{***}		
			(1.716)	(1.590)		
Canada					23.641^{***}	20.172^{***}
					(6.996)	(6.466)
Kleibergen-Paap LM p-value (Under-id)			0.01	0.02	0.00	0.00
Kleibergen-Paap Wald F statistic (Weak inst)			9.76	4.61	7.30	5.10
Anderson-Rubin Wald test p-value			0.08	0.09	0.05	0.06

Notes: For IV Method 1, the instruments are interactions of indicators for positive exports to a destination in 2008 (the year just before our sample) and leave-firm-i-out shares of exports towards the destination in the current season. For IV Method 2, the instruments are interactions of indicators for positive exports to destination in 2008 and leave-Peru-out share of fishmeal exports towards the considered destination. Each observation is a firm over one fishing season. Robust standard errors in parenthesis * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 6: SUPPLIER BEHAVIOR AND VERTICAL INTEGRATION

Dep. var:	Log(Quantity fished)	Log(Maximum Distance from the Port)	Log(Total time spent at sea)	Log(Time between last fishing location and Port)	Boat goes out at sea
	(1)	(2)	(3)	(4)	(5)
Boat is VI	-0.055^{***}	-0.042^{***}	-0.034^{***}	-0.008	0.051^{***}
	(0.017)	(0.016)	(0.011)	(0.013)	(0.004)
Date FEs	Yes	Yes	Yes	Yes	No
Boat $\times$ Plant FEs	Yes	Yes	Yes	Yes	No
Boat FEs	No	No	No	No	Yes
N	244 075	134 548	156 479	144 479	1 237 015

Notes: *Quantity fished* is the amount of fish a boat brings back to the port per fishing trip. *Maximum Distance from the Port* is the maximum distance a specific boat is from port during a fishing trip. *Total Time spent at sea* is the the total time spends out of the port to fish. *Time between last fishing location and Port* is the time it takes the boat to travel back to the port after the last fish catch. Fish catches are proxied by a speed lower than 2.9kms/hour maintained for at least half an hour (Natividad, 2014). *Boat goes out at sea* is the likelihood that the boat goes out fishing on that day. A positive and significant coefficient means that after integration, VI boats go out at sea to fish more. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7: QUALITY, SUPPLIER BEHAVIOR AND VERTICAL INTEGRATION

Dep. var:	Log(Quantity fished)	Log(Maximum Distance from the Port)	Log(Total time spent at sea)	Log(Time between last fishing location and Port)
	(1)	(2)	(3)	(4)
Boat is VI $\times$I[Low Quality]	-0.097^{***}	0.042	0.006	0.065^{**}
	(0.038)	(0.037)	(0.026)	(0.030)
Boat is VI $\times$I[High Quality]	-0.030	-0.072^{***}	-0.056^{***}	-0.047^{***}
	(0.022)	(0.021)	(0.015)	(0.017)
Date FEs	Yes	Yes	Yes	Yes
Boat $\times$ Plant $\times$ High Quality FEs	Yes	Yes	Yes	Yes
N	244 075	148 018	156 479	144 479
p-val - Test: 2 coefficients equal	0.12	0.00	0.04	0.00

Notes: *Quantity fished* is the amount of fish a boat brings back to the port per fishing trip. *Maximum Distance from the Port* is the maximum distance a specific boat is from port during a fishing trip. *Total Time spent at sea* is the the total time spends out of the port to fish. *Time between last fishing location and Port* is the time it takes the boat to travel back to the port after the last fish catch. Fish catches are proxied by a speed lower than 2.9kms/hour maintained for at least half an hour (Natividad, 2014). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 8: QUALITY, VERTICALLY INTEGRATED SHARE OF INPUTS AND BAD FISHING CONDITIONS

	Dep. var: Log(unit price)		Dep. var: Protein content	
	(1)	(2)	(3)	(4)
Share of inputs from VI suppliers	0.139^{**}	0.114^{**}	1.221^{***}	0.942^{**}
	(0.060)	(0.056)	(0.466)	(0.452)
Bad conditions		-0.140^{**}		-1.542^{**}
		(0.062)		(0.727)
Share VI $\times$ Bad conditions		0.185^{**}		1.660^{**}
		(0.072)		(0.789)
High technology share of capacity	0.056^{**}	0.060^{**}	0.699^{**}	0.715^{**}
	(0.025)	(0.027)	(0.306)	(0.344)
Season FEs	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
Mean of Dep. Var.	7.20	7.20	65.4	65.4
N	178	178	178	178

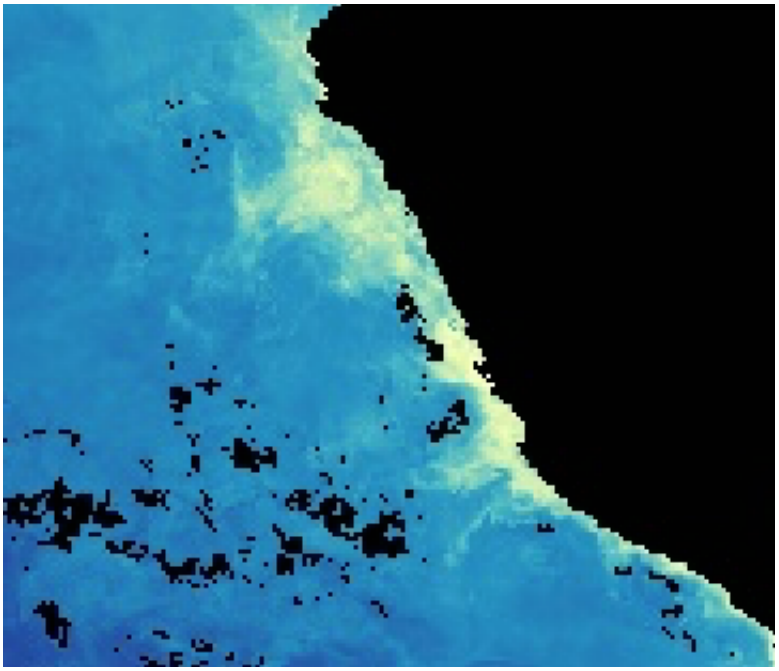
Notes: *Bad conditions* is a dummy equal to 1 when the share of good fishing locations $\big[$Log(plankton concentration)$>0.5\big]$ around a specific port on a specific day is less than 10 percent (the bottom 20th percentile in the distribution of share of good fishing locations in our sample). The above regressions are at the firm-season level while that dummy is defined at the port-day level, so the *Bad conditions* dummy variable is averaged by firm-season. It can then be interpreted as the share of days when the conditions are bad for a specific firm during a fishing season. The variable is normalized to a mean equal to 0 in our sample so that the first row of this table can be interpreted as the correlation between the *Share of inputs from VI suppliers* and quality. Robust standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 9: SUPPLIER BEHAVIOR, VERTICAL INTEGRATION AND BAD FISHING CONDITIONS

Dep. var:	Log(Quantity fished)	Log(Maximum Distance from the Port)	Log(Total time spent at sea)	Log(Time between last fishing location and Port)
	(1)	(2)	(3)	(4)
Boat is VI $\times$I[Bad conditions $= 0$]	-0.061^{***}	-0.027	-0.026^{**}	-0.004
	(0.018)	(0.017)	(0.012)	(0.014)
Boat is VI $\times$I[Bad conditions $= 1$]	-0.071	-0.247^{***}	-0.190^{***}	-0.213^{***}
	(0.063)	(0.076)	(0.054)	(0.066)
Date FEs	Yes	Yes	Yes	Yes
Boat $\times$ Plant $\times$ Bad conditions FEs	Yes	Yes	Yes	Yes
N	220 821	132 098	139 448	128 932
p-val - Test: 2 coefficients equal	0.88	0.00	0.00	0.00

Notes: *Quantity fished* is the amount of fish a boat brings back to the port per fishing trip. *Maximum Distance from the Port* is the maximum distance a specific boat is from port during a fishing trip. *Total Time spent at sea* is the the total time spends out of the port to fish. *Time between last fishing location and Port* is the time it takes the boat to travel back to the port after the last fish catch. Fish catches are proxied by a speed lower than 2.9kms/hour maintained for at least half an hour (Natividad, 2014). *Bad conditions* is a dummy equal to 1 when the share of good fishing locations $\left[\text{Log(plankton concentration)}>0.5\right]$ around a specific port on a specific day is less than 10 percent (the bottom 20th percentile in the distribution of share of good fishing locations in our sample). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

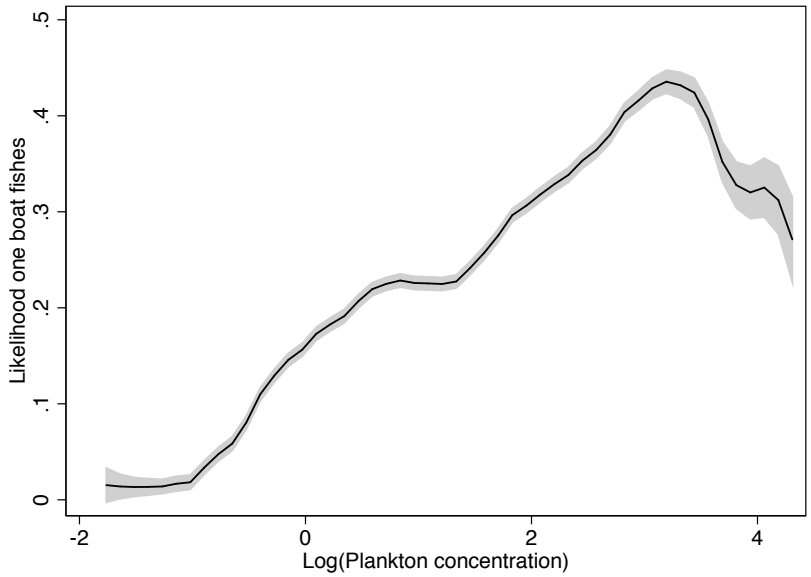
FIGURE 1: MAP OF PHYTOPLANKTON CONCENTRATION ALONG THE COAST PERU



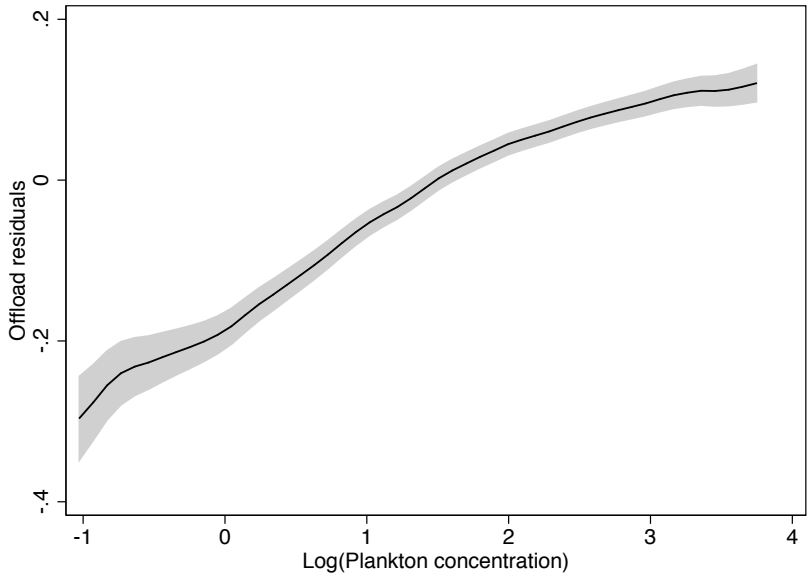
Notes: This figure is a map of plankton concentration during one month of our sample (Dec. 2012) outside of the coast of Peru. One pixel corresponds to a 0.1°-latitude$\times 0.1^{\circ}$-longitude square. A lighter color means that the plankton concentration, and so the light emitted is higher.

FIGURE 2: PHYTOPLANKTON CONCENTRATION, FISHING LOCATIONS AND FISH CAPTURED

(a)



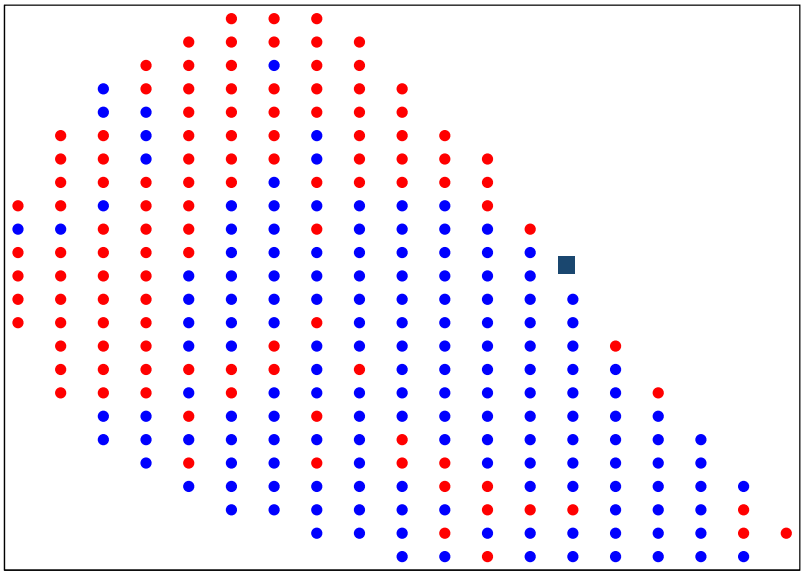
(b)



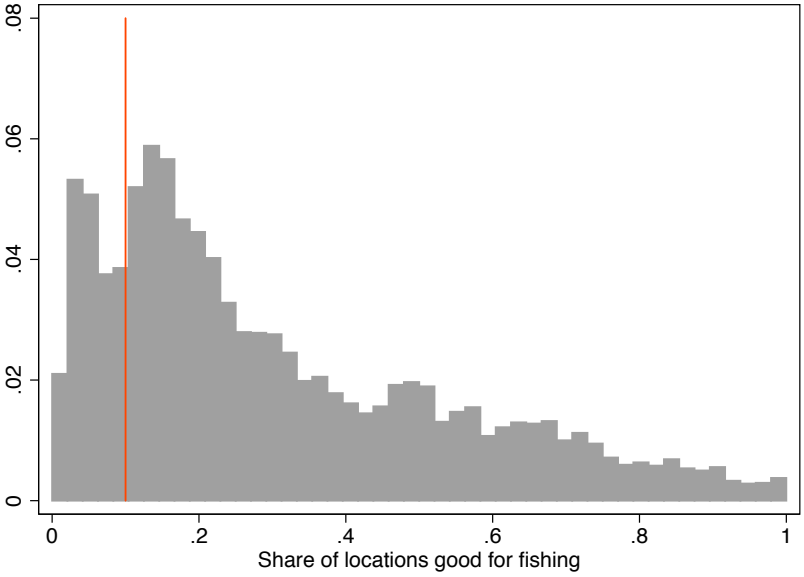
Notes: Figure (a) shows the likelihood that at least one boat fishes at a specific location (a 0.1°-latitude×0.1°-longitude square) as a function of Log(Plankton concentration). We keep only the locations where at least one boat fishes at some point in time and only the days when at least one boat fishes. Figure (b) shows offloads (or quantity fished) residuals (the residuals from a regression with boat FEs) as a function of the Log(Plankton concentration) at the last fishing location of the boat on a fishing trip. (A fishing location is determined by the last location where the boat maintains a fishing speed lower than 2.9kms/hour for at least half an hour).

FIGURE 3: PHYTOPLANKTON CONCENTRATION, FISHING LOCATIONS AND FISH CAPTURED

(a)

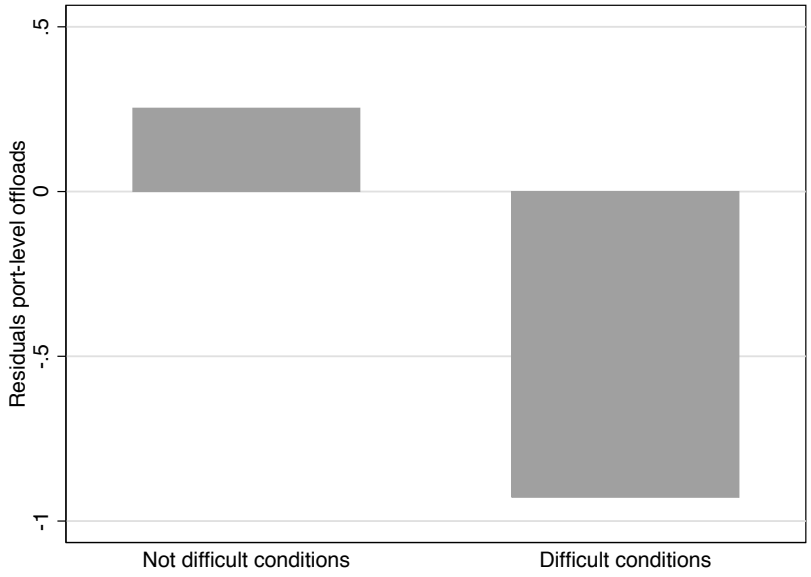


(b)



Notes: Figure (a) is an example of a map of a port (in this case, Chimbote, the largest fishing port in Peru) on a specific day with all the fishing locations available around the port (we take only the locations that are within a distance of 145kms from the port - the 95th percentile of the maximum distance at which boats fish from the ports). The position the port is indicated with the grey square. The red dot indicate that the location is *good for fishing* [Log(plankton concentration)>0.5] and the blue that it is not. From there, for each port on each day, we compute the share of locations around the port that are *good for fishing*. Figure (b) shows the distribution across days and ports of the share of locations that are *good for fishing*. We define that the conditions for a port-day are *bad* if the share of locations that are *good for fishing* is lower than the 20th percentile (around 10%).

FIGURE 4: ***Difficult conditions***



Notes: This graph shows how port residualized offload (in logs) varies with fishing conditions.