Unfair Trade?

Monopsony Power in Agricultural Value Chains

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Abstract

Exporter market power prevents farmers from benefiting from international trade. Using microdata from Ecuador, I link exporters to the farmers who supply them across the universe of cash crops. I document that farmers earn significantly less when they sell crops in export markets that are highly concentrated. I propose a model in which farmers choose a crop to produce and an exporter to supply. Exporter market power is driven by two key elasticities, which govern heterogeneity in farmer costs of switching crops and switching exporters. I develop a method to estimate them using exporter responses to international price shocks. The estimates imply that farmers earn half of their marginal revenue product as a result of market power. I evaluate the effectiveness of agricultural support policies in this setting. Fair Trade emerges as a practical tool for fighting market power and helping farmers share in the gains from globalization.

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1 Introduction

Exporters are critical links in agricultural value chains. They connect smallholder farms in emerging economies to lucrative international markets. At the same time, export markets for cash crops are often dominated by a few large firms. These exporters can use their bargaining power to depress farmgate prices, limiting the benefits of globalization for low income farmers. Several studies have measured the market power of intermediaries in emerging markets. However, they typically focus on local traders buying and selling a few products domestically.[1] This paper is the first to quantify the effect of exporter monopsony power on farmer income across the universe of exported cash crops.

Measuring market power in this setting requires information on the entire value chain for a large number of products. I use confidential firm-to-firm VAT records from Ecuador to trace over 100 agricultural goods from local farmers to exporters. I link these with firm-level customs records, where I observe prices and quantities in international markets. This allows me to infer monopsony power directly from the firm-level pass-through of trade shocks to farmer income.[2] To do so, I develop a discrete choice model of farmer cropping decisions. Exporter monopsony power in the model is determined by the ability of farmers to substitute across crops and across exporters within a crop. Variation in pass-through between small and large exporters in the data then reveals these elasticities of subsitution.[3]

The estimated model further allows me to conduct a rich set of counterfactual exercises. First, I simulate the first-best economy with no monopsony power. Farmer income is substantially higher due to reallocation of exporter profits and greater efficiency from farmers substituting to more productive corps. Next, I compare two popular second-best policies: a Fair Trade program and a broad price floor. The Fair Trade program, in which an exporter enters the market and pays farmers a competitive price, raises farmer income more than a broad price floor. However, the difference between these policies shrinks as crops become more substitutable. Other papers have evaluated Fair Trade in coffee markets,[4] but this is the first to consider its impact across the entire agricultural sector and highlight the role of farmer substitution patterns.

I begin by constructing the value chain for all exported agricultural products in Ecuador. I link customs data, which measure exporter prices and quantities on international markets, with VAT data, which measures

[1] For example, cocoa in Sierra Leone (Casaburi, Reed, Casaburi, and Reed, 2019), bananas in Costa Rica (Van Patten and Mendez-Chacon, 2020), potatoes in India (Mitra, Mookherjee, Torero, and Visaria, 2018), maize in Kenya (Bergquist and Dinerstein, 2020), grain in India (Chatterjee, 2019), and fish in the Amazon (Bartkus, Brooks, Kaboski, and Pelnik, 2021).

[2] Chatterjee (2019) infers monopsony power from variation in farmgate prices and intermediary competition over space. Dhingra and Tenreyro (2020) compare how farmer income and intermediary profits respond to a policy encouraging intermediaries. Neither paper directly links traders to farmers.

[3] Variation in cost pass-through is often used to estimate seller market power (Bergquist and Dinerstein, 2020; Atkin and Donaldson, 2015; Nakamura and Zerom, 2010; Atkeson and Burstein, 2008; Rubens, 2020). Berger, Herkenhoff, and Mongey (2019) estimate buyer market power directly using the pass-through of tax shocks to firm wages and employment.

[4] Dragusanu and Nunn (2018) find positive impacts, while De Janvry, McIntosh, and Sadoulet (2015) find mixed results. Dragusanu, Giovannucci, and Nunn (2014) provide a comprehensive review. Macchiavello and Miquel-Florensa (2019) examine more complex certifications involving the entire value chain in Colombia.

their payments to domestic suppliers, and firm registry data, which identifies agricultural suppliers.[5] The resulting dataset traces every dollar earned by exporters all the way back to farmers for products as diverse as bananas and shrimp. Importanlty, I account for the full structure of value chains, including domestic intermediaries and non-agricultural suppliers.

I document three new facts about agricultural value chains using this dataset. First, agricultural markets in Ecuador are highly concentrated, with just a few exporters in each crop purchasing the entire value produced by farmers. Second, the income earned by farmers of a given crop is low relative to exporter sales of the same crop. Either exporters add a lot of value to crops, or they exert a lot of market power. Third, I show that farmer income as a share of exporter sales – the *farmer share* – is lower when the exporter controls more of the crop market, even after controlling for observable measures of exporter value added. Since exporters are small on international markets, this last fact points to potential monopsony power.

To measure market power directly, I extend a frontier model of monopsony in labor markets (Berger et al. 2019; Atkeson and Burstein 2008) to the context of crop markets.[6] Farmers choose which crop to produce and which exporter to supply. They trade off the price offered by each exporter with their idiosyncratic shocks for producing that crop and reaching that exporter. Through these shocks, the model captures the land's suitability for different crops and proximity to different exporters, two key dimensions of heterogeneity in models of agricultural trade.[7] The more costly it is for farmers to switch from coffee to cocoa, or to switch from one coffee exporter to another, the greater the scope for monopsony power.

Exporters act strategically when purchasing crops, internalizing their influence over prices. The optimal price they pay to farmers is marked down from the price they receive on international markets, where they do not act strategically. The price is lower when the exporter controls more of the crop market – precisely the relationship I find in the data. In the model, the strength of the relationship is determined by the elasticities of substitution across crops and across exporters within a crop. The lower are these elasticities, the greater the monopsony power of large exporters, and the faster that prices fall with exporter size.

The elasticities are therefore crucial to measuring monopsony power. To estimate them, I exploit the fact that Ecuador is a small open economy and use variation in how small and large exporters respond to changes in international prices. Intuitively, the sensitivity of large exporters to demand shocks is driven by how easily farmers can substitute across crops, while the sensitivity of small exporters is driven by how

[5] Similar data have been used to construct value chains for the manufacturing products in various countries (Kikkawa, Magerman, and Dhyne, 2019; Huneeus, 2018; Adao, Carrillo, Costinot, Donaldson, and Pomeranz, 2019; Alfaro-Ureña, Manelici, and Carvajal, 2019)

[6] An alternative approach measures market power indirectly by controlling for *unobserved* value added through production function estimation (De Loecker and Warzynski, 2012; Morlacco, 2019; Rubens, 2020; De Loecker, Goldberg, Khandelwal, and Pavcnik, 2016).

[7] This heterogeneity is typically estimated using highly disaggregated spatial data (Costinot, Donaldson, and Smith, 2016; Sotelo, 2020; Farrokhi and Pellegrina, 2020; Bergquist, Faber, Fally, Hoelzlein, Miguel, and Rodriguez-Clare, 2019), but I will use a completely different and more widely available source.

easily farmers can substitute across exporters within a crop. Formally, the average pass-through of demand shocks to producer prices is low when the elasticity of substitution across exporters is low, and declines with exporter size when the elasticity of substitution across crops is low. I find that both elasticities are small, indicating that crop supply is relatively inelastic and exporters have substantial monopsony power.

The model allows me to measure monopsony power in several ways. I show that farmer prices are marked down by 51% of their marginal revenue products, implying large gains simply from eliminating markdowns and redistributing exporter profits to farmers. Indeed, a counterfactual economy with perfectly competitive exporters would see a 77% increase in farmer income, two thirds of which is explained by redistribution. The remaining third are efficiency gains from farmers reallocating across crops and across exporters within crops. The largest gains are in the most concentrated crops, such as coffee.

In the final part of the paper, I use the estimated model to study the impact of two popular agricultural support policies: Fair Trade programs and broad price floors. Fair Trade is the fastest-growing certification program for sustainable farming. Buyers pay higher prices to promote the economic well-being of certified farmers, which they recover by selling a differentiated Fair Trade product to consumers who care about farmer well-being. I model Fair Trade by introducing an exporter who behaves competitively and therefore pays a premium relative to other exporters. This has a positive direct effect on the farmers who supply the Fair Trade exporter. It also has a positive *indirect* effect, since the Fair Trade exporter reduces the market power of other exporters, forcing them to raise prices. Together, these effects can raise farmer income up to 25%.

To highlight the effectiveness of Fair Trade, I consider a second policy in which the government sets a broad price floor in each crop. This also has a positive direct effect on prices, since exporters can no longer offer prices below the floor. Unlike Fair Trade, however, it has a *negative* indirect effect. The smallest exporters contract, increasing the market power of larger exporters who can afford to pay the minimum price. Because of these offsetting effects, high price floors are required to realize the income gains from a modest Fair Trade program. However, the difference between these two policies shrinks as exporters and crops become more substitutable, demonstrating the interaction between pro-competitive policies and farmer substitution patterns.

The paper is organized as follows. In Section 2, I provide an overview of agriculture exports in Ecuador, discuss the construction of my value chain dataset, and present key facts. In Section 3, I develop a model of farmer crop choice and exporter strategic pricing to quantify market power. In Section 4, I estimate the model and validate it. In Section 5, I use the estimated model to measure the market power faced by farmers. In Section 6, I conduct counterfactual analyses of Fair Trade and other agricultural support policies. I conclude in Section 7 by discussing the limitations of the current study and the directions for future research.

2 Data

In this section, I map the entire value chain across the universe of exported crops in Ecuador. To do so, I combine administrative microdata on firm-product exports from Customs declarations, firm-to-firm transactions from VAT declarations, and firm characteristics from a national registry. I document three new facts about value chains using this dataset, which together point to the importance of exporter market power.

2.1 Ecuador: an ideal setting

Ecuador is a microcosm of the issues surrounding agricultural trade in emerging economies. GDP per capita in Ecuador is a little over \$6,000, close to the global median. Agriculture employs almost 30% of the workforce and accounts for over half of export revenues. Across all developing countries, agriculture employs 40% of the workforce and generates a third of export revenues (Cheong, Jansen, and Peters 2013).

Despite its small size, Ecuador is an important producer of cash crops such as cocoa, coffee, bananas, palm, shrimp, tuna, and cut flowers. More generally, developing countries account for more than a third of agricultural trade, and more than half of seafood trade (Aksoy and Beghin 2004). Cash crops are typically produced by many small farms, and exported by only a handful of large firms. Domestic consumption of cash crops is low, as they command much higher prices in international markets. Across South America, the largest 5% of exporting firms receive 80% of export revenue (Cunha, Reyes, and Pienknagura 2019). In contrast, most crops are produced on small farms, and average farm size has been decreasing over time (Lowder, Skoet, and Raney 2016). Even in the banana sector, which has historically been dominated by vertically-integrated, multinational giants like Chiquita and Dole, there has been a trend toward divestment from plantations (FAO 2014). In Ecuador, these multinationals control less than 20% of the export market, and most of the remaining exporters do not produce bananas themselves, but instead source from thousands of producers (Wong 2008).

A disproportionate share of the poor work in agriculture, both in Ecuador and across developing countries (Townsend 2015). Income gains in the agricultural sector are therefore crucial for reducing poverty. Ecuador offers an ideal setting for studying an important barrier to such gains: the lack of competition among exporters.[8] To examine this barrier on a large scale, I partner with the Tax Authority of Ecuador (*Servicio de Rentas Internas*, henceforth SRI) to access several administrative databases, which together allow me to trace the value of crops all the way from farm to port.

2.2 Measuring agricultural value chains

A key challenge to tracing the value of crops is that farmers typically do not export directly. To overcome this challenge, I proceed in several steps: (1) calculate the value received by exporters, (2) match exporters to their suppliers, (3) calculate the value received by each supplier, and (4) identify which suppliers are farmers. To do so, I combine several administrative datasets obtained in collaboration with the SRI.

The first dataset covers the universe of export transactions from 2008-2011. The data are compiled from Customs declarations and contain the value (in USD) and quantity (in kg) traded internationally for each firm, product, and year.[9] I use these data to calculate the price and value received by exporters (step 1). I restrict my attention to animal products, vegetable products, and foodstuffs (HS 2-digit codes 01-24), which represent roughly half of all exports from Ecuador.[10]

The second dataset captures the universe of domestic firm-to-firm transactions from 2008-2011. The data are derived from value added tax (VAT) declarations and measure the value transacted for each buyer-seller pair in each year. Using these data, I construct the network of suppliers for each exporter in (step 2) . I can then calculate the value paid by each exporter to each of his suppliers (step 3).[11]

The third dataset contains basic characteristics for all firms active in 2011. The data are pulled from a national register and include the industry and location of each firm.[12] I use these data to identify which suppliers are farmers (step 4). Taxpayers in the agriculture, forestry, and fishing industries (ISIC 2-digit codes 01-03) are classified as farmers.[13]

My novel agricultural value chain dataset comprises over 800 exporters selling 157 agricultural products sourced from almost 50,000 farmers.[14] Table 1 summarizes the farmers and exporters in my dataset. The median exporter earns over $1 million in revenue and employing more than 20 people.[15] Exporters report

[8] In interviews I conducted in Ecuador, producers frequently cited low bargaining power as a barrier to receiving higher prices.

[9] Products are classified at the HS 6-digit level.

[10] Kg is a meaningful unit of measurement for these products, unlike for more complex products.

[11] Since I only observe the quantity at the port, I cannot calculate the price paid to each supplier.

[12] Industries are classified at the ISIC 5-digit level.

[13] For suppliers in the wholesale sector, I repeat the matching procedure. After performing the procedure 3 times, I find that 90% of crop purchases are made directly by exporters (chain length 1), 9% by a single domestic intermediaries (chain length 2), and less than 1% by chains of domestic intermediaries (chain length 3). As a result, I restrict my analysis to chains of length no greater than 2. This resembles the average length of imported goods in Nigeria (Grant and Startz, 2021).

[14] See the appendix for a breakdown by product category.

[15] A fourth dataset includes matched employee-employer information from 2008-2011. The data are derived from Social Security Tax declarations and record the earnings and employers for each worker and year. Using these data, I can calculate the employment and wage bill for each firm.

large payments to workers and domestic suppliers, but earn an average profit rate of 25%. In contrast, the median farm is tiny, earning less than $9,000 annually. Furthermore, 94% of farmers are self-employed. Almost three quarters of exporters are in the wholesale sector, implying that few farmers export directly.[16] However, 75% of farmer sales are indirectly exported, indicating the importance of constructing the value chain.

A few important concerns arise when using tax information to study agricultural value chains. First, information may be missing due to informal labor in the agricultural sector. Several factors mitigate this concern. The VAT records underlying my dataset are filed by the purchasing firm, in this case an exporter. If anything, large firms have an incentive to *over-report* the value they pay to farmers, as their tax liability is assessed on the difference between sales and purchases.[17] Later, I show that larger exporters pay farmers less, and that their payments are less responsive to demand shocks. To generate these two facts from measurement error, larger exporters would have to both report lower costs on average and change their optimal level of reporting following a shock. This is inconsistent with standard tax evasion models (Carrillo et al., 2017).[18]

Table 1: Farmer and exporter statistics

(a) Exporters

$ Sales	1,177,543
$ Purchases	543,053
$ Wage Bill	108,246
# Employees	21
% Wholesale	74
% Single-product	76
Observations	804

(b) Farmers

$ Sales	8,678
$ Purchases	0
$ Wage Bill	0
# Employees	0
% Self-employed	94
% Export Intensity	75
Observations	49,475

Notes: Table summarizes agricultural exporters and the farmers who supply them. Panel A shows summary statistics across exporters. Panel B shows summary statistics across farmers. Rows 1-4 show medians. Rows 5-6 show means. "Wholesale" indicates exporters in ISIC 2-digit sector 46-47; "Single-product" indicate exporters sell a single HS 6-digit product; "Self-employed" indicates farmers filed the simplified F102 tax form; "Export Intensity" indicates the share of farmer sales indirectly exported.

A second concern is that the data may not be capturing small family farms, but rather large factory farms. The median farm does not report any employees or wages, consistent with the high rate of self-employment.[19] In principle, I could calculate farmer income as the sum of (a) sales of self-employed farmers

[16] An exception is the cut flower industry, where many small farms export directly. I exclude direct exporters from the analysis and exclude the cut flower industry entirely.

[17] Pomeranz (2015) shows that the VAT is an effective deterrent to tax evasion. Carrillo, Pomeranz, and Singhal (2017) show that to the extent that firms still cheat, they tend to over-report costs.

[18] Exporters with negligible market share often report no costs, consistent with under-reporting. To control for this measurement error, I include an indicator for these firms in my regressions.

[19] Interviews with officials at the Tax Authority and Ministry of Agriculture confirmed the interpretation of self-employed

and (b) wages paid by larger farms to their employees.[20] However, not all farm employees are farmers. To avoid distributing farm sales among employees and arbitrarily deciding who is a farmer, I measure farmer income as sales, making no distinction between farms and farmers. This overestimates farmer income and underestimates the number of farmers. Importantly, I estimate market power without using any information on the number of farmers or the size of farms. [21]

A final limitation is that VAT records measure trade between firms in general rather than trade of a particular *product* between firms. A few features of agricultural value chains in Ecuador allow me to overcome this limitation. First, unlike in more complex value chains, where firms in different industries produce important components of the final product, the key producers in agricultural value chains are farmers and fishers. They are the ones who harvest fruits from plants and fish from water, and since I observe them in my dataset, I can pin down both ends of the value chain.[22] If the exporter at one end only exports coffee, I assume that the product he purchases from the farmer at the other end is coffee.[23] This is a reasonable assumption for Ecuador, where (a) the majority of exported crops are produced exclusively for the international market and (b) the majority of exporters export a single crop. Table 1 shows that 76% of exporters fall into this category.[24] Finally, farmers typically sell to a single exporter, so it is unlikely that farmers produce multiple different crops for export. Together, these facts imply that I can infer the product being traded between farmers and exporters in my dataset.

Table 2 summarizes the funnel-like structure of agricultural value chains. The median exporter buys from 24 farmers, but the median farmer only sells to a single exporter. This is true both on aggregate and within many of the top exported products. For example, shrimp is the second most important product, with over 2 billion dollars in export sales. There are almost 6,000 shrimp producers along the coast, but only 50 shrimp exporters. This creates the potential for unequal sharing of the gains from globalization. Next, I leverage the micro-structure of my dataset to document this inequality in detail.

farmers as family farms

[20] Adao et al. (2019) follow this approach for manufacturing firms, which are more likely to report wages and employment.

[21] I compare the number of farms in my dataset to industry reports for select products and verify that they are generally of the same order of magnitude.

[22] Importing and re-exporting agricultural products for are not common in my dataset.

[23] Alternatively, I can classify products based on the 5-digit ISIC code of the farmer. Because ISIC codes typically contain multiple HS codes, this yields more aggregated product categories and hence less concentrated markets. Nevertheless, my stylized facts remain qualitatively true.

[24] I assign multi-product exporters to their top product, which accounts for 93% of exports for these firms.

Table 2: Exporter-farmer relationships

	$ Exports (Millions)	# Exporters	# Farmers	Exporter Indegree	Farmer Outdegree
All Crops	16,954	804	49,745	24	1
Bananas	6,038	188	9,685	81	3
Shrimp	2,208	50	5,729	77	1
Tuna	2,043	22	1,825	54	1
Cocoa	1,314	56	17,686	363	2
Palm oil	616	13	7,821	1,640	2
Coffee	110	17	1,611	28	1

Notes: Table summarizes exporter-farmer relationships across 157 crops. Crops are defined as HS 6-digit products in chapters 01-24. Row 2 shows all crops. Rows 3-8 show a selection of important crops. Columns 2-4 show totals. Column 5 shows the median number of farm suppliers across exporters. Column 6 shows the median number of exporting customers across farmers.

2.3 Exporter concentration and the farmer share

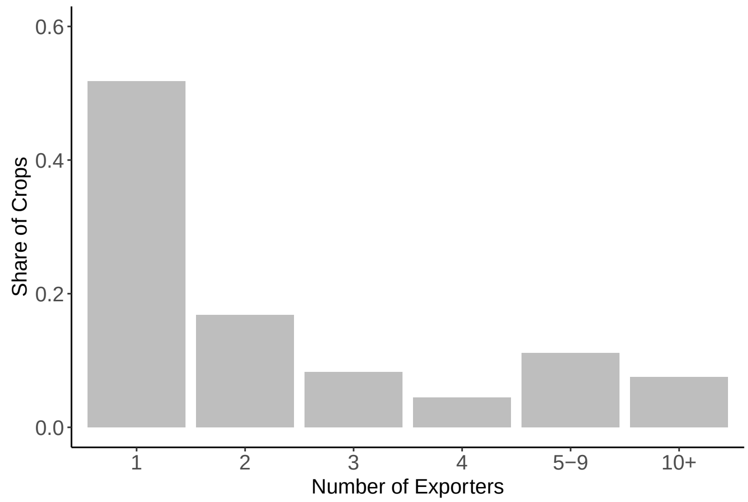
I document three new facts about supply chains of agricultural exports from Ecuador. Together, they suggest that exporters exercise market power in crop markets, and they motivate the development of a model to explore the consequences for small farmers.

2.3.1 Crop markets are highly concentrated

The number of exporters in crop market may understate the degree of concentration. For example, the cocoa market has 56 exporters in Table 2, but the top 4 cocoa exporters control almost the entire export market. I take advantage of the micro-structure of my dataset and define the *effective number of exporters* as the number of exporters required to control 90% of the market for a given crop.

To examine the potential for market power across a broad range of crops, I divide crops into six bins based on the effective number of exporters: 1, 2, 3, 4, 5-9, 10+. Figure 1 plots the distribution across these bins for more than 100 crops. The majority of crop markets are highly concentrated: the median crop is dominated by a single firm, and almost all crops have fewer than 10 exporters. However, concentration on its own does not imply market power. To provide further evidence, I take advantage of matched exporter-farmer nature of my dataset in the next fact.

Figure 1: Crop market concentration



Notes: Figure plots the distribution of the effective number of exporters across 157 exported crops. "Effective number of exporters" is defined as the minimum number of exporters required to reach 90% market share in the domestic market for crop purchases. Bars indicate the proportion of crops with 1, 2, 3, 4, 5-9, and 10 or more exporters.

2.3.2 Farmers receive a small share of the export value of their crops

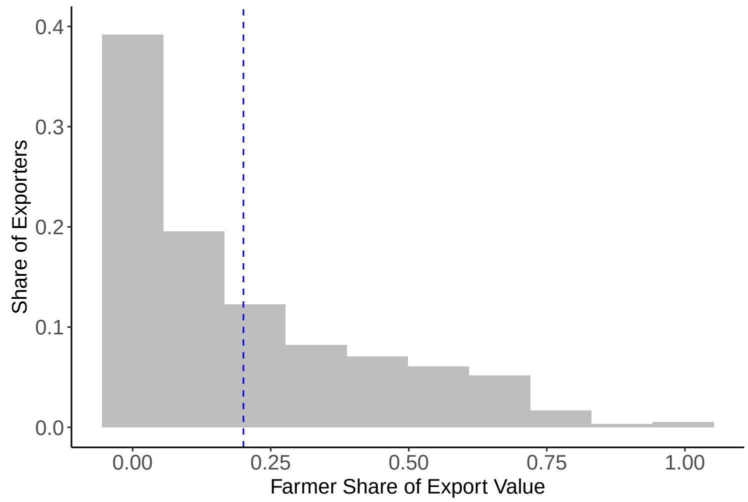
Exporters exercise market power over farmers by forcing them to accept lower prices. To investigate this in my dataset, I compute the value that each exporter pays to farmers as a share of the value he earns from selling their crops on the international market.[25] I refer to this as the *farmer share* for exporter i of crop j:

$$\text{farmer share}_{ij} \equiv \frac{\text{exporter } i\text{'s purchases of crop } j}{\text{exporter } i\text{'s sales of crop } j}$$

Figure 2 shows the distribution of the farmer share across all exporters. The blue line indicates an average farmer share of 0.24, meaning that for every dollar of agricultural products exported from Ecuador, farmers earn 24 cents. Many exporters have farmer shares lower than 10%, while very few have shares above 50%.

[25]Because I do not observe the quantity purchased from each farmer, I cannot compute this share at the farmer level. Larger exporters purchase from many more farmers, but only purchase slightly more volume per farmer. This supports aggregating across farmers for a given exporter.

Figure 2: Farmer share of export value



Notes: Figure plots the distribution of the farmer share across exporters. "Farmer share" is defined as an exporter's purchases of a crop from farmers divided by his sales of the same crop on international markets. The dashed blue lines indicates that the average farmer share is 0.24.

An alternative explanation for the low farmer shares depicted in Figure 2 is that exporters add value to crops by transforming or transporting them. For example, a cocoa exporter may re-package the beans he purchases from farmers before selling them internationally, or ship them from the eastern Amazon provinces, where a substantial share of cocoa, is grown to the coastal port of Guayaquil. In my dataset, this could appear as wages or payments to suppliers who are *not* classified as farmers. I exploit this dimension of the data to establish the next fact.

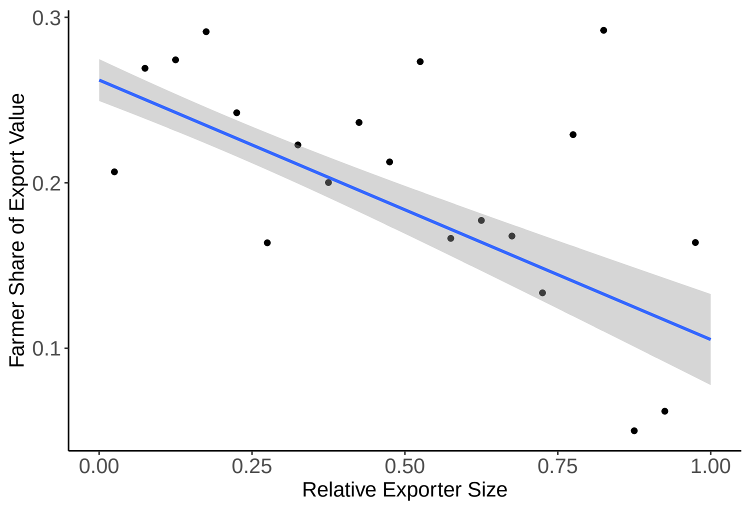
2.3.3 The farmer share is lower when exporters are more concentrated

Neither the high exporter concentration in fact 1 nor the low farmer shares in fact 2 alone are sufficient evidence of market power. To establish a connection between them, I define the *relative size* of exporter i in crop j as the value purchased by exporter i as a share of the total market for crop j.

$$\text{exporter size}_{ij} \equiv \frac{\text{exporter } i\text{'s purchases of crop } j}{\text{total purchases of crop } j}$$

An exporter with relative size near 1 controls the entire market for a crop and is therefore a *monopsonist*, while an exporter with relative size near 0 exerts little control. If the relative size of an exporter measures his potential for market power, and he realizes this potential by forcing farmers to accept lower prices, then we should see a negative relationship between farmer shares and relative exporter size. Figure 3 confirms this: on average, an exporter who controls all of the market pays 20 percentage points less to farmers than an exporter who controls none of it. At the mean farmer share of 0.25 in Figure 2, this represents an 80% decrease.

Figure 3: Farmer shares and exporter concentration



Notes: Figure plots exporter size on the x-axis and farmer shares on the y-axis. "Exporter size" is defined as the share of the domestic market for a given crop purchased by a given exporter. "Farmer share" is defined as an exporter's purchases of a crop divided by his exports of the same crop. Each dot indicates the average farmer share within bins of 5% market share. Solid blue line indicates predictions from a linear regression where each observation is an exporter-crop-year. Grey area indicates a 95% confidence interval.

Figure 3 pools exporters across all crops. However, farmer shares should be lower in crops that require extensive transformation or transportation. If this in turn requires large fixed investments in machines or vehicles, such crops may have fewer exporters in equilibrium. For example, the shrimp market may have more exporters and larger farmer shares than the cocoa market simply because shrimp is sourced along the coast, whereas cocoa is sourced as far as the Amazon, removed from major ports. In this case, farmer shares and relative exporter size would be negatively correlated, even if exporters did not exercise market power. A similar phenomenon may play out within crops. For example, 80% of cocoa is grown in coastal provinces. If sourcing the remaining 20% from inland provinces requires large fixed investments that only large exporters can afford, the same spurious correlation would arise.

To explore the negative relationship between farmer shares and relative exporter size in more detail, I estimate a series of regressions:

$$\log(\text{farmer share}_{ijt}) = \beta \text{exporter size}_{ijt} + \mathrm{X}'_{ijt}\Gamma + \delta_{jt} + \varepsilon_{ijt}$$

where X is a vector of controls, δ is a crop-year fixed effect, ε is an error term, and t indexes the year. The coefficient of interest, β, measures the relationship between exporter size and farmer shares. Table 3 displays the results. Column 1 shows the baseline specification with no controls or fixed effects, consistent with Figure 3. Column 2 includes product-year fixed effects to control for unobserved differences in processing and fixed costs of sourcing across crops.[26] Because many 6-digit products (crops) are controlled by a single exporter, fixed effects are at the 2-digit product level. Column 3 controls for systematic differences across exporters by adding wages, payments to non-farm suppliers, and log export prices.[27] Wage payments help capture exporter-specific value added. Non-farm payments help measure flow costs of sourcing.[28] Log export prices help control for quality differences.[29]

Table 3: Farmer shares and exporter concentration

	Log Farmer Share	Log Farmer Share	Log Farmer Share
	(1)	(2)	(3)
Exporter Size	-0.823	-0.681	-0.530
	(0.158)	(0.185)	(0.180)
FE	No	Yes	Yes
Controls	No	No	Yes
Observations	1,923	1,923	1,923
R^2	0.014	0.355	0.397

Notes: Table summarizes OLS regressions of log farmer shares on relative exporter size. Each observation is an exporter-crop-year. Column 1 shows the regression without controls. Column 2 adds crop-year fixed effects. Column 3 adds time-varying controls: log wage bill, log payments to non-farmer suppliers, log export unit values, and an indicator for exporters with market share smaller than 1%. Clustered standard errors are shown in parentheses.

My preferred specification in Column 3 effectively compares two exporters selling the same crop internationally with similar value added. If one purchases 99% of production in Ecuador and the other purchases the remaining 1%, the coefficient indicates that the former pays farmers a 53% smaller share of his export revenue.[30] This suggests that larger exporters have market power over farmers. To quantify the importance of market power, I develop a framework in the next section that links exporter size to farmgate prices via farmer substitution patterns across crops and across exporters within a crop. Unobserved exporter-specific fixed costs, such as branding, remain an alternative to market power. To help rule this, I will rely on variation within exporters over time to estimate the model.

[26] Relative exporter size is highly correlated over time, which precludes the use of the exporter fixed effects.

[27] I also include an indicator for exporters with relative size less than 1%, which helps control for measurement error in the farmer share for extremely small firms, as in Huneeus (2018).

[28] This includes all 2-digit ISIC sectors except agriculture (01-03) and domestic wholesale (45-47). The next largest sector is transportation and storage (49-53).

[29] Surprisingly, larger exporters earn marginally higher prices, suggesting that quality does not drive the results.

[30] This relationship is robust to classifying crops based on the farmer's ISIC code, aggregating crops to the HS 4-digit level, including direct exporters, and excluding the largest crop (bananas).

3 Theory

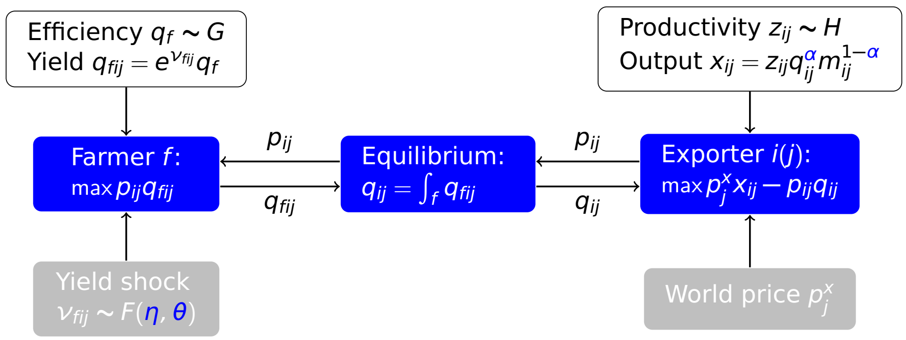
In this section, I develop a model of imperfect competition among exporters in the market for crops. Farmers choose a crop to produce and sell to exporters, who have market power. The concentration of exporters, and hence their market power, differs across and within crops and impacts farmer well-being. The formulation of the model builds on the work of Atkeson and Burstein (2008) and Berger et al. (2019). I model the farmer's choice of crop and exporter as a discrete choice problem, which yields a nested CES supply curve for crops. Given this supply curve and Cournot (or Bertrand) competition among exporters, the equilibrium farmer share is a decreasing function of relative exporter size, consistent with Section 2.3.3. The shape of this function is determined by two key elasticities which govern the heterogeneity of costs in the farmer's choice problem. Intuitively, the more heterogeneous are farmer costs, the greater the consequences of exporter market power. In this way, the model also connects to the work of Costinot et al. (2016) and Sotelo (2020).

3.1 The value chain

The value chain consists of two agents: a continuum of farmers and a finite number of exporters. Crops such as shrimp and cocoa are indexed by $j \in \{1, \ldots, M\}$. Each crop is sold by an exogenous, finite number of exporters, indexed by $i(j) \in \{1, \ldots, N(j)\}$. Each exporter purchases the crop from farmers, adds some value, and sells it internationally. For example, cocoa exporters may pack beans into bags or ship them across the country before selling them abroad. Crops are produced by a continuum of farmers, indexed by $f \in [0, 1]$. Consistent with the empirical setting, farmers choose a single crop to produce and a single exporter to supply, and exporters sell a single crop.[31] Figure 4 summarizes the structure of the model.

[31] These assumptions are not essential. Empirically, multi-product exporters are rare in Ecuador, and farmers typically sell to a single exporter.

Figure 4: Model structure



Notes: Endowments and technologies shown in white boxes. Model shocks shown in grey boxes. Optimization and equilibrium conditions shown in blue boxes. Black arrows denote the flow of goods and payments. Blue text denotes key model parameters. See text for details.

3.2 Farmer crop choices

Farmer f is endowed with a unit of land, which she farms inelastically with efficiency $q_f \sim G$. This is the only source of ex-ante heterogeneity among farmers and reflects differences in farmer productivity and land quality. The farmer makes two decisions: which crop to produce and which exporter to supply. She receives an idiosyncratic shock ν_{fj}^c for producing each crop j and an idiosyncratic shock $\nu_{fi(j)}^e$ for supplying each exporter $i(j)$. Since each exporter buys and sells a single crop, $i(j)$ uniquely identifies an exporter. For convenience, I drop the parentheses in subscripts, so that ν_{fij}^e becomes shorthand for $\nu_{fi(j)}^e$.

A farmer with efficiency q_f can supply q_{fij} units of crop j to exporter i:

$$q_{fij} = e^{\frac{\nu_{fj}^c}{1+\theta}} e^{\frac{\nu_{fij}^e}{1+\eta}} q_f$$

where η and θ are two key elasticities discussed in detail below.[32] The idiosyncratic shocks determine her yield: the higher are ν_{fj}^c and ν_{fij}^e, the more she can supply if she chooses crop j and exporter i. In this sense, ν_{fj}^c models the land's suitability for growing crop j in a stochastic way, while ν_{fij}^e models geographic proximity to exporter i in a stochastic way.

Each exporter buys and sells a single product, offering price p_{ij} to all farmers. Farmers trade off higher prices with lower idiosyncratic shocks: a shrimp exporter in the coastal port of Guayaquil may pay a high

[32] The use of η and θ as notation is inspired by Berger et al. (2019).

price, but it does them little good if they happen to live far away in the Ecuadorian Amazon, where the shock for producing shrimp and reaching Guayaquil is prohibitively low. If the farmer chooses crop j and exporter i, she earns profits $p_{ij}q_{fij}$. She chooses a crop and exporter by solving:

$$\arg\max_{i,j} p_{ij}q_{fij} = \arg\max_{i,j}\{\log p_{ij} + \log q_f + \frac{\nu^c_{fj}}{1+\theta} + \frac{\nu^e_{fij}}{1+\eta}\}$$

The probability that farmer f chooses crop j and exporter i, $\Pr(fij)$, is independent of her efficiency, q_f.[33] This implies that the model can accommodate any distribution of land quality or farmer productivity. I assume ν^e_{fij} follows an extreme value distribution, and ν^c_{fj} is distributed such that the sum $\nu_{fij} = \frac{\nu^c_{fj}}{1+\theta} + \frac{\nu^e_{fij}}{1+\eta}$ follows a Gumbell distribution (Cardell 1997).[34] Under this assumption, $\Pr(fij)$ follows a nested logit structure: it can be written as a product of the marginal probability of choosing crop j and the conditional probability of choosing exporter i, conditional on choosing crop j:

$$\Pr(f \text{ chooses exporter } i\text{,crop } j) = \underbrace{\frac{p_{ij}^{1+\eta}}{\sum_{i(j)} p_{ij}^{1+\eta}}}_{\Pr(f \text{ chooses exporter } i|j)} \times \underbrace{\frac{(\sum_{i(j)} p_{ij}^{1+\eta})^{\frac{1+\theta}{1+\eta}}}{\sum_j (\sum_{i(j)} p_{ij}^{1+\eta})^{\frac{1+\theta}{1+\eta}}}}_{\Pr(f \text{ chooses crop } j)}$$

This expression has an intuitive interpretation: conditional on choosing crop j, the probability of choosing exporter i, $\Pr(i|j)$ depends on how large the price of exporter i (numerator) is relative to the price index of crop j (denominator), which is a CES aggregate of prices across exporters within a crop. The unconditional probability of choosing crop j, $\Pr(j)$, then depends on how large the price index of crop j (numerator) is relative to the overall price index (denominator), which is a CES aggregate of price indexes across crops.

If $\eta > \theta$ (McFadden 1978), the nested logit shocks have the interpretation that farmers maximize profits by choosing a crop and an exporter conditional on each crop, a natural nested choice. Although the theory does not require $\eta > \theta$, the data will turn out to satisfy this condition. I discuss the practical meaning of the condition below.[35]

As η increases, the price becomes more important in determining whether a farmer chooses exporter i, conditional on choosing crop j. In the limit, as $\eta \to \infty$, the entire market goes to the exporter with an infinitesimally higher price than the other exporters. As η decreases, the price becomes less important. In the limit, as $\eta \to 0$, the entire market only goes to an exporter with an *infinitely* higher price. Similarly, as θ decreases, the price index becomes less important in determining whether a farmer chooses crop j. As $\theta \to 0$, even a crop with a low price index will attract some farmers. As θ increases, the price index becomes more important. As $\theta \to \eta$, terms cancel and the problem collapses to a single choice.

[33] See the appendix for a proof.

[34] The joint distribution of the shocks is therefore $F(\nu_{11}, \ldots, \nu_{N(M)M}) = \exp\left[-\sum_j \left(\sum_{i(j)} e^{-(1+\eta)\nu_{ij}}\right)^{\frac{1+\theta}{1+\eta}}\right]$.

[35] If instead $\theta > \eta$, the nests are reversed, so that farmers choose an exporter and a crop conditional on the exporter. While this may be reasonable in other contexts, it is not the case in Ecuador, where exporters tend to sell a single crop.

Aggregating across farmers yields a nested CES supply curve for exporter i and crop j:

$$q_{ij} = \left(\frac{p_{ij}}{p_j}\right)^{\eta} \left(\frac{p_j}{P}\right)^{\theta} \frac{Y}{P} \tag{1}$$

where $p_j = \left(\sum_{i(j)} p_{ij}^{1+\eta}\right)^{\frac{1}{1+\eta}}$ is the price index for crop j, $P = \left(\sum_j p_j^{1+\theta}\right)^{\frac{1}{1+\theta}}$ is the overall price index, and $Y = \sum_{i,j} p_{ij} q_{ij}$ is total farmer income. It will be convenient to work with the inverse supply curve:

$$p_{ij} = \left(\frac{q_{ij}}{q_j}\right)^{\frac{1}{\eta}} \left(\frac{q_j}{Q}\right)^{\frac{1}{\theta}} \frac{Y}{Q} \tag{2}$$

where $q_j = \left(\sum_{i(j)} q_{ij}^{\frac{1+\eta}{\eta}}\right)^{\frac{\eta}{1+\eta}}$ is the quantity index for crop j and $Q = \left(\sum_j q_j^{\frac{1+\theta}{\theta}}\right)^{\frac{\theta}{1+\theta}}$ is the overall quantity index.[36]

3.3 Interpreting the elasticities η and θ

The model offers three intuitive interpretations of the parameters η and θ. First, θ governs the correlation of crop-specific shocks. The higher is θ, the more correlated are the farmer's productivity draws across crops. Since her idiosyncratic productivity for two different crops is likely to be similar, the prices of the crops will determine her choice. Intuitively, θ will be high if the land is suitable for growing many different crops, so that there is little heterogeneity in productivity. In Section 4.3, I relate my estimates of θ to a large literature that estimates this heterogeneity directly. Finally, θ is the elasticity of substitution across crops in the CES supply function. The higher is θ, the more substitutable are different crops from the point of view of farmers. In a dynamic setting, higher substitutability would correspond to higher rates of farmer switching across crops.

Similarly, η governs the correlation of exporter-specific shocks. The higher is η, the more correlated are the farmer's draws across exporters within a crop. Since her idiosyncratic proximity to two different exporters is likely to be similar, the prices they offer will be more important. If η is high, farmers will be able to reach many different exporters, and there will be little heterogeneity in the cost of accessing exporters. In Section 4.3, I relate my estimates of η to a large literature that estimates trade costs directly. Finally, the higher is η, the more substitutable are exporters from a farmer's point of view, and the more often a farmer would switch exporters.

[36] See the appendix for a full derivation.

Under these interpretations, the condition $\eta > \theta$ can several reasonable interpretations: a) idiosyncratic cost shocks are more strongly correlated between two different exporters of the same crop than between two different crops; b) there is more heterogeneity in the productivity of growing different crops than in the costs of reaching different exporters; and c) exporters are more substitutable within crops than across crops from the point of view of farmers.

3.4 Exporter price setting

Each product j is exported by a set of exporters, which I take to be exogenous. Exporter i purchases q_{ij} units of crop j from farmers, combines them with m_{ij} units of other inputs, and exports x_{ij} units of the finished product. His production function is

$$x_{ij} = z_{ij} q_{ij}^{\alpha} m_{ij}^{1-\alpha}$$

where $z_{ij} \sim H$ is an idiosyncratic productivity term. This is the only source of ex-ante heterogeneity across exporters within a given product.[37]

Exporters of product j exert market power over farmers, which I model as Cournot or Bertrand competition for crops. When deciding what quantity to purchase (Cournot) or what price to offer (Bertrand) for a crop, exporters form expectations about how farmers respond. In other words, they internalize the upward sloping crop supply curve in Equations 2 (Cournot) and 1 (Bertrand): each additional unit they purchase increases the price of every other unit. Because Cournot competition yields intuitive expressions for farmer shares at the crop level (see Equation 9), I present the equilibrium under Cournot competition here and show the equilibrium under Bertrand competition in the appendix. Later, I will estimate the model and perform measurement exercises under both forms of competition.

The domestic price of other inputs, p_j^m, and the international price of output, p_j^x, are exogenous. Each exporter maximizes profits

$$\max_{q_{ij}, m_{ij}} \{ p_j^x x_{ij} - p_{ij} q_{ij} - p_j^m m_{ij} \}$$

subject to the (inverse) supply curve in Equation 2. The first order condition for crops, q_{ij}, can be written:

$$\text{farmer share}_{ij} = \frac{p_{ij} q_{ij}}{p_j^x x_{ij}} = \alpha \times \underbrace{\left(1 + \frac{1}{\epsilon_{ij}}\right)^{-1}}_{\text{markdown}} \tag{3}$$

[37] Throughout the paper, I assume constant returns to scale for exporters and market power only in the market for crops. The theory and estimation can accommodate non-constant returns, as well as market power in output and labor markets. Additional equilibrium conditions and moments necessary for estimation can be derived from the first order conditions for inputs other than crops (Morlacco, 2019).

where $\frac{1}{\epsilon_{ij}} \equiv \frac{\partial \log p_{ij}}{\partial \log q_{ij}}$ is the (inverse) price elasticity of crop supply.

Equation 3 says that the farmer share defined in Section 2.3.2 depends on two things: value added (captured by α) and market power (captured by ϵ_{ij}). Under perfect competition, $\frac{1}{\epsilon_{ij}} = 0$, so that the farmer share of exporter revenue equals the output elasticity of crops, α. When the exporter has market power, he internalizes the upward sloping supply of crops, $\frac{1}{\epsilon_{ij}} > 0$, and the farmer share is "marked down" from the perfectly competitive level. The steeper the supply curve faced by the exporter (higher $\frac{1}{\epsilon_{ij}}$), the more market power he has, the wider the markdown, and the lower the farmer share. Alternatively, the more value the exporter adds to the crop (lower α), the lower the farmer share. These are exactly the two explanations for low farmer shares discussed in Section 2.3.2.

3.5 Exporter market power in equilibrium

Given Cournot competition between exporters trying to procure crop j[38] and the supply curve in Equation 2, the supply elasticity has the following closed form:

$$\frac{1}{\epsilon_{ij}} = \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij} \tag{4}$$

where $s_{ij} = \frac{p_{ij} q_{ij}}{\sum_{i(j)} p_{ij} q_{ij}}$ is the relative size of exporter i in crop j as defined in Section 2.3.3. In other words, the supply elasticity, ϵ_{ij}, is the weighted harmonic mean of the elasticity of substitution across crops, θ, and across exporters, η, where the relative sizes of exporters form the weights.[39] Substituting into Equation 3 yields the equilibrium farmer share:

$$\text{farmer share}_{ij} = \alpha \times \left[1 + \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij}\right]^{-1} \tag{5}$$

Since $\eta > \theta$, Equation 5 implies a negative relationship between the farmer share and the relative size of the exporter, precisely the relationship documented in Section 2.3.3. The elasticity of substitution across crops, θ, and across exporters, η, determine the strength of this relationship. Equation 5 therefore forges a connection between my stylized facts about agricultural value chains and my theory of crop choice and exporter market power.

[38] I assume no strategic interaction across crops, so that exporters of crop j take the price indexes of $k \neq j$ as given. This is reasonable given the large number of crops in Ecuador.

[39] This is analogous to Atkeson and Burstein (2008), where the exporter-specific *demand* elasticity is a weighted harmonic mean of the elasticities of substitution across and within nests from the point of view of *consumers* and the weights are determined by exporter market shares of the *output* market.

Definition: Given a set of international prices for output $\{p_j^x\}_j$, domestic prices for other inputs $\{p_j^m\}_j$, and parameters $\{\alpha, \eta, \theta\}$, an *equilibrium* is a vector of relative exporter sizes $\{s_{ij}\}_{i,j}$ consistent with farmer optimization (Equation 2) and exporter optimization (Equation 5).

To provide intuition on how market power works in this setting, fix the elasticities of substitution η and θ. As s_{ij} increases toward 1, the substitutability across crops, θ, receives more weight. In contrast, as s_{ij} decreases toward 0, the substitutability across exporters within a crop, η, receives more weight. Since $\eta > \theta$, the supply elasticity ϵ_{ij} decreases as s_{ij} increases. Larger exporters face steeper supply curves and pay farmers a lower share of export revenue. Intuitively, when a single exporter dominates the market for a given crop, farmers can only switch to other crops. Since it is harder for farmers to plant a new crop than to find a new exporter in the same crop than to plant a new crop ($\eta > \theta$), farmers will be less sensitive to prices than if the exporter had a smaller market share. The less price-sensitive are farmers, the more market power the exporter can exert.

Now, fix the size of the exporter. As substitutability across crops, θ, decreases, so does the supply elasticity, ϵ_{ij}. All exporters face steeper supply curves and pay farmers a lower share of export revenue. Intuitively, it has become harder for the farmer to switch to other crops. As a result, prices will play a smaller role in farmer decisions, so that supply will be less elastic and exporters will have more market power. A similar argument holds for substitutability across exporters within a crop, η.

Proposition: Crop supply becomes less elastic, exporter market power increases, and the crop-level farmer share falls as s_{ij} increases, θ decreases, or η decreases.

To make the connection between theory and data more explicit, take logs on both sides of Equation 5. In addition, let the log output elasticity vary by crop. Finally, take a linear approximation of the log markdown. This yields the regression equation in Column 3 of Table 3:

$$\log(\text{farmer share}_{ij}) = \underbrace{\log \alpha_j + \log \frac{\eta}{1+\eta}}_{\delta_j} - \underbrace{\frac{\eta}{1+\eta}\left(\frac{1}{\theta} - \frac{1}{\eta}\right)}_{-\beta} s_{ij} + \varepsilon_{ij} \tag{6}$$

where ε_{ij} captures classical measurement error. The size of the coefficient, β, is informative of the difference between η and θ. However, I cannot disentangle them with this regression alone, as the fixed effect, δ_j, contains both η and α_j. This is a well-known issue in the markup literature (De Loecker and Warzynski, 2012), typically addressed by estimating the production function and backing out market power. In the next section, I discuss how the structure of the model allows me to estimate η and θ directly.

4 Estimation

In the model, two key elasticities govern market power: the elasticity of substitution across crops, θ, and the elasticity of substitution across exporters within a crop, η. In this section, I estimate these elasticities using exporter responses to international demand shocks. I also conduct validation exercises.

4.1 Identification using pass-through of demand shocks

Consider what happens when there is a sudden increase in the international price for exporter i of crop j. In order to expand exports and meet the growing demand, he must first purchase more crops from farmers by offering a higher price. However, because he has market power and internalizes the upward sloping supply curve for crops, he knows that each additional unit raises the price of every other unit. As a result, he expands crop purchases by less than if his supply curve were flat. The more market power he has, the steeper his supply curve, and the lower the pass-through of the demand shock to farmer income.[40]

In the appendix, I show that the pass-through of a shock to the international price of crop j, $\Delta \log p_j^x$, to the farmer price offered by exporter i, $\Delta \log p_{ij}$, takes the following form (holding fixed the behavior of other exporters:

$$\rho(s_{ij}) \equiv \frac{\Delta \log p_{ij}}{\Delta \log p_j^x} = \left[1 + \frac{(\frac{1}{\theta} - \frac{1}{\eta})s_{ij}(1 - s_{ij})(1 + \eta)}{1 + \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta}s_{ij}}\right]^{-1} \tag{7}$$

Clearly, $\eta > \theta$ implies that $\rho < 1$, so that pass-through is incomplete under market power. In the appendix, I show that ρ is also decreasing in s_{ij} under this condition. Equation 7 implies that for a given change in international prices the corresponding change in farmer price will be smaller for relatively large exporters.[41] This reflects the intuition that pass-through declines with relative exporter size and forms the basis of my estimation procedure.

In practice, strategic interaction among exporters implies that I *cannot* hold fixed the behavior of other exporters. To illustrate, suppose a relatively large exporter purchases more crops from farmers in response to an idiosyncratic demand shock. This acts as a negative supply shock to the remaining exporters, so that they purchase fewer crops from farmers. This, in turn, acts as a *positive* supply shock to the large exporter. The large exporter's desired increase in crop quantity therefore requires a smaller price increase than suggested by his supply curve prior to the shock. The opposite is true for a small exporter: his desired increase in

[40] This is analogous to a monopolist who faces a sudden decrease in marginal cost but does not pass it through to consumers.

[41] Subject to the identifying assumption that international price shocks are orthogonal to exporter productivity shocks, $\Delta \log z_{ij}$.

crop quantity following a demand shock requires a larger price increase than expected. Strategic interaction thus implies that pass-through declines *more* steeply with exporter size, so that estimating η and θ from Equation 7, e.g. using Nonlinear Least Squares, will yield biased results.

4.2 Estimation in the presence of strategic interaction

The model has three key parameters: the elasticity of substitution across exporters, η, the elasticity of substitution across crops, θ, and the output elasticity of crops, α. Because of strategic interaction, I recover them through indirect inference, implemented as Simulated Method of Moments (SMM). Other parameters include: the means and standard deviations of the distribution of exporter productivities, (μ_z, σ_z^2), and the distribution of demand shocks, (μ_d, σ_d^2); the number of crops, M; and the number of exporters in each market, $\{N(j)\}_j$. I estimate all parameters jointly, but outline the estimation procedure separately for each group of parameters. Appendix A.3.2 provides further details.

4.2.1 Estimating η and θ

In order to take Equation 7 to the data, I estimate the following pass-through regression:

$$\Delta \log p_{ijt} q_{ijt} - \Delta \log x_{ijt} = \delta_{jt} + \beta s_{ij,t-1} + \gamma \Delta \log p^x_{ijt} + \zeta s_{ij,t-1} \times \Delta \log p^x_{ijt} + \varepsilon_{ijt} \tag{8}$$

where ε_{ijt} is an error term. The coefficient γ measures the average pass-through of the demand shock, while the coefficient ζ measures how pass-through varies with exporter size. As discussed above, these coefficients are informative of the elasticities η and θ. However, because of strategic interaction among exporters, I use the full structure of the model to back out the elasticities from pass-through coefficients.

I proceed in several steps: (1) estimate Equation 8 in the actual data, (2) simulate Equation 8 in the model, (3) pick η and θ so that the coefficients γ and ζ from the model match their counterparts in the data.[42] In addition to being tractable, this procedure mitigates the concern with under-reporting of purchases from farmers, as only differential *changes* in under-reporting among exporters of different sizes would threaten the estimates.

In order to estimate Equation 8 in the data, I first construct the demand shocks. I follow a standard shift-share specification combining exporter trade shares from my microdata with shifts in international prices from COMTRADE:[43]

$$\Delta \log p^x_{ijt} = \textstyle\sum_d \lambda_{ijd,t-1} \Delta \log p^x_{jdt}$$

[42] Berger et al. (2019) estimate market power from the pass-through of demand shocks to producer prices *relative to* quantities. I implement this approach in the appendix and obtain similar results.

[43] In the appendix, I also consider shifts in international expenditures, although these do not map directly into the model.

where d indicates a destination country, $\lambda_{ijd,t-1}$ is the share of exporter i's sales to that country, and $\Delta \log p^x_{jdt}$ is the log change in price for imports of product j in the destination country (excluding imports from Ecuador). Figure 12 in the appendix plots the distribution of the shocks.

Table 4 displays the results of pass-through regressions using these shocks. Column 1 shows the baseline specification from Equation 8. Column 2 includes product and year fixed effects to control for systematic differences across products and years. Column 3 controls for time-varying exporter characteristics, as in Table 3. The coefficients, denoted $\hat{\gamma}$ and $\hat{\zeta}$, are consistent with the predictions in Section 4.1. Pass-through is incomplete ($\hat{\gamma} < 1$), and it decreases with relative exporter size ($\hat{\zeta} < 0$). The magnitudes in Column 3 imply that the largest exporters increase farmer prices by only $\frac{.355-.239}{.355} = 32.7\%$ as much as the smallest exporters following an international price shock.

Table 4: Exporter responses to price shocks

	$\Delta \log pq - \Delta \log x$	$\Delta \log pq - \Delta \log x$	$\Delta \log pq - \Delta \log x$
	(1)	(2)	(3)
s	0.061	0.073	0.073
	(0.054)	(0.068)	(0.073)
$\Delta \log p^x$	0.228	0.354	0.355
	(0.118)	(0.124)	(0.124)
$s \times \Delta \log p^x$	-0.093	-0.226	-0.239
	(0.256)	(0.268)	(0.269)
FE	No	Yes	Yes
Controls	No	No	Yes
Observations	767	767	767
R^2	0.008	0.049	0.052

Notes: Table summarizes price pass-through regressions. Dependent variable is the change in log farmer price, defined as the change in log payments to farmers minus the change in log quantity exported. Independent variables are the change in the log international price, calculated from COMTRADE data using a shift-share approach described in the text, the lagged exporter size, and their interaction. Column 1 shows estimates without controls. Column 2 adds crop and year fixed effects. Column 3 adds changes in the wage bill and payments to non-farm suppliers, and an indicator for exporters with lagged market share less than 1%. Clustered standard errors are shown in parentheses.

To estimate Equation 8 in the model, I proceed in several steps (see Appendix A.3.1 for further details). First, I draw the productivity of each exporter from a distribution. For each guess of η, θ, and the other parameters, I solve the model. Next, I shock the model with demand shocks drawn from another distribution. I solve the model again to create a simulated panel. Finally, I estimate Equation 8 using the simulated panel. The resulting pass-through coefficients, denoted $\gamma(\eta, \theta)$ and $\zeta(\eta, \theta)$, are functions of η and θ.

I pick η and θ so that the pass-through coefficients estimated from the simulated data match the coefficients estimated from the actual data and reported in Table 4:

$$(\hat{\eta}, \hat{\theta}) = \arg\min_{\eta,\theta} \left\{ ||\hat{\gamma} - \gamma(\eta, \theta)|| + ||\hat{\zeta} - \zeta(\eta, \theta)|| \right\}$$

4.2.2 Estimating α

Aggregating 5 across exporters yields an intuitive expression for the crop-level farmer share:

$$\text{farmer share}_j = \alpha \times \left[1 + \frac{1}{\eta}\Big(1 - HHI_j\Big) + \frac{1}{\theta} HHI_j \right]^{-1} \tag{9}$$

where $HHI_j \equiv \sum_{i(j)} s_{ij}^2$ is the sum of squared exporter sizes, also known as the Herfindahl-Hirschman Index of market concentration.[44] Equation 9 implies that the lower the effective number of exporters for a given crop (higher HHI), the lower the overall farmer share.

I pick α so that the overall farmer share generated by the model matches the farmer share observed in the data. For each guess of α and the other parameters, I solve the model and calculate the crop-level farmer share from Equation 9, taking HHI_j is taken from the simulated data. Let $\phi(\alpha)$ denote the average farmer share. I pick α so that $\phi(\alpha)$ matches its counterpart in the data, denoted $\hat{\phi}$ and reported in Figure 2:

$$\hat{\alpha} = \arg\min_{\alpha} ||\hat{\phi} - \phi(\alpha)||$$

4.2.3 Other parameters

I assume that (log) exporter productivity, $\log z$, and price shocks, $\Delta \log p^x$, follow normal distributions:[45]

$$\log z \sim N(\mu_z, \sigma_z^2) \text{ and } \Delta \log p^x \sim N(\mu_d, \sigma_d^2)$$

For exporter productivity, I choose (μ_z, σ_z^2) to match the distribution of log exporter revenue in the data. For demand shocks, I choose (μ_d, σ_d^2) to match the distribution of log changes in international prices in the data.

Finally, the number of crops, M, and the number of exporters for each crop, $\{N_j\}_j$, are chosen to match the histograms in Figure 1.

[44] The *inverse* concentration index, HHI_j^{-1}, measures the effective number of exporters competing for crops. To illustrate, consider a market with two exporters. If the exporters split the market, $HHI_j^{-1} = 2$, so that the market is a duopsony. Instead, if one controls 99% of the market and the other controls 1%, $HHI_j^{-1} = 1.02$, so that the market is *effectively* a monopsony.

[45] In the appendix, I show how to estimate these non-parametrically.

4.2.4 Parameter estimates

Table 5 summarizes the baseline estimated model under Cournot competition.[46] The elasticities of substitution across exporters, η, and across crops, θ, are small, indicating that exporters face steep supply curves and exercise market power over farmers. The output elasticity of crops, α, is large relative to the farmer share, further indicating a high degree of market power. I explore the economic meaning of these estimates in detail below.

Table 5: Parameter estimates

Parameter	Estimate	Moment	Value
(a) Key parameters			
η	1.93	Baseline pass-through, $\hat{\gamma}$	0.35
θ	0.40	Decline in pass-through with size, $\hat{\zeta}$	-0.23
α	0.45	Average farmer share, $\hat{\phi}$	0.24
(b) Other parameters			
μ_z	13.98	Terciles of log exporter revenue	
σ_z	2.27		
μ_d	0.02	Terciles of log price changes	
σ_d	0.11		
M	157	Number of crops	
N_j	1-10	Number of exporters per crop	

4.3 Model validation

I validate the model by (a) comparing moments not targeted in the estimation procedure between the model and the data; (b) testing auxiliary predictions of theory; and (c) comparing the heterogeneity in production and transport costs implied by the model with estimates from the agricultural trade literature.

4.3.1 Auxiliary predictions

The theory predicts that the pass-through of international price shocks to farmer prices is (a) incomplete and (b) declines with exporter size. In the appendix, I show that pass-through to farmer *quantities* also declines with exporter size, and declines more steeply than prices. I test these predictions by estimating the following regression:

[46] I estimate five additional versions of the model in the appendix. The first is identical to the baseline, except with Bertrand competion. The next two are overidentified models, where I match the relationship between farmer share and exporter size in addition to the price pass-through moments. The last two are models where I construct moments from the relative pass-through to prices vs. quantities, following Berger et al. (2019). I estimate each version under both Cournot and Bertrand competition.

$$\Delta \log x_{ijt} = \delta_{jt} + \beta s_{ij,t-1} + \gamma \Delta \log p^x_{ijt} + \zeta s_{ij,t-1} \times \Delta \log p^x_{ijt} + \varepsilon_{ijt} \tag{10}$$

where the terms are defined as in Equation 8. Table 6 displays the results of different specifications analogous to those of Table 4. As predicted by the theory, quantity pass-through decreases significantly with size. The point estimate on the interaction term is more negative than in Table 4, indicating that quantity pass-through declines more steeply.[47] The positive correlation between price responses in Table 4 and quantity responses in Table 6 support the interpretation of international price shocks as demand shocks for exporters.[48] By shifting the demand curve for exporters, these shocks trace out their supply curves and identify buyer market power.

Table 6: Quantity responses to price shocks

	$\Delta \log x$	$\Delta \log x$	$\Delta \log x$
	(1)	(2)	(3)
s	-0.138	0.001	0.130
	(0.103)	(0.131)	(0.139)
$\Delta \log p^x$	0.055	0.014	0.063
	(0.226)	(0.238)	(0.237)
$s \times \Delta \log p^x$	-0.575	-0.685	-0.735
	(0.493)	(0.516)	(0.514)
FE	No	Yes	Yes
Controls	No	No	Yes
Observations	767	767	767
R^2	0.005	0.047	0.062

Notes: Table summarizes quantity pass-through regressions. Dependent variable is the change in log quantity exported. Independent variables are the change in the log international price, the lagged exporter size, and their interaction. Column 1 shows estimates without controls. Column 2 adds crop and year fixed effects. Column 3 adds changes in the wage bill and payments to non-farm suppliers, and an indicator for exporters with lagged market share less than 1%. Clustered standard errors are shown in parentheses.

4.3.2 Non-targeted moments

Figure 5 plots the negative relationship between farmer share and relative exporter size, in the model and in the data. The latter was first documented in Figure 3. The relationship in the model, which is influenced by η and θ, is somewhat steepr than in the data, but the two slopes are not statistically distinguishable.

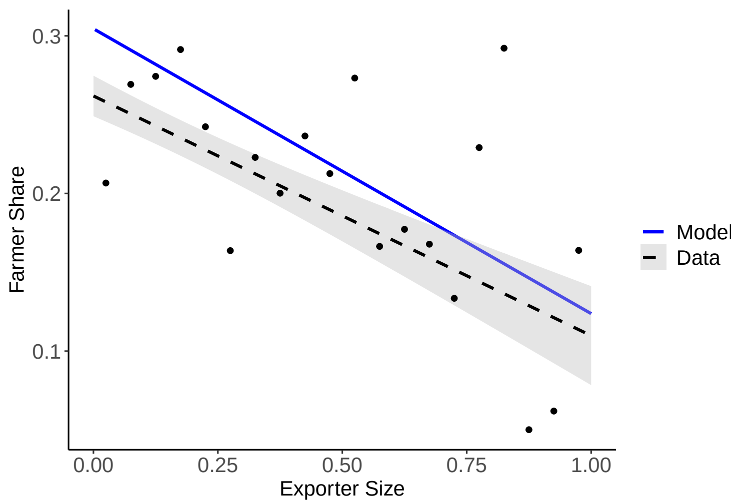
[47] The theory makes no clear prediction for average quantity pass-through, but the data suggest it is substantially lower than average price pass-through.

[48] The steeper decline in quantity pass-through further implies that exporters face convex supply curves.

Although the average farmer share was targeted in estimation, the relationship between farmer shares and exporter size was not.

To further validate the model, I estimate Equation 6 and compare the results to Column 1 of Table 3. The coefficient on relative exporter size is slightly more negative at -0.87, but not statistically distinguishable. In the appendix, I estimate an overidentified version of the model which matches this coefficient in addition to the coefficients from the pass-through regression, and obtain similar results.

Figure 5: Farmer shares and exporter concentration, model vs. data



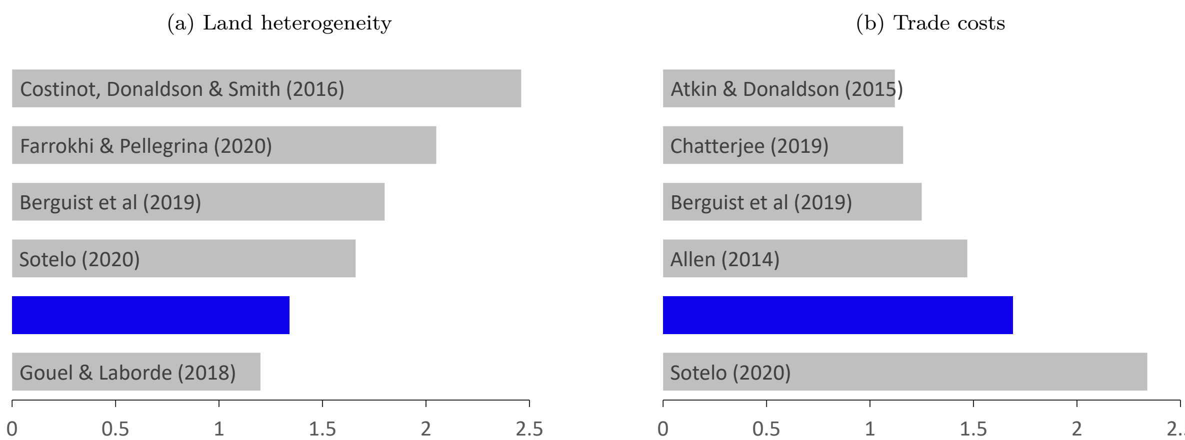
Notes: Figure plots exporter size on the x-axis and farmer shares on the y-axis. Each dot indicates the average farmer share within bins of 5% market share in the data. Dashed black line indicates predictions from a linear regression in the data where each observation is an exporter-crop-year. Grey area indicates a 95% confidence interval. Solid blue line indicates predictions from the same linear regression in the simulated data.

4.3.3 External validation

I validate the model externally by comparing my estimates of θ and η to those implied by the literature on agricultural production and trade in developing countries. Recall the interpretation of θ in Section 3.3 as a measure of land heterogeneity: the higher is θ, the less heterogeneous is the land, and the more suitable it is for producing a variety different crops. Several studies estimate this heterogeneity directly using data on land use and yields across crops. In the appendix, I show how to calculate the land heterogeneity implied by my estimate of θ. Figure 6 compares this value to those from the literature. They are generally larger than my estimate of 1.35, indicating a smaller degree of heterogeneity than in my setting. Importantly, I include the largest number of distinct products, which may explain why I find more heterogeneity. Consistent with this explanation, Gouel and Laborde 2018 is both the only other study to include animal products and the only study to find lower heterogeneity. Sotelo 2020 finds a value similar to mine in Peru, the most agroclimactically similar country to Ecuador among those studied.

Now, recall the interpretation of η in Section 3.3 as a measure of heterogeneity in costs of reaching different exporters. To the best of my knowledge, no study estimates this heterogeneity directly in an agricultural setting. However, a large literature estimates iceberg trade costs across space. I show in the appendix that under some assumptions, my estimate of η implies an average iceberg trade cost of 1.69. Figure 6 shows the average estimated trade cost for several studies that focus on agriculture in developing countries. They are generally smaller than my estimate, indicating lower trade costs on average. The most comparable study is Chatterjee 2019, where trade costs allow local intermediaries in India to exercise market power over farmers. Lacking the kind of spatial data he uses to define each geographic market, I define a single market for each crop, which may explain why my estimates are larger. On the other hand, my estimates are *smaller* than in Sotelo 2020, which uses spatial data from Peru, the country most geographically similar to Ecuador among those studied.[49]

Figure 6: Comparing θ and η to estimates from the literature



Notes: Panel A plots estimates of land heterogeneity parameters from selected papers in grey, and the corresponding value implied by $\hat{\theta}$ in blue. See text of Appendix A.3.10 for conversion details. See Table 15 for source details. Panel B plots estimates of iceberg trade costs from selected papers in grey, and the corresponding value implied by $\hat{\eta}$ in blue. See text of Appendix A.3.9 for conversion details. See Table 14 for source details.

[49]The countries represented are Ethiopia, Nigeria, India, Ghana, Philippines, and Peru.

5 Measurement

Equipped with estimates of η and θ, I turn to interpreting them in my empirical context. First, I use the actual data to calculate the implied markdowns faced by farmers in Ecuador. Second, I conduct simulations to compare the level of farmer income between the estimated model and a counterfactual in which exporters behave competitively, rather than strategically. Third, I decompose the aggregate effect of market power into different channels and examine heterogeneity across crops. Finally, I discuss alternate explanations for the results.[50]

5.1 Measuring crop markdowns in Ecuador

To explore the microeconomic impacts of market power, I combine parameter estimates with value chain data in order to measure how much farmer prices are marked down from their marginal revenue products. Rearranging Equation 5 yields an expression for this markdown as a function of key elasticities and relative exporter sizes:

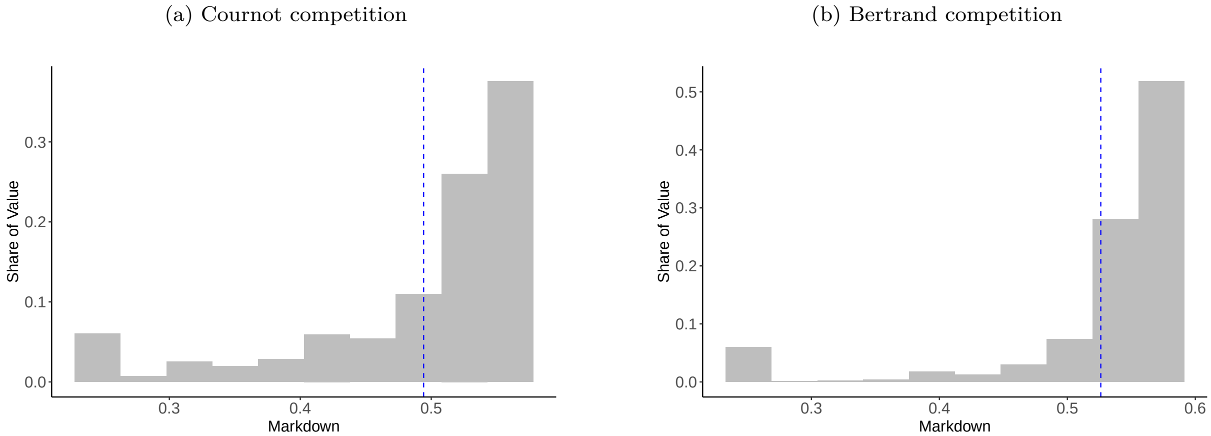
$$\text{markdown}_{ij} = \left[1 + \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij}\right]^{-1} \tag{11}$$

Panel A of Figure 7 plots the distribution of markdowns under Cournot competition, obtained by plugging in the estimated η and θ and observed s_{ij} into Equation 11. The weighted average is 0.49, implying that farmers receive around half of their marginal revenue product. While the majority of exporters pay farmers 50-60% of their marginal product, some exporters, including of important crops like coffee and palm, pay less than 30%.

Panel B plots the distribution of markdowns under Bertrand competition. As expected, the distribution shifts to the right, indicating that exporters pay farmers a larger share of their marginal revenue product and hence are more competitive. The weighted average is only 0.53, so market power is still substantial.

[50]Throughout this section, I use parameters estimated from the least competitive Cournot specification and the most competitive Bertrand specification among all specifications I estimate.

Figure 7: Distribution of markdowns



Notes: Figure plots the distribution of markdowns across exporters. Markdowns were calculated from using s_{ij} from the data and the estimated η and θ. Panel A assumes Cournot competition (Equation 11), and Panel B assumes Bertrand competition (Equation 16 in the appendix). Dashed blue line indicates average markdowns of 49% and 53%, respectively.

5.2 What if markets were perfectly competitive?

To explore the aggregate implications of market power, I consider a counterfactual economy in which exporters act competitively, rather than strategically. Under perfect competition, exporters still face upward sloping crop supply curves, whose shapes are determined by the parameters η and θ. However, they do not internalize their influence over the price, but rather perceive a perfectly elastic supply curve, $\frac{1}{\epsilon_{ij}} = 0$. Crop prices are no longer marked down from their marginal revenue product, so that farmers receive the perfectly competitive farmer share, α.

This has two effects. First, farmers earn higher income for supplying the same crop to the same exporter, since markdowns are eliminated across the entire sector. This is a pure redistribution from exporters to farmers. However, there are also efficiency gains. In my theory of crop choice, farmers trade off the price of a given exporter and a given crop with their idiosyncratic shock for producing that crop and supplying that exporter. This implies that some farmers do not produce the crop in which they are most productive, simply because its price index is too low. Conditional on a crop, some farmers do not supply the exporter that is closest to them, simply because his price is too low. Removing market power lessens this tradeoff and allows some farmers to produce their best crop and supply their closest exporter. These are efficiency gains.

To quantify these channels, I first simulate the model with and without market power. The total impact of market power is the log difference in farmer income between the two scenarios. To measure the gains from redistribution, I calculate farmer income using quantities from the market power baseline and prices from the perfect competition counterfactual. To measure efficiency gains, I do the opposite, using market power prices and perfect competition quantities:

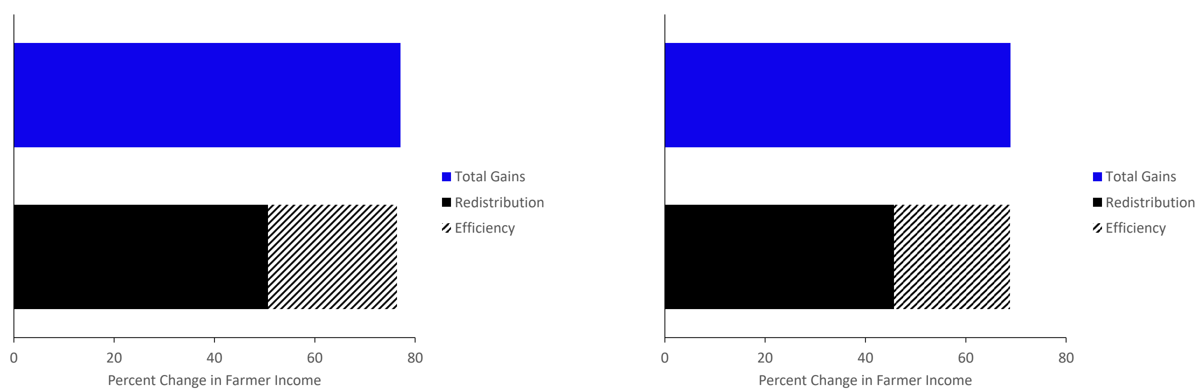
$$\underbrace{\log \sum_i p_{ij}^{PC} q_{ij}^{PC} - \log \sum_i p_{ij}^{MP} q_{ij}^{MP}}_{\text{total gains}} = \underbrace{\log \sum_i p_{ij}^{PC} q_{ij}^{MP} - \log \sum_i p_{ij}^{MP} q_{ij}^{MP}}_{\text{redistribution}} + \underbrace{\log \sum_i p_{ij}^{MP} q_{ij}^{PC} - \log \sum_i p_{ij}^{MP} q_{ij}^{MP}}_{\text{efficiency}} + \text{interactions}$$

where the superscript MP denotes the baseline with market power and PC denotes the counterfactual with perfect competition.

Figure 8 displays the results of the decomposition. In Panel A, I assume Cournot competition and find that farmer income would be 77.1% higher in the absence of market power.[51] Redistribution from exporters to farmers increases income by 50.7%, accounting for almost two thirds of the gains.[52] Greater efficiency accounts for the remaining third, a 25.6% increase in farmer income. In Panel B, I assume Bertrand competition. As expected, the overall gains (66.1%) from perfect competition are lower, but the breakdown between redistribution (43.4%) and efficiency (21.9%) is similar.

Figure 8: Farmer income gains from perfect competition

(a) Cournot competition (b) Bertrand competition



Notes: Figure shows percent increase in farmer income between the estimated model with monopsony power and a counterfactual model with perfect competition. Blue area indicates total gains. Black area indicates gains from redistributing exporter profits to farmers. Shaded area indicates gains from greater efficiency. Panel A assumes Cournot competition among exporters, and Panel B assumes Bertrand competition.

[51] With fixed costs to exporting, reducing exporter profits by removing markdowns may cause some exporters to exit. Although I abstract from fixed costs in my analysis, I argue in the appendix that they are unlikely to be so large as to undo the gains from perfect competition.

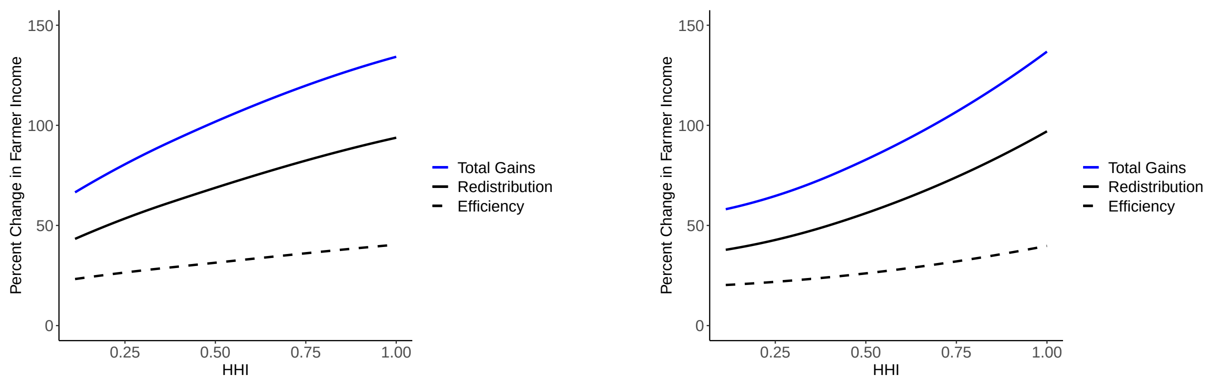
[52] In terms of welfare, redistribution represents a gain for farmers and a loss for exporters. If exporter profits are rebated to farmers, the overall welfare gain may be small or even negative. However, this assumption in unreasonable is this context.

Although all farmers gain from perfect competition, the gains are not equally shared. Panel A of Figure 9 shows how increases in farmer income vary with the baseline level of crop market concentration, HHI_j, under Cournot competition. Gains range from around 67% in relatively competitive crops, such as bananas, to 134% in the least competitive crops, including cocoa. Both redistribution and efficiency gains increase with crop market concentration, but redistribution increases disproportionally more.

Panel B shows a similar pattern for Bertrand competition. Note that the gains are smaller than under Cournot competition for the least concentrated markets, but larger for the most concentrated markets. This is related to the result that the Lerner Index is linear in market shares under Cournot competition, but convex under Bertrand competition (Alviarez, Head, and Mayer 2020).

Figure 9: Farmer income gains and crop market concentration

(a) Cournot competition (b) Bertrand competition



Notes: Figure plots the HHI from the estimated model with monopsony on the x-axis and the percent change in farmer income between the estimated model and a counterfactual with perfect competition on the y-axis. HHI is defined as the sum of squared market shares within each crop. Solid blue line indicates total gains by crop. Solid black line indicates gains from redistribution. dashed black line indicates efficiency gains. Panel A assumes Cournot competition, and Panel B assumes Bertrand competition.

5.3 Do exporters offer insurance?

Section 5.2 suggest that farmer income is lower when exporters have more market power. At the same time, Section 4.1 imply that farmer income is less responsive to international demand shocks. In other words, market power reduces the *variance* of farmer income in additon to the mean. A competing explanation for this mean-variance trade-off is that exporters insure farmers against shocks.

If larger exporters offer more insurance, this trade-off will be correlated with exporter size, as in Tables 3 and 4. In this case, exporters should help smooth the effects of both positive and negative shocks. To test this, I estimate the following regression:

$$
\begin{aligned}
\Delta \log p_{ijt}q_{ijt} - \Delta \log x_{ijt} = \delta_{jt} + \beta s_{ij,t-1} + \kappa \mathbf{1}(\Delta \log p^x_{jt} > 0) + \gamma \Delta \log p^x_{jt} \\
+ \lambda \mathbf{1}(\Delta \log p^x_{jt} > 0) \times s_{ij,t-1} + \mu \mathbf{1}(\Delta \log p^x_{jt} > 0) \times \Delta \log p^x_{jt} \\
+ \zeta s_{ij,t-1} \times \Delta \log p^x_{jt} + \xi \mathbf{1}(\Delta \log p^x_{jt} > 0) \times s_{ij,t-1} \times \Delta \log p^x_{jt} + \varepsilon_{ijt}
\end{aligned} \tag{12}
$$

where $\mathbf{1}(\Delta \log p^x_{jt} > 0)$ is an indicator for whether the international price shock is positive and the other terms are defined as in Equation 8. The coefficient on the triple interaction term, ξ, indicates whether large exporters respond differentially to positive shocks compared to small exporters. Table 7 displays the results. The negative and marginally significant coefficients in the third row suggest that the decline in pass-through with exporter size is driven by *positive* shocks. In constrast, negative shocks have similar pass-through among small and large exporters. If insurance were the sole mechanism at play, the pass-through of international price shocks would not depend on sign of the shock.

Table 7: Asymmetric responses to price shocks

	$\Delta \log pq - \Delta \log x$	$\Delta \log pq - \Delta \log x$	$\Delta \log pq - \Delta \log x$
	(1)	(2)	(3)
$\Delta \log p^x$	0.290	0.394	0.382
	(0.487)	(0.509)	(0.509)
$s \times \Delta \log p^x$	0.148	0.085	0.099
	(0.656)	(0.687)	(0.688)
$\mathbf{1}(\Delta \log p^x > 0) \times s \times \Delta \log p^x$	-1.395	-1.300	-1.359
	(0.924)	(0.965)	(0.968)
FE	No	Yes	Yes
Controls	No	No	Yes
Observations	947	947	947
R^2	0.010	0.050	0.050

Notes: Table summarizes asymmetric pass-through regressions. Dependent variable is the change in log farmer price. Independent variables are the change in the log international price, the lagged exporter size, an indicator for positive changes in the log international price, and all interactions. Column 1 shows estimates without controls. Column 2 adds crop and year fixed effects. Column 3 adds changes in the wage bill and payments to non-farm suppliers, and an indicator for exporters with lagged market share less than 1%. Clustered standard errors are shown in parentheses.

The model further allows me to quantify how risk averse farmers would have to be to prefer the baseline equilibrium with market power to the counterfactual with perfect competition (and hence no insurance). In the data, farmer income increases 42% on average following a 100% increase in the international price shock. Under perfect competition, this pass-through would equal 100%. Assuming Cournot competition at baseline, farmer income would be 71% higher under perfect competition. In the appendix, I show that these estimates imply a coefficient of relative risk aversion greater than 5. This is somewhat higher than estimates of risk aversion among farmers in Ethiopia (Yesuf and Bluffstone, 2009), and much higher than estimates from a large sample developing countries (Gandelman and Hernandez-Murillo, 2014). If insurance were the only mechanism at play, farmers would have to be unreasonably risk averse to prefer the baseline equilibrium.

6 Policy Counterfactuals

Perfectly competitive markets are conceptually interesting, but they are a far cry from the policies currently in place to curtail market power around the world. In this section, I use the estimated model to examine two of the most common such policies: Fair Trade certifications and mandated minimum prices. I model Fair Trade as a perfectly competitive exporter in each crop and show that this raises farmer income both directly and indirectly, by reducing the market power of other exporters. In contrast, a price floor in each crop raises farmer income, but *increases* the market power of some exporters, partially offsetting the direct effect. As a result, Fair Trade is more effective in raising farmer incomes. Finally, I examine some limitations of Fair Trade.[53]

6.1 Fair Trade

Fair Trade is a series of product certifications designed to foster the sustainable production of commodities.[54] Certified commodities include flowers, bananas, sugar, coffee, cocoa, and other fruits and vegetables. Similar certifications exist for fish and meat. In order for a product to be certified, both exporters and producers must meet certain criteria. Exporters agree to pay a minimum price that covers the cost of sustainable farming, as well as a Fair Trade premium typically earmarked for further investment in farming communities. In return, farmers guarantee safe working conditions and sound environmental practices. Because these guarantees are costly, only a subset of producers are Fair Trade certified.[55] For coffee – the largest product in the Fair Trade market – less than 40% of available quantity is certified. I abstract from non-monetary benefits and costs of certification. [56]

[53] Throughout this section, I use parameters from the baseline model in Table 5, exactly identified from price pass-through and assuming Cournot competition.

[54] See Dragusanu et al. (2014) for a comprehensive survey of Fair Trade certifications and related research.

[55] The net effect of selection is unclear. Higher quality farmers may face lower costs of certification, so that there is positive selection (Dragusanu and Nunn 2018). In this case, my model will underestimate the gains. On the other hand, lower quality farmers may perceive higher benefits from certification, so that there is negative selection (Ruben and Fort 2012). In that case, my model will overestimate the gains. For a theoretical model that incorporates selection, see Podhorsky (2015).

[56] Certification costs reduce the net benefits of Fair Trade for farmers, so that my model will overestimate the gains. However, existing estimates of such costs correspond to a 25% reduction in the gains (De Janvry et al., 2015), so that farmer income still increases by 9% in my preferred specification. On the other hand, non-monetary aspects of Fair Trade increase the net benefits to farmers, so that my model will underestimate the gains.

Fair Trade has taken off globally since 2011, but was not widespread before then. I model the potential impact of Fair Trade in Ecuador by introducing a perfectly competitive exporter in each market. In addition to being tractable, this flexibly captures many of the ways that Fair Trade works in practice (Podhorsky 2015). In the appendix, I show that the model can accommodate two popular variations of Fair Trade: (a) buyers specifying a menu of Fair Trade prices and certified quantities and (b) buyers maximizing a weighted sum of profits and farmer income.

The Fair Trade exporter faces the same supply curve as other exporters of a given product, but pays farmers their marginal revenue product, which is higher than the oligopsony price.[57] One reason the Fair Trade exporter is able to pay higher prices is that it has access to consumers who are willing to pay a premium for Fair Trade branded products (Hainmueller, Hiscox, and Sequeira 2015). Additionally, the Fair Trade exporter can represent a cooperative, which allows farmers to export directly (Bacon, Mendez, and Stuart 2008). Since farmers own the cooperative, they internalize markdowns and behave competitively.[58] I abstract from the downstream demand of Fair Trade products and the fixed costs of exporting directly. [59]

A new exporter would increase competition and force other exporters to raise prices, even if he behaved strategically. That he instead behaves competitively, and therefore pays a higher price conditional on his productivity, further raises prices. Fair Trade therefore has a positive direct and indirect effect on prices. These effects reflect the primary goals of Fair Trade: increasing prices and improving bargaining power among farmers. Furthermore, their importance has been documented both theoretically (Podhorsky 2015) and empirically (Dragusanu and Nunn 2018).

The overall effect of Fair Trade depends on the productivity of the new exporter. The more productive he is, the higher the price he can offer to farmers, and the more of the market he can pull away from exporters with market power. Figure 10 summarizes how the increase in farmer income varies with how productive the Fair Trade exporter is relative to other exporters. The blue solid line shows that even a Fair Trade exporter with the median productivity level increases farmer income by 12%.[60] As the new exporter becomes among the most productive in the economy, the gains increase to 25%, or about one third of the gains from perfect competition in Figure 8. These gains are quantitatively similar to causal estimates from the coffee sector (De Janvry et al. 2015; Dragusanu and Nunn 2018; Macchiavello and Miquel-Florensa 2019), but apply to a

[57] This implies the elasticity of substitution between a regular exporter and a Fair Trade exporter is the same as between two regular exporters (η). The other extreme is that the elasticity of substitution between a regular exporter and a Fair Trade exporter is so different that they effectively sell distinct products (θ). The former overestimates the effect of Fair Trade, while the latter underestimates it.

[58] In the appendix, I show that this maximizes farmer income.

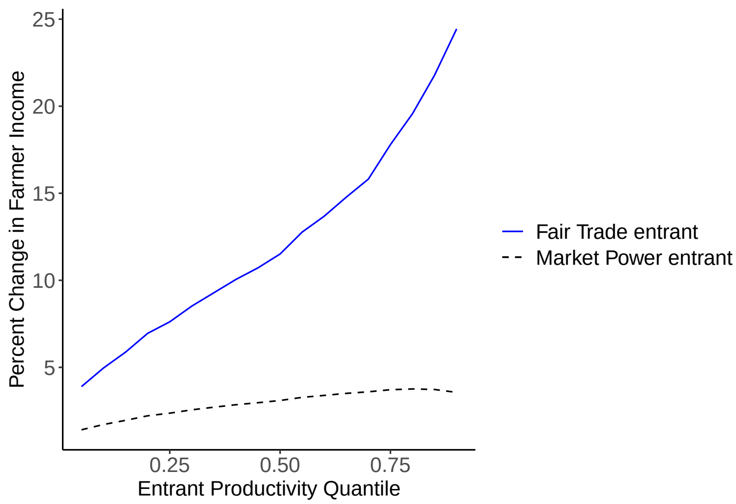
[59] Experimental evidence suggests that *sales* of Fair Trade products in supermarkets are 10% higher than those of identical conventional products (Hainmueller et al., 2015). Since farmers earn such a small share of sales to begin with, this more than covers the 12% increase in farmer payments in my preferred specification. If the fixed cost of exporting directly is such that the marginal strategic exporter is indifferent between entering and not entering, then the indirect effect of Fair Trade implies a cost of no more than 4% of farmer income. This is modest relative to the increase in farmer income caused by the policy.

[60] The Fair Trade exporter purchases around 20% of crop quantity – within the ballpark of what is typically certified.

much broader range of products.

To get a sense of the indirect and direct effects of the Fair Trade exporter, I estimate how farmer income would change if the new exporter behaved strategically. The dashed black line indicates that the gains from Fair Trade are driven by the direct effect on participating farmers.

Figure 10: Effect of Fair Trade on farmer income



Notes: Figure plots the productivity of a counterfactual exporting entrant in each crop on the x-axis and the resulting percent change in farmer income relative to the baseline model on the y-axis. Productivity is measured as a percentile of the estimated distribution of exporter productivity. The dashed black line indicates the counterfactual in which the exporter has monopsony power like all other exporters. The solid blue line indicates the counterfactual in which the exporter implements a Fair Trade policy and is perfectly competitive.

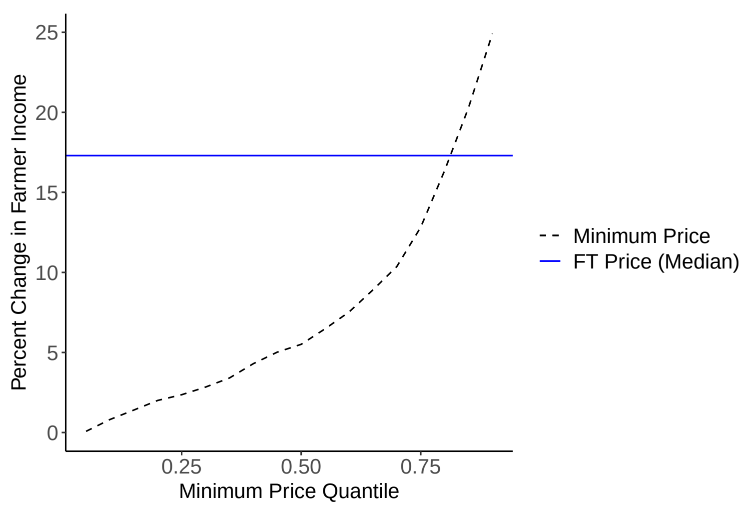
6.2 Minimum prices

A common alternative to Fair Trade is for governments to set a price floor across *all* exporters of a given product. In Ecuador, bananas and palm are the only exported products with price floors (Cunha et al. 2019). Minimum price support is growing, especially for exported commodities in developing countries (Anderson 2009). Compared to conditional subsidies, these policies are more straightforward to implement, but create more distortions.

To illustrate how price floors influence the equilibrium of the model, consider exporters for whom the minimum price is binding. These exporters move along their supply curves. If they are productive enough that they can still earn profits, they will pay the minimum price and purchase more crops at a lower markdown. If they are not productive enough to earn positive profits moving along their supply curves, they will pay the minimum price and purchase *fewer* crops until the marginal revenue product equals the minimum price. This increases the market power of more productive firms and undoes some of the positive price effects. The strength of these effects depends crucially on the level of the minimum price. If the minimum price is low, most exporters will be able to pay, and the net effect will be positive.[61] As the minimum price becomes too high, no exporters can afford to pay, and demand contracts so much that farmers may be worse off.

The dashed black line in Figure 11 summarizes how farmer income changes under a uniform price floor as the floor varies. The blue solid line shows the gains from implementing a policy where only the Fair Trade exporter is subject to a price floor at the median of the price distribution. In order for the uniform price floor to achieve the same gains, it would have to be much higher, near the 75th percentile of the baseline price distribution.[62] Fair Trade implements a price floor without distorting the behavior of smaller exporters (Podhorsky 2015), making it more effective for raising farmer income.

Figure 11: Effect of price floor on farmer income



Notes: Figure plots the level of a counterfactual price floor in each crop on the x-axis and the resulting percent change in farmer income relative to the baseline model on the y-axis. Price levels are measured as a percentile of the estimated distribution of farmer prices. The dashed black line indicates the counterfactual in which the price floor applies ot all exporters. The solid blue line indicates the counterfactual in which a price floor equal to the median price applies only to the Fair Trade exporter.

7 Conclusion

Recent decades have seen the rise of both concentration and globalization. Understanding the consequences of concentration is especially important in the agricultural sector in emerging economies, where globalization

[61] This is analogous to a minimum wage increasing employment in the presence of labor market power (Berger et al. 2019).

[62] Appendix Figure 13 further implies that for any price level, a broad price floor increases farmer income less than a price floor for Fair Trade products.

offers millions of farmers a path out of poverty. I show that these consequences are large in the context of export value chains in Ecuador.

To overcome the challenge of measuring inequality in value chains, I link three administrative data sources. Customs microdata capture exporter revenue, VAT microdata capture exporter payments to suppliers, and firm registry data identify which suppliers are farmers. I exploit the unique network structure of my dataset to document that farmers earn significantly less if they sell to an exporter who dominates the market for a crop. To quantify the importance of market power, I develop a model in which farmers choose a crop to produce and an exporter to supply. The more costly it is for farmers to switch crops or switch exporters within a crop, the more that farmer shares fall with exporter size. The elasticities of substitution across crops and across exporters within a crop are therefore crucial to measuring market power. I develop a method to estimate them using exporter responses to international price shocks. The estimated model implies that farmers in products as diverse as fruit and fish receive a fraction of their marginal revenue products. Despite the prevalence of market power, globalization can still provide farmers a path out of poverty. Fair Trade increases farmer income substantially while avoiding the distortions created by broad price floors.

My approach combines administrative tax data with a tractable model of buyer-supplier relationships, estimated using a common source of exogenous variation. Similar data are increasingly available through collaborations with government statistical agencies worldwide. In addition, many commodity markets are dominated by a handful of buyers. My approach can be applied in these settings to measure market power, estimate the potential impact of pro-competitive policies, and examine how they interact with supplier substitution patterns.

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A Appendices

A.1 Data appendix

A.1.1 Additional statistics

Table 8 summarizes the network of exporters and farmers across 2-digit products.

Table 8: Value chain statistics by product

2-digit Product	No. Exporters	No. Farmers
Live animals	3	3
Fish and crustaceans	180	8,650
Dairy produce	6	1,406
Other animal products	4	23
Live plants	476	1,153
Vegetables	44	2,162
Fruit and nuts	301	11,301
Coffee, tea, spices	33	2,486
Cereals	22	6,446
Mill products	7	50
Oil seeds	20	159
Vegetable extracts	2	2
Other vegetable products	8	36
Animal or vegetable fats and oils	25	17,909
Meat and fish preparations	43	2,533
Sugars and sugar confectionery	11	3,724
Cocoa and cocoa preparations	77	25,336
Cereal preparations	12	1,299
Vegetable and fruit preparations	47	7,988
Other preparations	14	2,827
Beverages	16	1,157
Waste from the food industries	31	4,159
Tobacco products	16	999

Notes: Table shows number of exporters and farmers for each 2-digit product.

A.2 Theory appendix

A.2.1 Derivation of CES supply curve

The farmer maximizes $y_{ij} = \log p_{ij} + \log q_f + \frac{\nu^c_{fj}}{1+\theta} + \frac{\nu^e_{fij}}{1+\eta}$ across i and j. The maximum satisfies $y_{ij} > y_{kl}$ for all k and l. For any k and l, the terms $\log q_f$ on both sides of the inequality cancel, so that the maximum is independent of farmer capacity.

The expected quantity supplied by farmer f to exporter i of crop j is $q_{fij} = q_f \times \Pr(fij)$. Integrating over farmers yields the total quantity of crop j supplied to exporter i:

$$q_{ij} = \int_0^1 \Pr(fij) q_f dG = \frac{p_{ij}^{\eta}}{\sum_{i(j)} p_{ij}^{1+\eta}} \frac{(\sum_{i(j)} p_{ij}^{1+\eta})^{\frac{1+\theta}{1+\eta}}}{\sum_j (\sum_{i(j)} p_{ij}^{1+\eta})^{\frac{1+\theta}{1+\eta}}} \underbrace{\int_0^1 p_{ij} q_f dG}_{Y}$$

Multiplying both sides by p_{ij} and summing across crops and exporters, we have $Y = \sum_{i,j} p_{ij} q_{ij}$, so that Y is total spending by exporters on crops.

Define the crop-level price and quantity indexes

$$p_j = \left(\sum_{i(j)} p_{ij}^{1+\eta} \right)^{\frac{1}{1+\eta}},\ q_j = \left(\sum_{i(j)} q_{ij}^{\frac{1+\eta}{\eta}} \right)^{\frac{\eta}{1+\eta}}$$

Substituting above yields the CES supply system for crops

$$q_{ij} = p_{ij}^{\eta} p_j^{\theta-\eta} \underbrace{\left(\sum_j p_j^{1+\theta} \right)^{-1} Y}_{X}$$

Note that $q_j = p_j^{\theta} X$, which implies that I can write the inverse supply curve

$$p_{ij} = q_{ij}^{\frac{1}{\eta}} q_j^{\frac{1}{\theta} - \frac{1}{\eta}} X^{\frac{1}{\theta}}$$

Finally, define the aggregate price and quantity indexes

$$P = \left(\sum_j p_j^{1+\theta} \right)^{\frac{1}{1+\theta}},\ Q = \left(\sum_j q_j^{\frac{1+\theta}{\theta}} \right)^{\frac{\theta}{1+\theta}}$$

Using these definitions and the fact that $q_j = p_j^{\theta} X = p_j^{\theta} \left(\sum_j p_j^{1+\theta} \right)^{-1} Y$, it is straightforward to show that $PQ = Y$. This implies that $X = \frac{Y}{P^{1+\theta}}$. Substituting into the supply curves yields the expressions in the main text.

A.2.2 Bertrand competition

Given Bertrand competition between exporters trying to procure crop j and the supply curve in Equation 1, the supply elasticity has the following closed form:

$$\epsilon_{ij} = \eta(1 - s_{ij}) + \theta s_{ij} \tag{13}$$

where s_{ij} is the relative size of exporter i in crop j. In other words, the supply elasticity, ϵ_{ij}, is the weighted mean of the elasticity of substitution across crops, θ, and across exporters, η, where the relative sizes of exporters form the weights. Substituting into Equation 3, the equilibrium farmer share is:

$$\text{farmer share}_{ij} = \alpha \times \left[1 + \frac{1}{\eta(1 - s_{ij}) + \theta s_{ij}} \right]^{-1} \tag{14}$$

Since $\eta > \theta$, Equation 14 implies a negative relationship between the farmer share and the relative size of the exporter, just like Equation 5. Aggregating across exporters yields the crop-level farmer share:

$$\text{farmer share}_j = \alpha \times \left[1 + \sum_{i(j)} \frac{s_{ij}}{\eta(1 - s_{ij}) + \theta s_{ij}}\right]^{-1} \tag{15}$$

This equation is analogous to 9, but difficult to interpret without an analog to the HHI.

One can show that for any $\eta \neq \theta$, the markdown under Bertrand competition:

$$\left[1 + \frac{1}{\eta(1 - s_{ij}) + \theta s_{ij}}\right]^{-1} \tag{16}$$

is greater than the markdown under Cournot competition:

$$\left[1 + \tfrac{1}{\eta}(1 - s_{ij}) + \tfrac{1}{\theta} s_{ij}\right]^{-1}$$

One can further show that for $\eta > \theta$, the pass-through of an international price change is lower under Cournot. For a given η, θ, and s_{ij}, Bertrand competition clearly implies less market power among exporters.

The implications of Bertrand competition for *estimating* market power are less clear. Given the relationship between pass-through and exporter size in the data, Bertrand competition will yield smaller estimates of η and θ than Cournot competition, indicating steeper supply curves and hence more market power. However, given η, θ, and the distribution of farmer shares in the data, Bertrand competition will also yield smaller estimates of α than Cournot competition, indicating narrower markdowns and hence less market power. These counteracting forces can simultaneously yield lower estimates of the market power parameters η and θ and smaller gains from removing market power.

A.2.3 Pass-through of international price changes

Log-linearize around the equilibrium in Equation 5:

$$\Delta \log p_{ij} q_{ij} = \Delta \log p_j^x + \Delta \log x_{ij} - \frac{(\frac{1}{\theta} - \frac{1}{\eta}) s_{ij}}{1 + \frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta}) s_{ij}} \Delta \log s_{ij}$$

Constant returns to scale imply that log changes in crop exports are the sum of log changes in crop quantities and log changes in exporter productivity: $\Delta \log x_{ij} = \Delta \log z_{ij} + \Delta \log q_{ij}$. Holding fixed the behavior of other exporters, the nested CES supply curve further implies that log changes in exporter size can be expressed in terms of log changes in crop prices: $\Delta \log s_{ij} = (1+\eta)(1-s_{ij})\Delta \log p_{ij}$. Substituting above and simplifying, we have:

$$\Delta \log p_{ij} = \left[1 + \frac{(\frac{1}{\theta} - \frac{1}{\eta})(1+\eta)s_{ij}(1-s_{ij})}{1 + \frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})s_{ij}}\right]^{-1} \times (\Delta \log p_j^x + \Delta \log z_{ij})$$

Assuming that international price shocks are orthogonal to productivity shocks and rearranging yields an expression for the *partial equilibrium* pass-through:

$$\rho(s_{ij}) \equiv \frac{\Delta \log p_{ij}}{\Delta \log p_j^x} = \left[1 + \frac{(\frac{1}{\theta} - \frac{1}{\eta})s_{ij}(1-s_{ij})(1+\eta)}{1+\frac{1}{\eta}(1-s_{ij}) + \frac{1}{\theta}s_{ij}}\right]^{-1}$$

Clearly, pass-through is incomplete as long as $\eta > \theta$. In addition, one can show that pass-through is lower on average for larger exporters.

First, note that the derivative of the pass-through as a function of exporter market size can be written as follows:

$$\frac{\partial \rho}{\partial s_{ij}} = \frac{(1+\eta)(\frac{1}{\theta} - \frac{1}{\eta})[(\frac{1}{\theta} - \frac{1}{\eta})s_{ij}(1-s_{ij}) - (1-2s_{ij})]}{\{1+\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})s_{ij}[(1-s_{ij})(1+\eta)+1]\}^2}$$

For exporter size near 0, this expression is negative and large in absolute value. For exporter size near 1, this expression is positive but small in absolute value. Pass-through declines rapidly as size increases near 0, but only increases slowly as size increases near 1. This suggests that pass-through is lower on average among larger exporters.

Next, recall from Section 4.1 that because of strategic interaction among exporters, the data do not reveal the partial equilibrium pass-through. Strategic interaction makes small exporters more responsive to price shocks and large exporters *less* responsive in general equilibrium. In other words, the partial equilibrium pass-through underestimates the general equilibrium pass-through for small exporters and *overestimates* it for large exporters. This magnifies the decline in pass-through in the previous paragraph.

The model also yields predictions for the pass-through of international price changes to *quantities*:

$$\frac{\Delta \log q_{ij}}{\Delta \log p_j^x} = \frac{\Delta \log p_{ij}}{\Delta \log p_j^x}\left(\frac{\Delta \log p_{ij}}{\Delta \log q_{ij}}\right)^{-1} = \rho(s_{ij}) \times \left(\frac{1}{\eta}(1-s_{ij}) + \frac{1}{\theta}s_{ij}\right)^{-1}$$

The first term is the price pass-through, which is less than 1 and declines with exporter size. The term in parentheses can be greater or less than 1, so there is no clear prediction for average quantity pass-through. However, since $\eta > \theta$, this term increases with exporter size, so that quantity pass-through unambiguously declines with size. Finally, note that if $\eta > 1$ and $\theta < 1$, quantity pass-through is higher than price pass-through as $s_{ij} \to 0$ and lower than price pass-through as $s_{ij} \to 1$. This implies that quantity pass-through must be declining *faster* with exporter size.

A.3 Estimation appendix

A.3.1 Solving the model

To solve the model, I first guess crop market shares. Then, I solve for scaled crop supply elasticities and prices and use the prices to update market shares, iterating until the shares converge. Finally, I rescale to obtain crop prices and quantities. For a vector of parameters (η, θ, α) and a draw of productivities $\{z_{ij}\}$, the algorithm is as follows:

- Guess equal market shares $s_{ij} = \frac{1}{N_j}$
- Scaled equilibrium
  - Calculate supply elasticity $\epsilon_{ij} = (\frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij})^{-1}$
  - Calculate scaled prices $\hat{p}_{ij} = (\alpha \frac{\epsilon_{ij}}{1+\epsilon_{ij}} z_{ij} s_{ij}^{-\frac{\eta-\theta}{1+\eta}})^{\frac{1}{1+\theta}}$
  - Update market shares $s_{ij} = \frac{\hat{p}_{ij}^{1+\eta}}{\sum_{i \in j} \hat{p}_{ij}^{1+\eta}}$
  - Iterate until market shares converge
- Unscaled equilibrium
  - Calculate scaled price indexes $\hat{p}_j = (\sum_{i \in j} \hat{p}_{ij}^{1+\eta})^{\frac{1}{1+\eta}}$, $\hat{p} = (\sum_j \hat{p}_j^{1+\theta})^{\frac{1}{1+\theta}}$
  - Re-scale prices $p_{ij} = \hat{p}_{ij} \times \hat{p}^{\theta}$
  - Re-scale price indexes $p_j = (\sum_{i \in j} p_{ij}^{1+\eta})^{\frac{1}{1+\eta}}$, $p = (\sum_j p_j^{1+\theta})^{\frac{1}{1+\theta}}$
  - Calculate quantities $q_{ij} = (\frac{p_{ij}}{p_j})^{\eta} (\frac{p_j}{p})^{\theta}$

A.3.2 Simulated Method of Moments

I estimate (η, θ, α) via Simulated Method of Moments. The details are as follows:

- Guess (η, θ, α). Draw productivities $\log z_{ij} \sim N(\mu_z, \sigma_z^2)$. Solve model and treat as data with $t = 1$.
- Draw shocks $\Delta \log p_{ijt}^x \sim N(\mu_p, \sigma_p^2)$. Solve model again and treat as data with $t = 2$.
- Estimate regressions in the simulated data

$$\Delta \log p_{ijt} = \delta_{jt} + \beta s_{ij,t-1} + \gamma \Delta \log p_{ijt}^x + \zeta s_{ij,t-1} \times \Delta \log p_{ijt}^x + \varepsilon_{ijt}$$

- Estimate regressions in the real data

$$\Delta \log p_{ijt} q_{ijt} - \Delta \log x_{ijt} = \hat{\delta}_{jt} + \hat{\beta} s_{ij,t-1} + \hat{\gamma} \Delta \log p_{ijt}^x + \hat{\zeta} s_{ij,t-1} \times \Delta \log p_{ijt}^x + \hat{\varepsilon}_{ijt}$$

- Calculate farmer shares in the simulated data

$$\phi = \sum_j \frac{p_j q_j}{\sum_k p_k q_k} \alpha \times \left[1 + \frac{1}{\eta}\Big(1 - HHI_j\Big) + \frac{1}{\theta} HHI_j\right]^{-1}$$

$$\hat{\phi} = \frac{\sum_{i(j),j} p_{ij} q_{ij}}{\sum_{k(l),l} p^x_{kl} x_{kl}}$$

- Pick (η, θ, α) to minimize $[\hat{m} - m(\eta, \theta, \alpha)]' W [\hat{m} - m(\eta, \theta, \alpha)]$.

where $\hat{m} = (\hat{\gamma}, \hat{\zeta}, \hat{\phi})'$ is the vector of data moments, $m(\eta, \theta, \alpha) = (\gamma(\eta, \theta, \alpha), \zeta(\eta, \theta, \alpha), \phi(\eta, \theta, \alpha))'$ is the vector of model moments, and W is a weighting matrix.

I perform the optimization using a Multi Level Single Linkage (MLSL) global algorithm with a Nelder-Mead local minimizer, as implemented by the NLOPTR package in R. This algorithm has been shown to perform well for Simulated Method of Moments (Arnoud, Guvenen, and Kleineberg 2019).

A.3.3 Specifying demand shocks

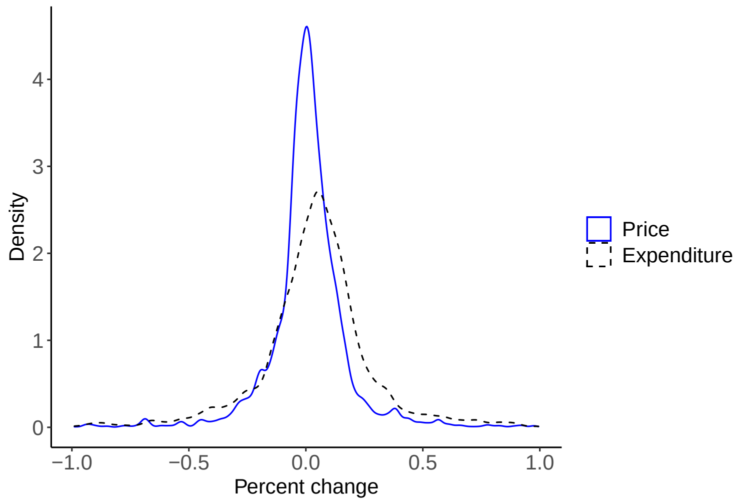
Figure 12 plots the distributions of demand shocks under two different specifications of the shift-share design described in Section 4.2. Both specifications use shares of export revenue by destination. The first, shown in blue, uses shifts in import prices at the destination (excluding imports from Ecuador) obtained from CEPII's *World Trade Flows Characterization* database. It is well-approximated by a normal distribution with mean 0.02 and standard deviation 0.11. The second, shown in black, uses shifts in import *expenditures* at the destination (again excluding imports from Ecuador) obtianed from CEPII's *BACI* database. This generates substantially more dispersion in demand shocks, and is well-approximated by a normal distribution with mean 0.05 and standard deviation 0.15. When solving the model, I can draw price shocks directly from the distributions in the data. For the sake of reproducibility, I draw from the fitted normal distributions instead.

A.3.4 Recovering exporter productivities

When estimating the model, I pick the mean and standard deviation of log exporter productivity to match the distribution of log exporter revenue in the data. However, it is possible to recover exporter productivities non-parametrically following the procedure in Berger et al. (2019). First, note that for exporters i and i' of crop j, dividing scaled crop prices from above yields:

$$\frac{\hat{p}_i}{\hat{p}_{i'}} = \left(\frac{\psi(s_i)}{\psi(s_{i'})}\right)^{\frac{1}{1+\theta}} \left(\frac{z_i}{z_{i'}}\right)^{\frac{1}{1+\theta}} \left(\frac{s_i}{s_{i'}}\right)^{-\frac{\eta-\theta}{(1+\eta)(1+\theta)}}$$

Figure 12: Percent change in international prices



Notes: Solid blue line plots density of percent change in international prices. Dashed black line plots density of percent change in international expenditures.

where I have suppressed the j subscript and $\psi(s_i) = (1 + \frac{1}{\epsilon_i})^{-1}$ is the optimal markdown as a function of exporter size. Note also that the equilibrium exporter size $s_{ij} = (\frac{\hat{p}_{ij}}{\hat{p}_j})^{1+\eta}$, which implies that $\frac{\hat{p}_i}{\hat{p}_{i'}} = (\frac{s_i}{s_{i'}})^{\frac{1}{1+\eta}}$. Substituting above and rearranging yields a simple expression for the relative productivities of i and i':

$$\frac{z_i}{z_{i'}} = \frac{\psi(s_{i'})/s_{i'}}{\psi(s_i)/s_i}$$

This equation says that a more productive exporter (higher z_i) pays farmers a lower markdown relative to his size (lower $\psi(s_i)/s_i$). Intuitively, more productive exporters in the model are both larger and pay lower markdowns, so it is reasonable to infer relative productivity from relative markdowns and relative sizes.

A.3.5 Bertrand competition

Table 9 shows estimates of the key parameters under Bertrand competition. Quantitatively, Bertrand competition indeed implies both a lower elasticity of subsitution across crops and lower levels of market power. However, the results are qualitatively similar to the case with Cournot competition.

Table 9: Key parameters, Bertrand competition

Parameter	Cournot	Bertrand	Moment	Value
η	1.93	2.00	$\hat{\gamma}$	0.35
θ	0.40	0.21	$\hat{\zeta}$	-0.23
α	0.45	0.38	$\hat{\phi}$	0.24

A.3.6 Overidentified model

In this section, I estimate an overidentified version of the model under both Cournot and Bertrand competition. I proceed as in Section 4.2, with one important modification. In addition to matching the baseline pass-through (γ in Equation 8), the decline in pass-through with exporter size (ζ in Equation 8), and the average farmer share, I match the decline in farmer share with exporter size (β in Equation 6). The theory implies that this coefficient is a function of η and θ, as discussed in Section 3.5. Furthermore, it is precisely estimated in Table 3, unlike the coefficient on the interaction term in Table 4. This will be particularly helpful for estimating θ.

To estimate the model under Bertrand competition, I make two modifications to the estimation procedure in Section 4.2. First, I compute the optimal farm price using the Bertrand supply elasticity (Equation 13) rather than the Cournot supply elasticity (Equation 4). Second, I choose the output elasticity α to match the Bertrand farmer share (Equation 15) rather than the Cournot farmer share (Equation 9).

Table 10 presents estimates of the key parameters. The overidentified model features stronger potential market power than the baseline model in the form of lower elasticities of substitution η and θ. However, the actual market power implied by the output elasticity α is similar to that of the baseline model. Note that the Cournot model matches all moments well, despite being overidentified. However, the Bertrand model struggles to generate both the steep decline in pass-through and the steep decline in farmer shares as a function of exporter size.

Table 10: Key parameters, overidentified model

Parameter	Cournot	Bertrand	Moment	Value (Data)	Value (Cournot)	Value (Bertrand)
η	1.90	1.94	$\hat{\gamma}$	0.35	0.36	0.44
θ	0.41	0.37	$(\hat{\zeta},\hat{\beta})$	(-0.23,-0.82)	(-0.22,-0.83)	(-0.16,-0.89)
α	0.44	0.38	$\hat{\phi}$	0.24	0.24	0.24

A.3.7 Standard errors

The variance-covariance matrix of the key parameters, V, is given by:

$$V = (1 + \tfrac{1}{S})(G'WG)^{-1}G'W\Omega WG(G'WG)^{-1}$$

where G is the matrix of partial derivatives of the model moments, $m(\eta,\theta,\alpha)$, with respect to (η,θ,α), Ω is the variance-covariance matrix of the moments, and S is the number of simulations (Gourieroux, Monfort, and Renault, 1993). The standard error of each parameter is then given by the square root of the corresponding element along the diagonal of V. Replacing W with the optimal weighting matrix, Ω^{-1}, we have:

$$V = (1 + \tfrac{1}{S})(G'\Omega^{-1}G)^{-1}$$

For the exactly-identified model, $m = (\gamma, \zeta, \phi)'$ as above, and G and Ω are 3x3 matrices. For the overidentified model, $m = (\gamma, \zeta, \phi, \beta)$, G is a 4x3 matrix, and Ω is a 4x4 matrix. I compute G using a 1% deviation in each of the estimated parameters. For Ω, I use the variance-covariance matrix of data moments. Table 11 below summarizes the standard errors for the two models under Cournot competition. Although η is precisely estimated in both models, θ is precisely estimated only in the overidentified model. This is because the coefficient on exporter size in the farmer share regression, β, is highly significant and informative of the difference between η and θ. Finally, note that α is imprecisely estimated in both specifications. In the model, α is calculated using estimates of η and θ and therefore inherits their uncertainty. In the data, there is considerable variation in farmer shares, which adds further uncertainty.

Table 11: Standard errors

Parameter	Estimate (Exactly Identified)	SE (Exactly Identified)	Estimate (Overidentified)	SE (Overidentified)
η	1.93	0.99	1.90	0.94
θ	0.40	0.36	0.41	0.14
α	0.45	1.70	0.44	0.47

A.3.8 Estimating η and θ from relative pass-through

In this section, I estimate the model using an alternative estimation technique and an alternative specification of demand shocks. Berger et al. (2019) estimate the elasticity of substitution across firms, η, and markets, θ, using the *relative* pass-through of demand shocks to prices and quantities, rather than just pass-through to prices. Taking the ratio of pass-through to crop prices and quantities above yields the crop supply elasticity:

$$\frac{\partial \log p_{ij} / \partial \log p_j^x}{\partial \log q_{ij} / \partial \log p_j^x} = \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij} \tag{17}$$

Letting $s_{ij} \to 0$, we have that the supply elasticity of small exporters identifies η. Letting $s_{ij} \to 1$, we have that the supply elasticity of large exporters identifies θ. Following Berger et al. (2019), I pick η and θ

so that exporter responses to shocks as a function of relative size, denoted by $\xi(s_{ij}) \equiv \frac{d\log p_{ij}/d\log p_j^x}{d\log q_{ij}/d\log p_j^x}$, match between the model and the data. I proceed in several steps: (1) estimate $\hat{\xi}(s)$ in the data, (2) simulate $\xi(s)$ in the model, (3) form moments from $\hat{\xi}(s)$ and $\xi(s)$, (4) minimize the distance between the moments.

To estimate $\hat{\xi}(s)$ in the data, I first estimate the following regressions:

$$\Delta \log p_{ijt}q_{ijt} = \delta_{jt}^v + \beta^v s_{ij,t-1} + \gamma^v \Delta \log p_{ijt}^x + \zeta^v s_{ij,t-1} \times \Delta \log p_{ijt}^x + \varepsilon_{ijt}^v \quad (18)$$

$$\Delta \log x_{ijt} = \delta_{jt}^q + \beta^q s_{ij,t-1} + \gamma^q \Delta \log p_{ijt}^x + \zeta^q s_{ij,t-1} \times \Delta \log p_{ijt}^x + \varepsilon_{ijt}^q \quad (19)$$

where v stands for "value" and q stands for "quantity." All other terms are defined as in Equation 8. Equation 18 represents the expenditure response to international price shocks, while Equation 19 represents the quantity response. I use Equation 18 rather than Equation 8 to avoid including quantity responses in both dependent variables. When constructing demand shocks following the shift-share design in Section 4.2, I use the log change in import expenditures at the destination rather than the log change in import prices.

Given estimates of Equations 18 and 19, I calculate the crop supply elasticity $\hat{\xi}(s)$ as follows:

$$\hat{\xi}(s) = \frac{\hat{\gamma}^v + \hat{\zeta}^v s}{\hat{\gamma}^q + \hat{\zeta}^q s} - 1 \quad (20)$$

Table 12 displays the regression results. As above, the estimated coefficients imply that (a) pass-through is imperfect, (b) pass-through declines with exporter size, and (c) shocks shift the demand curve and trace out the supply curve. The last two rows of Table 12 report the supply elasticities implied by the estimates for relatively small exporters, $\hat{\xi}(0)$, and relatively large exporters, $\hat{\xi}(1)$. Notice that larger exporters indeed face steeper supply curves.

Table 12: Exporter responses to expenditure shocks

	$\Delta \log pq$	$\Delta \log x$
	(1)	(2)
$\Delta \log p^x$	0.479	0.267
	(0.272)	(0.140)
s	0.888	0.345
	(0.470)	(0.242)
$\Delta \log p^x \times s$	-1.078	-0.525
	(0.646)	(0.332)
FE	Exporter	Exporter
Observations	1,058	1,058
R^2	0.507	0.533
$\hat{\rho}(0)$	0.789	
$\hat{\rho}(1)$	1.331	

Notes: Column 1 shows estimates of Equation 18. Column 2 shows estimates of Equation 19. $\hat{\xi}(0)$ and $\hat{\xi}(1)$ were calculated using Equation 20. Both specifications include product and year fixed effects. Clustered standard errors are shown in parentheses.

To simulate $\xi(s)$ in the model, I proceed as above, guessing η and θ, solving the model, shocking the model, solving again, estimating Equations 18 and 19 in the simulated data, and calculating $\xi(s; \eta, \theta)$ using Equation 20. Notice that the supply elasticity in the model depends on η and θ.

The crop supply elasticity faced by relatively small exporters identifies η,while the supply elasticity faced by relatively large exporters identifies θ. Therefore, I pick η and θ so that the elasticities $\xi(0; \eta, \theta)$ and $\xi(1; \eta, \theta)$ generated by the model match the elasticities $\hat{\xi}(0)$ and $\hat{\xi}(1)$ estimated from the data and reported in Table 12:

$$(\hat{\eta}, \hat{\theta}) = \arg\min_{\eta,\theta} \left\{ ||\hat{\xi}(0) - \xi(0; \eta, \theta)|| + ||\hat{\xi}(1) - \xi(1; \eta, \theta)|| \right\}$$

Table 13 reports the three key parameters of the model estimated using the relative pass-through of demand shocks, which I will call the Berger-Herkenhoff-Mongey procedure. Notice that this procedure implies *higher* market power than the procedure in the main text: the estimated η and θ are lower, while the estimated α is higher.

Table 13: Key parameters, Berger-Herkenhoff-Mongey procedure

Parameter	Cournot	Bertrand	Moment	Value
η	1.32	1.31	$\hat{\xi}(0)$	0.79
θ	0.34	0.33	$\hat{\xi}(1)$	1.33
α	0.55	0.49	$\hat{\phi}$	0.24

A.3.9 External validation of η

To compare exporter-specific cost shocks in my model to those in the agricultural trade literature, assume there is a single crop, so that the only relevant shock is $\frac{\nu_{fi}}{1+\eta}$. A farmer with efficiency q_f delivers $e^{\frac{\nu_{fi}}{1+\eta}} q_f = e^x q_f$ units to exporter i, where x follows a Gumbel distribution with scale parameter $\frac{1}{1+\eta}$. In addition, assume that trade costs are the only source of heterogeneity in exporter-specific costs. In the literature, trade costs are typically deterministic and takes an iceberg form. As a result, I compare the mean trade cost estimates from the literature to the mean implied by my estimates, expressed in iceberg form.

Following the derivation above, the Gumbel distribution with scale parameter $\frac{1}{1+\eta}$ is equivalent to the Frechet distribution with scale parameter $1+\eta$. The mean of a Frechet distribution with scale parameter $1+\eta$ is $\Gamma(1-\frac{1}{1+\eta})$, where $\Gamma(\cdot)$ is the gamma function. Substituting my estimate of $\eta = 1.72$ yields a mean of 1.42. To convert this to iceberg form, I divide the 90th percentile of the Frechet distribution by the average, yielding an average trade cost of 1.69. The following table reports this estimate, along with those from a selection of papers.

Table 14: Sources for Figure **??**

Reference	Iceberg trade cost	Source
Atkin and Donaldson 2015	1.12	Section 4.3
Chatterjee 2019	1.16	Section 6.1.1
Bergquist et al. 2019	1.25	Section 4
Allen 2014	1.47	Table 7
This paper	1.69	Section A.3.9
Sotelo 2020	2.34	Reported in Table 4

A.3.10 External validation of θ

To compare crop-specific productivity shocks in my model to those in the agricultural trade literature, assume there is a single exporter for each crop, so that the only relevant shock is $\frac{\nu_{fj}}{1+\theta}$. A farmer with efficiency q_f

now produces $e^{\frac{\nu_{fj}}{1+\theta}} q_f = e^x q_f$ units of crop j, where x follows a Gumbel distribution with scale parameter $\frac{1}{1+\theta}$. In the literature, land heterogeneity typically follows a Frechet distribution with shape parameter $\tilde{\theta}$. It remains to convert the cost shock to a productivity shock, and the Gumbel parameter to the associated Frechet parameter.

Rewrite the cost shock $z = e^x$. The CDF of z is $G(z) = P(e^x \leq z) = P(x \leq \log z) = F(\log z)$, where F is the CDF of x. Substituting $\log z$ into the CDF for the Gumbel distribution, we obtain the CDF of the Frechet distribution with shape parameter $1+\theta$. Therefore, my estimate of $\hat{\theta} = 0.35$ corresponds to a shape parameter of 1.35 for the distribution of land heterogeneity. The following table reports this estimate, along with those from a selection of papers.

Table 15: Sources for Figure **??**

Reference	Land heterogeneity	Source
Costinot et al. 2016	2.46	Table 2
Farrokhi and Pellegrina 2020	2.05	Table 2
Bergquist et al. 2019	1.80	Section 4
Sotelo 2020	1.66	Section 5
This paper	1.34	Section A.3.10
Gouel and Laborde 2018	1.2	Section 6.2

A.4 Measurement appendix

A.4.1 External validation of markdowns

Table 16 situates my estimated markdowns within the broader literature on buyer market power. Although studies of buyer power differ widely in empirical context and modeling choices,[63] they all employ markdowns as a measure of market power. Most of these studies estimate considerably higher markdowns, meaning that buyers have *less* market power than in my setting. However, the most directly comparable study, Rubens (2020), which estimates the market power of cigarette manufacturers over tobacco farmers in China, finds *lower* markdowns. Moreover, several of these studies focus on workers in US labor markets (Lamadon et al. 2019; Berger et al. 2019; Azar et al. 2019), who are likely more mobile than farmers in Ecuador.

[63] For example, Lamadon, Mogstad, and Setzler (2019); Berger et al. (2019); Azar, Berry, and Marinescu (2019) take three different approaches to study market power in US labor markets.

Table 16: Estimates of markdowns from the literature

Reference	Average markdown	Source
Lamadon et al. 2019	0.85	Section 6.1
Azar et al. 2019	0.83	Section 4.1
Berger et al. 2019	0.74	Figure 8
Morlacco 2019	0.51	Table 4
This paper	0.49	Section 5.1
Rubens 2020	0.35	Section 4

A.4.2 Fixed costs to exporting

If exporters face a common fixed cost f to exporting, they will only export if profits are sufficiently large to cover the fixed cost. Substituting the first order conditions for q_{ij} and m_{ij} into the profit function,we have:

$$p_{ij}q_{ij} \times \left(\frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta}s_{ij}\right) \geq f$$

The smallest exporter across all crops has negligible market share. Plugging in $\eta = 1.72$, $\theta = 0.35$, and $s_{ij} = 0$, this implies that the fixed cost is no larger than 58% of the farmer income paid by the smallest exporter. Aggregating the profit function across all exporters yields the expression for average profits:

$$\overline{pq} \times \left(\frac{1}{\eta}(1 - HHI) + \frac{1}{\theta}HHI\right) - f$$

where $\overline{pq}$ is the average farmer income across all exporters and HHI is the weighted average Herfindahl index across all crops. Plugging in $\eta = 1.72$, $\theta = 0.35$, $HHI = 0.24$, and the expression for f implies that average profits equal:

$$1.13\overline{pq} - 0.58\underline{pq} > 0.55\overline{pq}$$

where $\underline{pq}$ denotes the income of the smallest exporter and I have used the fact that $\overline{pq} > \underleftarrow{pq}$. This implies that we could reduce the average exporter's profits by 55% of his payment to farmers without forcing the exporter to exit. Figure 8 implies that perfect competition would redistribute 51% of farmer income away from the exporter profits, so that the average exporter could continue operating.

A.4.3 Farmer risk aversion

Recall from above that log changes in international prices are approximately normally distributed with mean $\mu_d = 0.02$ and variance $\sigma_d^2 = 0.11$. Starting from an equilibrium, farmer income Y_t follows a Geometric Brownian Motion:

$$dY_t = \rho\mu_d Y_t dt + \rho\sigma_d Y_t dW_t$$

where ρ is the pass-through rate and W_t is a Wiener process. In a one-period model with initial income Y_0, farmer income follows a log-normal distribution with mean $\mu_y = \log Y_0 + \rho\mu_d - \frac{\rho^2\sigma_d^2}{2}$ and variance $\sigma_y^2 = \rho^2\sigma_d^2$.

Suppose that farmers have Constant Relative Risk Aversion (CRRA) preferences with coefficient γ. Given a log-normal income process with mean μ_y and variance σ_y^2, the certainty equivalent, x, is:

$$x = e^{\mu_y + \frac{\sigma_y^2(1-\gamma)}{2}}$$

The farmer is indifferent between receiving x with certainty and receiving income according to the risky log-normal process. Therefore, the farmer is indifferent between two income processes if they have the same certainty equivalent. Substituting the expressions for μ_Y and σ_Y^2 into the certainty equivalent formula, we have:

$$Y_0^{PC} e^{\rho_{PC}\mu_d - \frac{\rho_{PC}^2\sigma_d^2\gamma}{2}} = Y_0^{MP} e^{\rho_{MP}\mu_d - \frac{\rho_{MP}^2\sigma_d^2\gamma}{2}}$$

where PC denotes the equilibrium with perfect competition and MP denotes the equilibrium with market power. Solving for γ yields:

$$\gamma = \frac{2\log(Y_0^{PC}/Y_0^{MP})}{2(\rho_{MP}-\rho_{PC})\mu_d + (\rho_{PC}^2 - \rho_{MP}^2)\sigma_d^2}$$

Plugging in $\mu_d = 0.02$, $\sigma_d^2 = 0.11$, $Y_0^{PC} = 1.77Y_0^{MP}$, $\rho_{PC} = 1$, and $\rho_{MP} = 0.42$ yields $\gamma = 7.36$. This corresponds to the highest category of risk aversion estimated in Yesuf and Bluffstone (2009).

A.5 Policy appendix

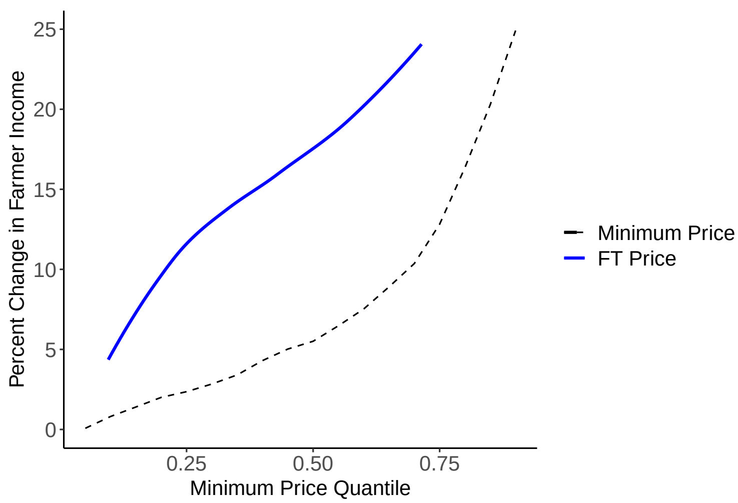
A.5.1 Alternative formulations of Fair Trade

In the main text, I model Fair Trade by introducing a perfectly competitive exporter with productivity drawn from the estimated distribution. Here, I show how this maps to different ways of implementing Fair Trade.

A popular way of implementing Fair Trade is to specify a minimum price for certified products (plus a premium). This is distinct from a broad price floor because only *certain* buyers must adhere to the minimum price, i.e. those participating in the Fair Trade program. As a result, the Fair Trade minimum price does not have the distortionary effect of a broad price floor. Fair Trade products can always be sold to conventional buyers. Therefore, the Fair Trade price must be higher than the conventional price to guarantee enough takeup from farmers. To prevent too much takeup, Fair Trade buyers typically specify a maximum certified quantity (Podhorsky, 2015). In the model, the Fair Trade exporter sets the optimal price given his productivity level and buys the market-clearing quantity. Price and quantity are strictly increasing in productivity, so that varying the productivity traces out the curve of Fair Trade prices and certified quantities.

Figure 13 compares the effect of a Fair Trade price to that of a universal price floor. The dashed black line indicates the percent change in farmer income as a function of the price quantile for a policy that specifies a minimum price for all exporters, as in Figure 11. The solid blue line does the same for a policy that specifies a minimum price only for Fair Trade exporters. For a given price, the Fair Trade policy yields larger gains.

Figure 13: Effect of Fair Trade prices



Notes: Figure plots the quantile of a counterfactual price floor on the x-axis and the resulting percent change in farmer income relative to the baseline model on the y-axis. The dashed black line indicates the counterfactuals with a broad price floor. The solid blue line indicates the Fair Trade counterfactual with the same Fair Trade price.

In Section 3.4, I show that a profit-maximizing exporter with market power offers farmers a price that is marked down from their marginal revenue product. In contrast, a perfectly competitive exporter offers farmers their marginal revenue product. Suppose an exporter with market power instead maximized farmer income subject to non-negative profits. He solves:

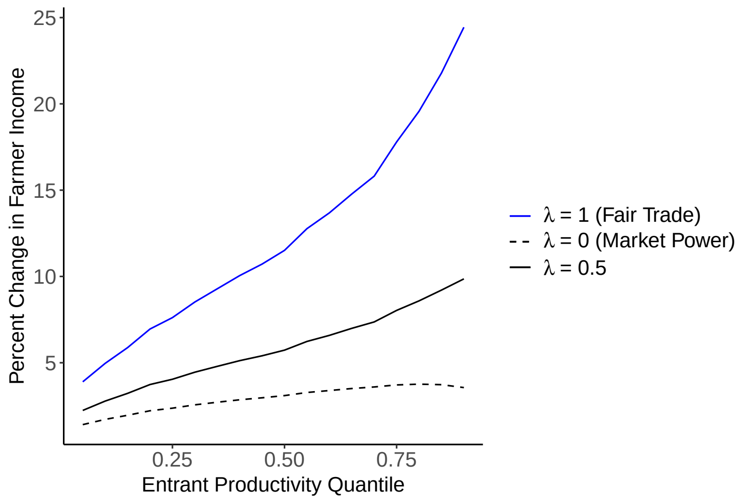
$$\max_{q_{ij}} \{p_{ij}q_{ij} - \mu[\alpha p_j^x x_{ij} - p_{ij}q_{ij}]\}$$

where μ is the Lagrange multiplier on the constraint I have used the fact that $p_j^m m_{ij} = (1-\alpha)p_j x_{ij}$. Clearly $\mu > 0$ for an interior solution. The first order conditions for q and μ, respectively, are:

$$p_{ij}q_{ij} = \frac{\mu}{\mu-1} \times \alpha^2 \times \left(1 + \frac{1}{\epsilon_{ij}}\right)^{-1} p_j^x x_{ij}$$

$$p_{ij}q_{ij} = \alpha p_j^x x_{ij}$$

Figure 14: Effect of Fair Trade on farmer income



Notes: Figure plots the productivity quantile of a counterfactual exporter on the x-axis and the resulting percent change in farmer income relative to the baseline model on the y-axis. The dashed black line indicates the counterfactuals in which the exporter maximizes profits. The solid blue line indicates the Fair Trade counterfactual in which the exporter maximizes farmer incom. The solid black line indicates the coutnerfactuals in which the exporter maximizes a weighted sum of profits and farmer income, with equal weights.

Both equations are satisfied when $\frac{\mu}{\mu-1} = \alpha^{-1} \times \left(1 + \frac{1}{\epsilon_{ij}}\right)$, which implies that exporters pay farmers their marginal revenue product. In other words, a strategic exporter who maximizes farmer income behaves like a perfectly competitive exporter.

A Fair Trade exporter may maximize a weighted sum of profits and farmer income(Podhorsky, 2015). In this case, he will pay farmers a price in between the marginal revenue product (offered by competitive exporters) and the marked down price (offered by strategic exporters). Figure 14 below shows the effect on farmer income when the Fair Trade exporter maximizes places weight λ on farmer income and $1 - \lambda$ on profits. The solid black line corresponds to the case where $\lambda = 0.5$. The blue line is the limiting case where $\lambda = 1$ (perfect competition), while the dashed line is the limiting case where $\lambda = 0$ (market power). Note that a relatively large weight on farmer income is required to approach the maximum Fair Trade gains.