Unfair Trade?

Market Power in Agricultural Value Chains

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Abstract

I show that 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 which export markets 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

Two-thirds of the world's poor work in agriculture. Many of them live in developing countries, where agriculture also accounts for a large share of export revenue. The division of surplus in agricultural value chains therefore has important distributional implications for farmer well-being. Many small farmers sell crops to a few large exporters, who control access to more lucrative international markets. This concentration creates the potential for both inefficiency and inequality, with adverse consequences falling on farmers. Exporters can use their bargaining power to depress crop prices and quantities, preventing farmers from receiving the benefits of globalization.

This paper quantifies the effect of exporter market power on farmer income in a developing country. Measuring market power in this setting is challenging, as it requires knowledge of farmer-exporter relationships at a micro level. Using confidential tax records from Ecuador, I assemble a rich new dataset which maps the value chain for over 100 exported agricultural products. I link Customs data, which measures the revenue of exporters, with Value Added Tax (VAT) data, which measures their payments to suppliers, and firm registry data, which allows me to identify which suppliers are farmers. To the best of my knowledge, this is the first paper to bring such data to bear on the question of buyer power.

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 over farmers. 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 measures of exporter value added. This last fact exploits the unique microstructure of the data in order to link the first two facts and suggest market power among exporters as a potential explanation.

To quantify the importance of market power, I extend a frontier model of oligopsony in labor markets (Berger, Herkenhoff, and Mongey 2019; Atkeson and Burstein 2008) to the context of crop markets. 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 stochastically captures the land's suitability for different crops and the farmer's proximity to different exporters, two key dimensions of heterogeneity in models of agricultural trade (Costinot, Donaldson, and Smith 2016; Sotelo 2020). 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 market 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 subsitution across crops and across exporters within a crop. The lower they are, the greater the market power of large exporters, and the faster that prices fall with exporter size.

The elasticities are therefore crucial to measuring market 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 easily farmers can substitute across intermediaries 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 a lot 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 market power.

The model allows me to measure market power in several ways. I show that farmer prices are marked down to 49% 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 and 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 35%.

To highlight the effectiveness of Fair Trade, I conside a second policy in which the government sets a 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 Fair Trade. Fair Trade emerges as a practical policy for reducing inequality and inefficiency without creating additonal distortions.

1.1 Related literature

Downstream buyers such as traders and processing firms are important links in agricultural supply chains, and a growing literature examines how they influence farmer welfare in developing countries. One way that buyers influence farmer income is by using their bargaining power to depress farmgate prices.[1] Studies of buyer power often focus on a single commodity in a single country.[2] While we know that buyer power adversely affects farmers in many of these markets, we know little about its prevalence and potential consequences across the entire economy. Chatterjee (2019) sheds light on both a specific mechanism through which intermediaries exert market power – spatial variation in bargaining power of farmers – and quantifies its impact across several crops in India. Dhingra and Tenreyro (2020) show that farmer income in Kenya is higher on average when they sell to large intermediaries, but less responsive to changes in international prices. Relative to these contributions, I leverage microdata on both farmers *and* buyers to measure market power across the universe of exported agricultural products in Ecuador.

A broader body of literature seeks to understand the distribution of surplus between buyers and sellers in value chains. In general, studies have focused on the manufacturing sector, and to the extent that they have considered the market power of firms, they have focused on adverse consequences for consumers. The typical approach involves first estimating a firm's production function and then using the estimates to purge reported profits of unobserved value added. The residual measures market power (De Loecker and Warzynski 2012). This approach mirrors the dominant industrial organization paradigm, which infers value added from the firm's *demand* function and has a rich history dating back to Bresnahan (1989).

Researchers have employed this approach to document substantial output market power and corresponding losses for consumers in various contexts (De Loecker, Eeckhout, and Unger 2020; De Loecker and Warzynski 2012; De Loecker and Goldberg 2014; De Loecker, Goldberg, Khandelwal, and Pavcnik 2016). Morlacco (2019) adapts the approach to a context where *buyers* have monopsony power over their suppliers. She shows that suppliers receive prices below their marginal revenue products, and consumers suffer losses from inefficiently low output.

I take a more direct approach, following the literature on buyer power in the labor market and its effects on workers. Several studies demonstrate that workers' wages in the United States are marked down from their marginal products, with large consequences for consumer welfare (Berger et al. 2019; Azar, Berry, and Marinescu 2019; Azkarate-Askasua and Zerecero 2020; Lamadon, Mogstad, and Setzler 2019). Of these,

[1] Another way is through relationships. In Costa Rica, long-term relationships between coffee farmers and buyers restrict trade relative to vertical integration (Macchiavello and Miquel-Florensa 2017). In Rwanda, long-term relationships raise farmer income (Macchiavello and Morjaria 2020).

[2] 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), and maize in Kenya (Bergquist and Dinerstein 2020).

my approach most closely resembles that of Berger et al. (2019), who extend the framework of Atkeson and Burstein (2008) to the context of buyer market power. Their framework features Cournot competition among manufacturing firms and a nested CES supply curve for labor derived from worker substitution across and within labor markets.

I focus on buyer market power of exporters in the agricultural sector, which is largely absent from this literature because of its focus on developed countries. My model also features Cournot competition among exporters and a nested CES supply curve for crops. I microfound the supply curve with a discrete choice model of farmer production decisions. In this way, I forge a connection with a body of literature that estimates farmer subsitution across and within crops using agricultural production data (Costinot et al. 2016; Sotelo 2020; Farrokhi and Pellegrina 2020; Bergquist, Faber, Fally, Hoelzlein, Miguel, and Rodriguez-Clare 2019).

I estimate buyer power based on how farmer income responds to changes in international prices and how this response varies with the size of the exporter. This approach resembles that of Atkin and Donaldson (2015) and Bergquist and Dinerstein (2020), who use variation in pass-through across firms and locations to measure *seller* market power. Rubens (2020) combines pass-through and production function techniques to measure the buyer market power faced by farmers in rural China, but focuses on a single product: tobacco. In contrast, I estimate market power in products as diverse as fruit and fish, and use the esimated model to evaluate policies designed to fight market power, such as Fair Trade.

Several studies evaluate the effectiveness of Fair Trade and related certification programs.[3] The key feature of these programs is that certified exporters pay certified farmers a premium for sustainably produced crops. Podhorsky (2015) argues that Fair Trade has both a direct effect on the farmers that participate in the program and a spillover effect on other farmers by reducing the market power of non-participating exporters. The majority of evidence on Fair Trade concerns a single product: coffee. Dragusanu and Nunn (2018) provide empirical evidence of both channels in the Costa Rican coffee sector. De Janvry, McIntosh, and Sadoulet (2015) document the adverse consequences of excess entry into Fair Trade certification by coffee farmers throughout Central America. Macchiavello and Miquel-Florensa (2019) examine the effects of more complex certifications involving international coffee buyers in addition to farmers and exporters. Relative to this literature, I incorporate Fair Trade into a general equilibrium structural model, which allows me to estimate its impact across many different products and compare it to alternative agricultural support policies, such as minimum producer prices.

To the best of my knowledge, I am the first to measure buyer power and estimate the impact of pro-farmer policies across such a broad range of crops. To do so, I combine firm-level data on agricultural exports from Ecuador with data on domestic buyer-supplier relationships. Other studies have employed similar datasets to

[3]See Dragusanu, Giovannucci, and Nunn (2014) for a comprehensive review.

examine how domestic networks shape the effects of globalization in various contexts (Kikkawa, Magerman, and Dhyne 2019; Huneeus 2018; Adao, Carrillo, Costinot, Donaldson, and Pomeranz 2019; Alfaro-Ureña, Manelici, and Carvajal 2019). Given the growing availability of network data through collaborations with government statistical agencies worldwide, bringing such data to bear on the question of buyer market power paves a path for future research.[4]

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, validate it, and use it to measure market power. In Section 5, I conduct counterfactual analyses of Fair Trade and other policies. I conclude in Section 6 by discussing the limitations of the current study and the lessons 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,

[4] Kikkawa et al. (2019) consider seller market power. Other papers assume perfect competition.

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.[5] 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 Mapping agricultural value chains

A key challenge to tracing the value of crops from farm to port 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. 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 and quantity traded internationally for each firm, product, and year.[6] For step (1), I use the data to calculate the value received by exporters. 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.

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

The third dataset contains basic characteristics for all firms active in 2011. The data are pulled from a

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

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

national register and include the industry and location of each firm.[7] In step (4), I use the data to identify which suppliers are farmers. Taxpayers in the agriculture, forestry, and fishing industries (ISIC 2-digit codes 01-03) are classified as farmers. [8]

My novel agricultural value chain dataset comprises almost 1,000 exporters selling 100 agricultural products sourced from 50,000 farmers. Table 1 summarizes the farmers and exporters in my dataset. The median exporter is large, earning over $1 million and employing more than 20 people. 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.[9] However, 75% of farmer sales are indirectly exported, indicating the importance of mapping 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 a large exporter. If anything, large firms have an incentive to *over-report* the value they pay to farmers, as their tax liablity is assessed on the difference between sales and purchases.[10] To the extent that they still under-report crop purchases, my estimates of the farmer income would be biased downward, and a measure of market power derived solely from farmer income would be biased upward. Instead, I infer market power from how farmer income responds to demand shocks, further mitigating the concern. I discuss this point in detail in the estimation section.

Table 1: Farmer and exporter statistics

A: Exporters					
$ Sales	$ Purchases	$ Wage Bill	# Employees	% Wholesale	% Single-product
1,177,543	543,053	108,246	21	74	76
B: Farmers					
$ Sales	$ Purchases	$ Wage Bill	# Employees	% Self-employed	% Exported
8,678	0	0	0	94	75

Notes: Table shows summary statistics across 804 exporters (Panel A) and 49,745 farmers (Panel B). Columns 1-4 show medians. Columns 5-6 show means.

A second concern is that the data may not be capturing small family farms, but rather large factory

[7]Industries are classified up to the ISIC 5-digit level.

[8]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 exporter.

[9]An exception is the cut flower industry, where many small farms export directly. I exclude these from the analysis.

[10]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.

farms. The median farm does not report any employees or wages, consistent with the high rate of self-employment. In principle, I could calculate farmer income as the sum of (a) sales of self-employed farmers and (b) wages paid by larger farms to their employees.[11] However, not all farm employees are farmers, and farm owners may be farmers themselves. To avoid distributing farm sales among employees and owners and arbitrarily deciding who is a farmer, I measure farmer income as sales, making no distinction between farms and farmers. This is equivalent to assuming that all employees and owners are farmers, which overestimates farmer income and underestimates the number of farmers. Importantly, I infer market power without using any information on farm size. To the extent that small farms face more market power than large farms, I will underestimate it.

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. If the exporter at one end only exports coffee and has few domestic sales, I can be confident that the product he purchases from the farmer at the other end is coffee. This is a reasonable approximation 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.[12] 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.[13] The median exporter buys from 24 farmers, but the median farmer only sells to a single exporter. This is true both in the 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 farmers 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 great detail.

[11] Adao et al. (2019) follow this approach for manufacturing industries in Ecuador.
[12] I assign multi-product exporters to their top product, which accounts for over 90% of exports for these firms.
[13] See the appendix for additional network statistics.

Table 2: Exporter-farmer networks

	\$ Exports ($\times 10^6$)	# Exporters	# Farmers	# Suppliers/Exporter	# Customers/Farmer
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 networks across 157 crops defined at HS 6-digit level. Row 2 shows all crops. Rows 3-8 show a selection of the top crops. Columns 2-4 show totals. Column 5 shows medians across exporters. Column 6 shows medians 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. They motivate the development of a model to explore the consequences for small farmers.

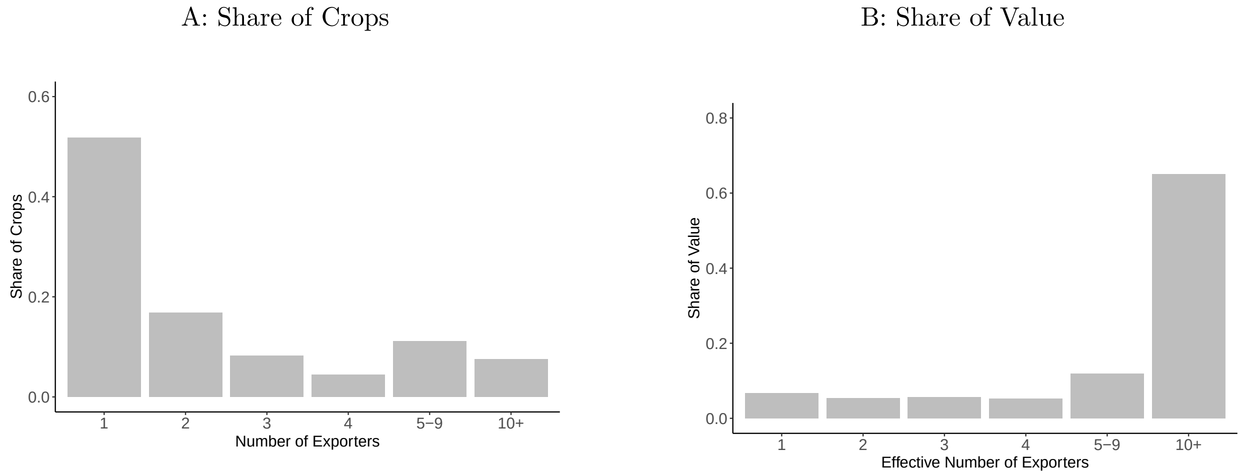
2.3.1 Crop markets are highly concentrated

To examine the potential for market power across a broad range of crops, I divide crops into six bins based on the number of exporters present: 1,2,3,4,5-9,10+. Figure 1 plots the distribution across these bins for more than 100 crops. Panel A indicates that the majority of crop markets are highly concentrated: the median crop is dominated by single firm, and almost all crops have fewer than 10 exporters.

On the one hand, Panel A may understate the degree of concentration in crop markets. As an example, consider the market for cocoa, which has 56 exporters in Table 2 and is therefore in the "10+" bin. However, the top 4 cocoa exporters control almost the entire export market, such that cocoa effectively belongs in the "4" bin. To capture this phenomenon more generally, 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. Then, the effective number of exporters for cocoa is 4. On the other hand, Panel A may overstate the *importance* of concentration in crop markets. For instance, the banana, Ecuador's largest exported crop by value, remains in the "10+" bin even after adjusting for the effective number of exporters.

Panel B of Figure 1 addresses both of these concerns: it plots the distribution of the effective number of exporters across crops, weighted by the share of total exports in each bin. Although concentration appears less stark than in Panel A, about 40% of crop value is still sold in markets with fewer than 10 exporters. Concentration on its own does not imply market power. To establish some evidence of market power, I take advantage of the matched nature of my dataset in the next fact.

Figure 1: Crop market concentration



Notes: Panel A plots the distribution of the number of exporters by crop across 157 exported crops. Panel B plots the effective number of exporters, defined as the minimum number requried to control 90% of the market, and weighted by the share of export value in each bin.

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, 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. I refer to this as the *farmer share* for exporter i of crop j:

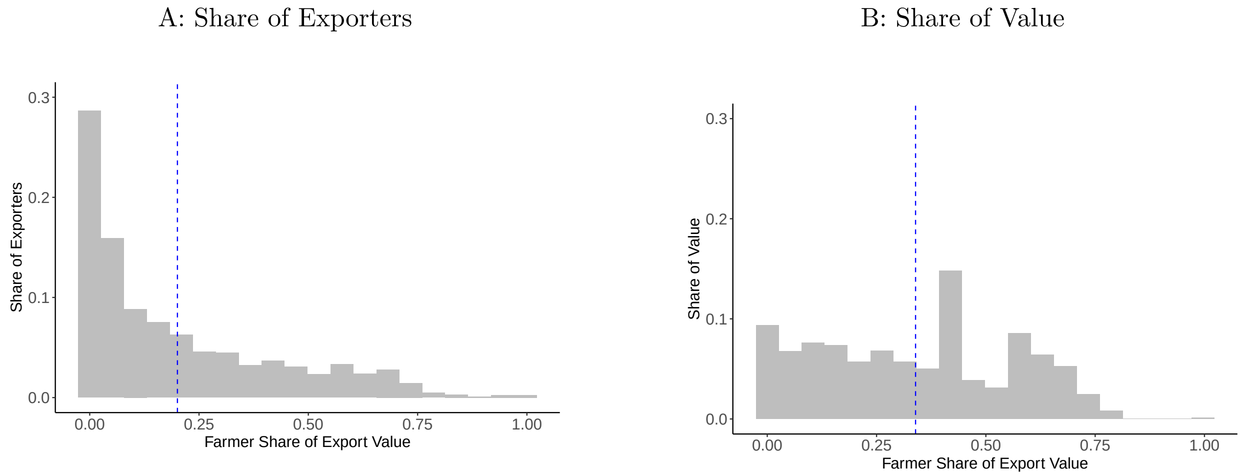
$$\text{farmer share}_{ij} \equiv (\text{purchases of crop } j \text{ by exporter } i)/(\text{exports of crop } j \text{ by exporter } i)$$

Panel A of Figure 2 shows the distribution of the farmer share across all exporters. The blue line indicates an average farmer share of around 0.25, meaning that for every dollar of agricultural products exported from Ecuador, farmers earn 25 cents. Many exporters have farmer shares lower than 10%, while very few have shares above 50%. As above, Panel A may not accurately reflect the distribution of farmer shares, since large exporters receive the same weight as small exporters.

To address this concern, Panel B shows the distribution weighted by the share of total exports. The distribution shifts to the right, indicating that exporters paying a larger share of export sales to farmers are generally larger exporters. Still, the weighted average farmer share is still less than one-third.

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 7% 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, and use the model to definitively distinguish between value added and market power.

Figure 2: Farmer share of export value



Notes: Panel A plots the distribution of the farmer share across exporters. Panel B plots the same distribution weighted by each exporter's share of total sales. The dashed blue lines depict the simple average and weighted average across exporters, respectively.

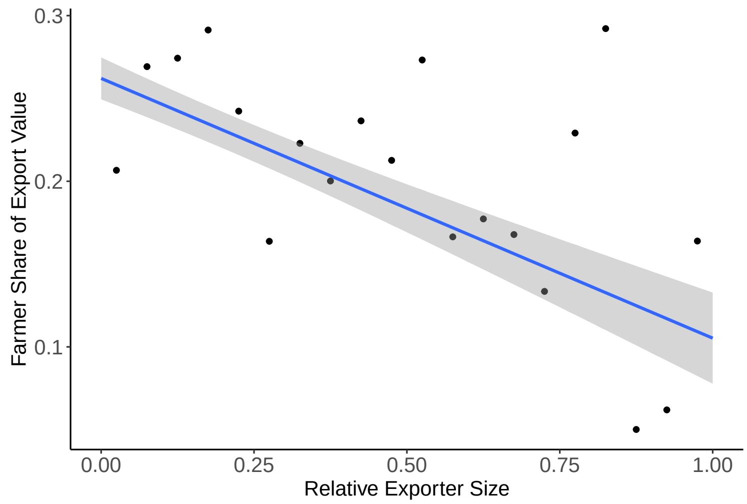
2.3.3 The farmer share is lower when exporters are more concentrated

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.

$$\text{exporter size}_{ij} \equiv (\text{purchases of crop } j \text{ by exporter } i)/(\text{total purchases of crop } j)$$

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 relative exporter size on the x-axis and farmer shares of export value on the y-axis. Dots indicate the average farmer share within bins. Solid blue line indicates predictions from a linear regression on full (unbinned) sample. 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 show that the negative relationship between farmer shares and relative exporter size is unlikely to be driven by systematic differences in technologies across crops and exporters, I estimate a series of regressions:[14]

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

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

[14] Alternative specifications are shown in the appendix.

Figure 3. Column 2 includes product-year fixed effects to control for systematic differences across crops.[15] Because some 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 an indicator for exporters with relative size less than 1%. In Column 4, exporters are weighted by their share of total exports to ensure that the relationship is not driven by variation within small crops.

Table 3: Farmer shares and exporter concentration

	Log Farm Share	Log Farm Share	Log Farm Share	Log Farm Share
	(1)	(2)	(3)	(4)
Exporter Size	-0.823	-0.681	-0.530	-0.542
	(0.158)	(0.185)	(0.180)	(0.066)
FE	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Weights	No	No	No	Yes
Observations	1,923	1,923	1,923	1,923
R^2	0.014	0.355	0.397	0.574

Notes: Column 1 shows regression of log farmer shares on relative exporter size. Column 2 adds product-year fixed effects. Column 3 adds time-varying controls described in text. Column 4 weights each observation by the share of total exports. Clustered standard errors are shown in parentheses.

My preferred specification in Column 3 indicates that farmers earn 50% less from the largest exporters, controlling for systematic differences across crops and exporters. This fact connects the first two and suggests market power among exporters as a potential explanation. To quantify the importance of market power, I develop a model in the next section. Later, I use all three facts to estimate and validate the model. Variation in exporter size conditional on fixed effects and controls comes from unobserved differences in exporter productivity, one of the primitives of the model. This variation explains farmer shares via substitution patterns across crops and across exporters within a crop, the other primitives of the model.

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

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

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.[16]

3.2 Farmer crop choices

Farmer f is endowed with a unit of land, which she farms inelastically with efficiency $q_f \sim G$. The distribution of efficiencies q_f is the only source of ex-ante heterogenity among farmers and reflects differences in farmer productivity and land quality. She makes two decisions: which crop to produce and which exporter to supply. She receives an idiosyncratic shock ν^1_{fj} for producing each crop j and an idiosyncratic shock $\nu^2_{fi(j)}$ 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^2_{fij} becomes shorthand for $\nu^2_{fi(j)}$.

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

$$q_{fij} = e^{\frac{\nu^1_{fj}}{1+\theta}} e^{\frac{\nu^2_{fij}}{1+\eta}} q_f$$

where η and θ are two key elasticities discussed in detail below. The idiosyncratic shocks determine her productivity: the higher are ν^1_{fj} and ν^2_{fij}, the more she can supply if she chooses crop j and exporter i. In this sense, ν^1_{fj} models the land's suitability for growing crop j in a stochastic way, while ν^2_{fij} models

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

geographic proximity to exporter i in a stochastic way. This will be important for interpreting the elasticities η and θ below.

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 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 impossibly 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:

$$\max_{i,j}\{\log p_{ij} + \log q_f + \tfrac{\nu^1_{fj}}{1+\theta} + \tfrac{\nu^2_{fij}}{1+\eta}\}$$

The probability that farmer f chooses crop j and exporter i, $\Pr_{fij}$, is independent of her efficiency, q_f.[17] This implies that the model can accommodate any distribution of land quality or farmer productivity. I assume ν^1_{fi} follows an extreme value distribution, and ν^2_{fij} is distributed such that the sum $\nu_{fij} = \frac{\nu^1_{fj}}{1+\theta} + \frac{\nu^2_{fij}}{1+\eta}$ follows a Gumbell distribution (Cardell 1997).[18] 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 on crop j:

$$\Pr_{fij} = \underbrace{\frac{p_{ij}^{1+\eta}}{\sum_{i\in j} p_{ij}^{1+\eta}}}_{\Pr_{i|j}} \times \underbrace{\frac{(\sum_{i(j)} p_{ij}^{1+\eta})^{\frac{1+\theta}{1+\eta}}}{\sum_j (\sum_{i(j)} p_{ij}^{1+\eta})^{\frac{1+\theta}{1+\eta}}}}_{\Pr_j}$$

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. As long as $\eta > \theta$ (McFadden 1978), the nested logit shocks have the interpretation that farmers maximize profits by *first* choosing a crop and *then* choosing an exporter within a crop, a natural sequence of decisions. I discuss the practical meaning of this restriction in the next section.[19]

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,

[17] See the appendix for a proof.

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

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

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.

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

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

where $p_j = \left(\sum_{i \in j} p_{ij}^{1+\eta}\right)^{\frac{1}{1+\eta}}$ 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:

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

where $q_j = \left(\sum_{i \in j} q_{ij}^{\frac{1+\eta}{\eta}}\right)^{\frac{\eta}{1+\eta}}$ 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.[20]

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 4.4, I relate my estimates of θ to a large literature that estimates this heterogeneity directly. Finally, θ is the elasticity of subsitution 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 4.4, 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.

[20] See the appendix for a full derivation.

Under these interpretations, the condition that $\eta > \theta$ can be interpreted in several ways: a) idiosyncratic cost shocks are more strongly correlated across exporters than across 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 sustitutable within crops than across crops from the point of view of farmers. These are reasonable assumptions.

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 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} is an idiosyncratic productivity term. This is the only source of ex-ante heterogeneity across exporters within a given product.[21]

Exporters of product j exert market power over farmers, which I model as Cournot competition for crops. In informational interviews I conducted in Ecuador, exporters revealed that they typically specify quantities when negotiating with producers.[22] They internalize the upward sloping crop supply curve in Equation 1: each additional unit they purchase increases the price of every other unit. 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 1. The first order condition for crops, q_{ij}, can be written:

$$\text{farmer share}_{ij} = \frac{p_{ij} q_{ij}}{p_j^x x_{ij}} = \alpha \times \underbrace{\left(1 + \frac{1}{\epsilon_{ij}}\right)^{-1}}_{\text{markdown}} \tag{2}$$

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

Equation 2 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

[21] Throughout the paper, I assume constant returns to scale for exporters. In the appendix, I discuss decreasing returns. I also estimate returns to scale using standard methods from the production function literature and fail to reject constant returns.

[22] In the appendix, I show that Bertrand competition yields a similar expression for farmer shares in equilibrium.

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.

Given Cournot competition between exporters trying to procure crop j[23] and the supply curve in Equation 1, the supply elasticity has the following closed form:

$$\frac{1}{\epsilon_{ij}} = \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij} \tag{3}$$

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 subsitution across crops, θ, and across exporters, η, where the relative sizes of exporters form the weights [24] Substituting into Equation 2, the equilibrium farmer share is:

$$\text{farmer share}_{ij} = \alpha \times \left[1 + \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij}\right]^{-1} \tag{4}$$

Since $\eta > \theta$, Equation 4 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 4 therefore forges a connection between my stylized facts about agricultural value chains and my theory of crop choice and exporter market power.

To make the connection between theory and data more explicit, take logs on both sides of Equation 4. In addition, let the log output elasticity vary by exporter, with a crop-specific and an idiosyncratic component: $\log \alpha_{ij} = \log \alpha_j + \varepsilon_{ij}$. Finally, take a linear approximation of the log markdown. This yields the regression equation in Column 3 of Table 3:

[23] I assume no strategic interaction across crops, so that exporters of crop j take the price indexes of $k \neq j$ as given.

[24] 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 weight are determined by exporter market shares of the *output* market.

$$\log(\text{farmer share}_{ij}) = \log\alpha_j + \log\frac{\eta}{1+\eta} - \frac{\eta}{1+\eta}\Big(\frac{1}{\theta} - \frac{1}{\eta}\Big)s_{ij} + \varepsilon_{ij} \tag{5}$$

The size of the coefficient is informative of the difference between η and θ. However, I cannot disentangle them with this regression alone, as the fixed effect contains both η and α_j. My model allows me to estimate them separately. In Section 4.2, I will show that my estimates of η and θ, together with Equation 5, are consistent with the coefficients in Table 3.

Aggregating 4 across exporters yields an intuitive expression for the crop-level farmer share:

$$\text{farmer share}_j = \alpha \times \left[1 + \frac{1}{\eta}\Big(1 - HHI_j\Big) + \frac{1}{\theta}HHI_j\right]^{-1} \tag{6}$$

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. 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 controlling 1%, $HHI_j^{-1} = 1.02$, so that the market is *effectively* like a monopsony. Equation 6 implies that the lower the effective number of exporters for a given crop, the lower the overall farmer share. This further links the theory to the data: the effective number of exporters is low in Figure 1, while the overall farmer share is low in Figure 2.

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 1) and exporter optimization (Equation 4).

3.5 Special case: symmetric markets

To provide intuition on how market power operates in this setting, I consider the case of symmetric exporters.[25] The market for each crop is evenly divided among exporters, so that $s_{ij} = \frac{1}{N_j}$ for every $i(j)$ and N_j is the number of exporters of crop j. Letting $HHI_j = \frac{1}{N_j}$ in Equation 6:

$$\text{farmer share}_j = \alpha \times \Big(1 + \frac{1}{\epsilon_j}\Big)^{-1} = \alpha \times \left[1 + \frac{1}{\eta}\Big(1 - \frac{1}{N_j}\Big) + \frac{1}{\theta}\frac{1}{N_j}\right]^{-1} \tag{7}$$

[25] This occurs when all exporters of a given crop have the same productivity, $z_{ij} = z_j$ for every $i(j)$.

This implies that the (inverse) elasticity of crop supply $\frac{1}{\epsilon_j}$ is a weighted average of the (inverse) elasticity of substitution across crops, $\frac{1}{\theta}$, and the (inverse) elasticity of substitution across exporters, $\frac{1}{\eta}$, where the weights are determined by the number of exporters competing in the market, N_j. As N_j falls, we approach monopsony, and the substitutability across crops, θ, receives more weight. As N_j increases, we approach monopsonistic competition, and the substitutability across exporters within a crop, η, receives more weight. Since $\eta > \theta$, the supply elasticity ϵ_j increases as N_j increases, so that crop supply becomes more elastic. Equation 7 then implies that ϕ_j increases, so that farmers receive a larger share of export revenue.

Intuitively, if there are many exporters, then no single exporter exerts too much influence, because farmers can always switch to other exporters of the same crop. On the other hand, if a single exporter controls the market, then farmers can only switch to other crops. Since it is easier for farmers to find a new exporter in the same crop than to plant a new crop ($\eta > \theta$), farmers will be more sensitive to prices when there are many exporters, so that crop supply will be more elastic. The more elastic is supply, the lower is the markdown on farmer shares. This captures the intuition that more competition among exporters is better for farmers.

The symmetric case also highlights how η and θ influence market power. To illustrate, fix the number of exporters, N_j, competing for a crop, so that the weights in Equation 7 are fixed. As the substitutability across exporters, η, increases, so does the supply elasticity, ϵ_j. Intuitively, the number of outside options is constant, but the ability of farmers to substitute between them increases. If outside options are more accessible, prices will play a larger role in farmer decisions, so that supply will be more elastic. This captures the idea that more substitutability across exporters is better for farmers. A similar argument holds for substitutability across crops, θ. Recall from Section 3.3 that an increase in η and θ can be interpreted as a reduction in the costs of reaching different exporters and growing different crops.

Proposition: Crop supply becomes more elastic, exporter market power falls, and the crop-level farmer share rises as each of the following increases:

- The number of exporters competing for crop j, N_j
- The elasticity of substitution across exporters within crops, η
- The elasticity of substitution across crops, θ

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 validate the estimated model internally, by recreating stylized facts from Section 2, and externally, by comparing my estimates to values of η and θ implied by the agricultural trade literature. To measure the consequences of market power, I compare the level of farmer income between the estimated model and a counterfactual in which exporters behave competitively, rather than strategically.

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.[26]

To see this more formally, log-linearize around the equilibrium in Equation 4:

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

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:

$$\Delta \log p_{ij} = \underbrace{\left[1 + \frac{(\frac{1}{\theta} - \frac{1}{\eta})(1+\eta) s_{ij}(1-s_{ij})}{1 + \frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta}) s_{ij}}\right]^{-1}}_{f(s_{ij})} \times (\Delta \log p_j^x + \Delta \log z_{ij}) \tag{8}$$

Clearly, $\eta > \theta$ implies that $f < 1$, so that pass-through is incomplete under market power. In the appendix, I show that f is decreasing in s_{ij}, provided θ is sufficiently small relative to η. Assuming exporter productivity is constant, $\Delta \log z_{ij} = 0$, Equation 8 implies that for a given change in international demand, $\Delta \log p_j^x$, the corresponding change in crop price, $\Delta \log p_{ij}$, will be smaller for relatively large exporters. This reflects the intuition that pass-through declines with relative exporter size. I also show that pass-through declines faster when η and θ are far apart. These two results form 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

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

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 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 8, 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 substituion across exporters, 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). I also estimate 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). I calibrate the number of crops, M, and the number of exporters in each market, $\{N_j\}_j$. I estimate the parameters jointly, but outline the procedure separately for each group of parameters. Appendix A.3.3 provides further details.

4.2.1 Estimating η and θ

In order to take Equation 8 to the data, I estimate the following pass-through regression:

$$\Delta \log p_{ijt} q_{ijt} - \Delta \log x_{ijt} = \gamma_0 + \gamma_1 s_{ij,t-1} + \gamma_2 \Delta \log p^x_{ijt} + \gamma_3 s_{ij,t-1} \times \Delta \log p^x_{jt} + \varepsilon_{ijt} \tag{9}$$

where ε_{ijt} is an error term. The coefficient γ_2 measures the average pass-through of the demand shock, while the coefficient γ_3 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 9 in the actual data, (2) simulate Equation 9 in the model, (3) pick η and θ so that the coefficients γ_2 and γ_3 from the model match their counterparts in the data.[27] 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 9 in the data, I first construct the demand shocks. I follow a standard

[27] 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.

Bartik specification combining exporter trade shares from my microdata with international prices from COMTRADE:

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

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 15 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 9. 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 such as wages and payments to non-farm suppliers, as in Table 3. The coefficients, denoted $\hat{\gamma}_2$ and $\hat{\gamma}_3$, are consistent with the predictions in Section 4.1. Pass-through is incomplete ($\hat{\gamma}_2 < 1$), and it decreases with relative exporter size ($\hat{\gamma}_3 < 0$). The magnitudes in Column 3 imply that the largest exporters increase farmer prices by only $\frac{.45-.385}{.45} = 14$ as much as the smallest exporters following a demand shock.[28]

Table 4: Exporter responses to demand shocks

	$\Delta \log pq - \Delta \log x$	$\Delta \log pq - \Delta \log x$	$\Delta \log pq - \Delta \log x$
	(1)	(2)	(3)
$\Delta \log p^x$	0.333	0.449	0.450
	(0.173)	(0.182)	(0.182)
s	-0.022	0.001	0.004
	(0.082)	(0.102)	(0.102)
$\Delta \log p^x \times s$	-0.410	-0.370	-0.385
	(0.412)	(0.429)	(0.430)
FE	No	Yes	Yes
Controls	No	No	Yes
Observations	941	941	941
R^2	0.004	0.040	0.040

Notes: Column 1 shows estimates of pass-through regressions (Equation 9). Column 2 adds product and year fixed effects. Column 3 adds time-varying controls described in text. Clustered standard errors are shown in parentheses.

To estimate Equation 9 in the model, I proceed in several steps (see appendix A.3.2 for further details). First, I draw the productivity of each exporter from a distribution described below. For each guess of η,

[28] In the appendix, I show that pass-through regressions with nonlinear and non-parametric interaction terms yield similar results.

θ, and the other parameters, I solve the model. Next, I shock the model with demand shocks drawn from the distribution of demand shocks $\Delta \log p_j^x$ in the data. I solve the model again to create a simulated panel. Finally, I estimate Equation 9 using the simulated panel. The resulting pass-through coefficients, denoted $\gamma_2(\eta, \theta)$ and $\gamma_3(\eta, \theta)$, 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:

$$(\hat{\eta}, \hat{\theta}) = \arg\min_{\eta,\theta} \left\{ ||\hat{\gamma}_2 - \gamma_2(\eta,\theta)|| + ||\hat{\gamma}_3 - \gamma_3(\eta,\theta)|| \right\}$$

4.2.2 Estimating α

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 6:

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

where HHI_j is taken from the simulated data. Taking a sales-weighted average across crops, I obtain the overall farmer share, denoted $\phi(\alpha)$. 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 demand shocks, $\Delta \log p^x$, follow normal distributions:[29]

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

For exporter productivity, I choose (μ_z, σ_z^2) to match the distribution of log exporter revenue in the data. For demands 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.

4.3 Parameter estimates

Table 5 summarizes the estimated model. 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

[29]In the appendix, I show how to recover productivities non-parametrically.

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

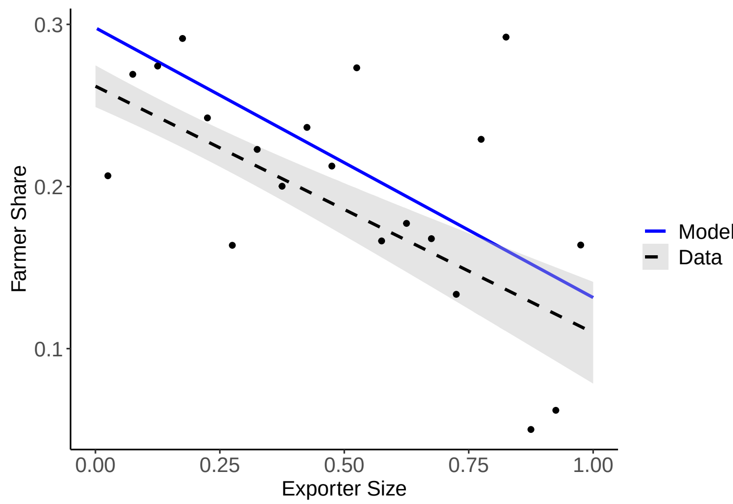
Parameter	Estimate	Moment	Value
Panel A: Key parameters			
η	1.32	Pass-through for small exporters, $\hat{\gamma}_2$	0.45
θ	0.34	Decline in pass-through as size increases, $\hat{\gamma}_3$	-0.39
α	0.75	Average farmer share across crops, $\hat{\phi}$	0.34
Panel B: Other parameters			
μ_z	13.98	Quantiles of log exporter revenue	
σ_z	2.27		
μ_d	0.04	Quantiles of log international price changes	
σ_d	0.17		
M	157	Number of crops	
N_j	1-10	Number of exporters per crop	

4.4 Model validation

I validate the model in several ways: internally, by comparing moments not targeted in the estimation procedure between the model and the data; and externally, by comparing the heterogeneity in production and transport costs implied by the model with estimates from the agricultural trade literature. Figure 4 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 the parameters (η, θ, α), is somewhat flatter than in the data, but the two slopes are not statistically distinguishable. Importantly, although the average farmer share was targeted in estimation, the relationship between farmer shares and exporter size is not targeted.

To further validate the model, I estimate Equation 5 and compare the results to Column 2 of Table 3. The coefficient on relative exporter size is slightly more negative at -0.79, but not statistically distinguishable. Note that my estimates of η and θ, together with Equation 5, imply a similar, but even more negative, coefficient: $-\frac{1.32}{2.32}\left(\frac{1}{0.34} - \frac{1}{1.32}\right) = -1.24$. This underscores the importance of simulating the full model.

Figure 4: Farmer shares and exporter concentration, model vs. data

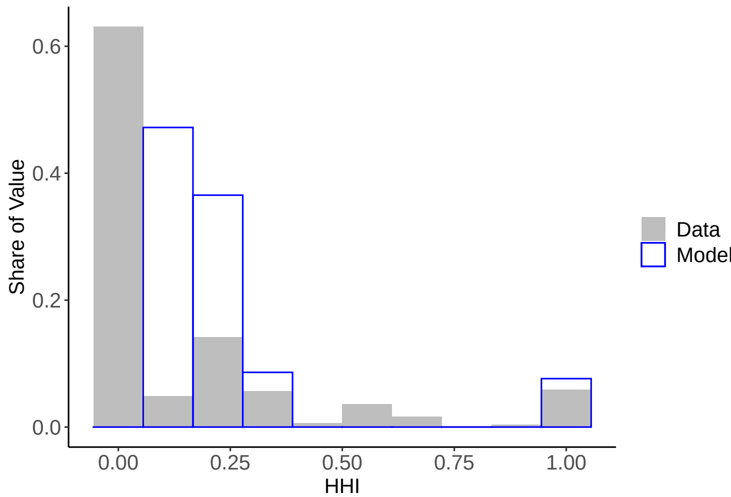


Notes: Figure plots relative exporter size on the x-axis and farmer shares of export value on the y-axis. Solid blue line indicates predictions from the model. Dashed black line indicates predictions from the data. Grey area indicates a 95% confidence interval.

The average farmer share targeted in the estimation is a function of the parameters (η, θ, α) and the concentration index of exporters in each crop, HHI_j. However, I did not target the concentration index directly. Figure 5 plots the distribution of HHI_j in the model and in the data, weighted by total exports. Although the model generates somewhat higher exporter concentration than the data, the distributions are similar. The weighted average across all crops is 0.24 in the model and 0.19 in the data, indicating that crop markets *effectively* 4-5 exporters per crop.[30]

[30] The unweighted average, which is partially targeted by specifying the number of exporters per crop, is 0.58 in both the model and 0.59 in the data.

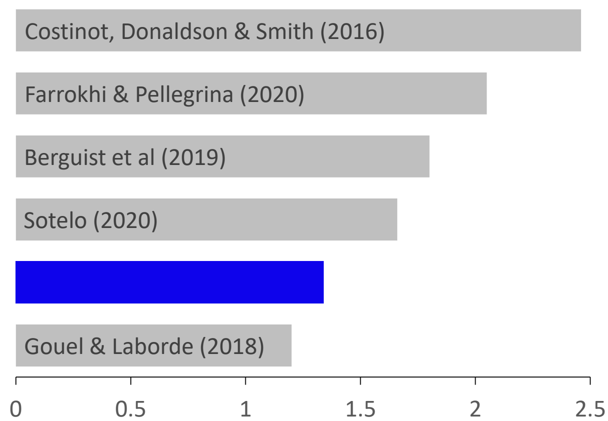
Figure 5: Crop market concentration, model vs. data



Notes: Figure plots the distribution of HHI across crops, weighted by the share of exports in each bin. Blue bars indicate the model. Grey bars indicate the data.

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 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 1.34, indicating a smaller degree of heterogenity 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 study to include animal products as I do and the only study to find lower heterogeneity than me. Sotelo 2020 finds a similar value to mine in Peru, the most agroclimactically similar country to Ecuador among those studied.

Figure 6: Estimates of land heterogeneity from the literature

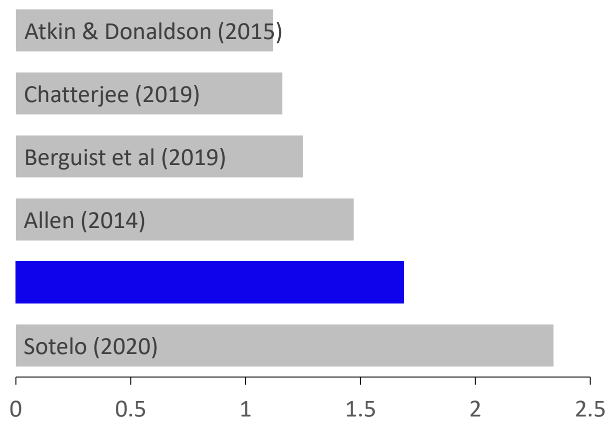


Notes: Figure plots estimates of land heterogeneity from selected papers in grey, and the corresponding value implied by $\hat{\theta}$ in blue. See text of appendix A.4.1 for conversion details. See Table 8 for source details.

Finally, 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 7 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 most geographically similar country to Ecuador among those studied.[31]

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

Figure 7: Estimates of trade costs from the literature



Notes: Figure plots estimates of trade costs from selected papers in grey, and the corresponding value implied by $\hat{\eta}$ in blue. See text of appendix A.4.2 for conversion details. See Table 9 for source details.

4.5 Measuring crop markdowns in Ecuador

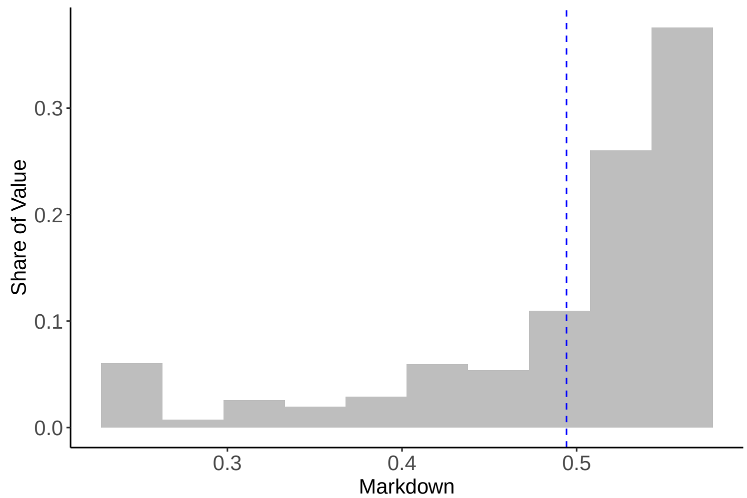
To explore the microeconomic impacts of market power, I combine parameter estimates with value chain data in order to measure how much farmer prices are marked down from their marginal revenue products. Rearranging Equation 4 yields an expression for this markdown as a function of key elasticities and relative exporter sizes:

$$\text{markdown}_{ij} = \left[1 + \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta}s_{ij}\right]^{-1} \tag{10}$$

Figure 8 plots the distribution of markdowns obtained by plugging in the estimated η and θ and observed s_{ij} into Equation 10. 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%.[32]

[32]The assumption of Cournot competition influences the estimated distribution of markdowns. In particular, Bertrand competition implies higher markdowns (less market power). In the appendix, I estimate the model under Bertrand competition. Although the markdown distribution shifts to the right, farmers still receive a fraction of their marginal revenue product. The weighted average is 0.53.

Figure 8: Distribution of markdowns

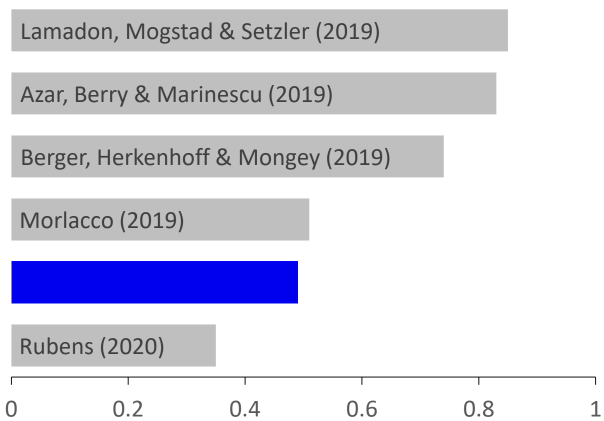


Notes: Figure plots the distribution of markdowns from Equation 10 across exporters, weighted by the share of exports in each bin. The dashed blue line depicts the average.

Table 10 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,[33] they all employ markdowns as a measure of market power. Most of these studies estimate considerably higher markdowns. 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 might face less market power than farmers in Ecuador.

[33] For example, Lamadon et al. (2019); Berger et al. (2019); Azar et al. (2019) take three different approaches to study market power in US labor markets.

Figure 9: Estimates of markdowns from the literature



Notes: Figure plots average markdown from selected papers in grey, and my average markdown in blue. See Table 10 for source details.

4.6 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 to 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.

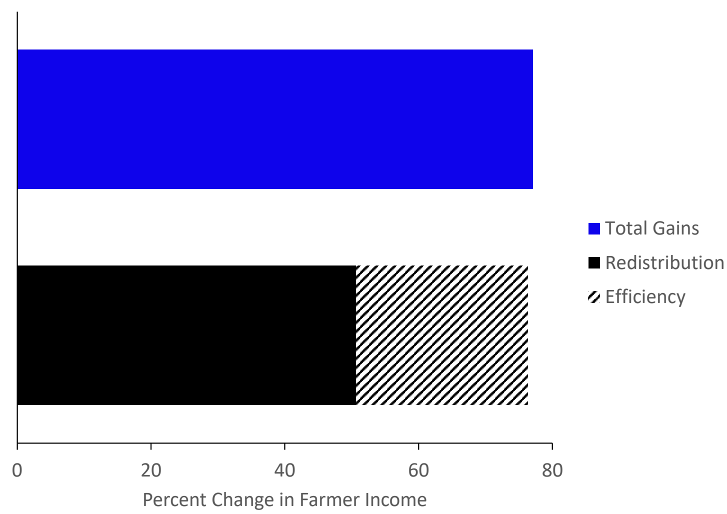
To quantify these channels, I first simulate the model with and without market power. The total impact of market power is the log difference in farmer income between the two scenarios. To measure the gains from redistribution, I calculate farmer income using quantities from the market power baseline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

$$\underbrace{\log\sum_i \tilde{p}_{ij}\tilde{q}_{ij} - \log\sum_i p_{ij}q_{ij}}_{\text{total gains}} = \underbrace{\log\sum_i \tilde{p}_{ij}q_{ij} - \log\sum_i p_{ij}q_{ij}}_{\text{redistribution}} + \underbrace{\log\sum_i p_{ij}\tilde{q}_{ij} - \log\sum_i p_{ij}q_{ij}}_{\text{efficiency}} + \text{interactions}$$

where $\tilde{p}$ and $\tilde{q}$ denote prices and quantities in the perfect competition counterfactual.

Figure 10 displays the results of the decomposition. I find that farmer income would be 77.1% higher in the absence of market power. Redistribution from exporters to farmers increases income by 50.7%, accounting for almost two-thirds of the gains.[34] Greater efficiency accounts for the remaining third, a 25.6% increase in farmer income.

Figure 10: Farmer income gains from perfect competition



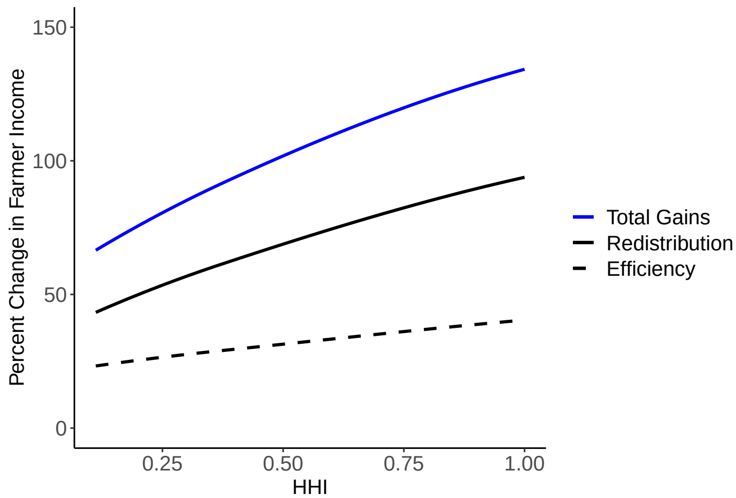
Notes: Figure shows percent increase in farmer income between model with market power and model with perfect competition. Decomposition is described in text.

Although all farmers gain from perfect competition, the gains are not equally shared. Figure 11 shows how increases in farmer income vary with the baseline level of crop market concentration, HHI_j. Gains

[34] 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, as shown in the appendix. However, this assumption in unreasonable in this context.

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 proportionally more.

Figure 11: Farmer income gains and crop market concentration



Notes: Figure plots the baseline HHI on the x-axis and the percent change in farmer income under perfect competition on the y-axis.

5 Policy

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 conduct two counterfactual policy exercises using the estimated model. 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.

5.1 Fair Trade

Fair Trade is a series of product certifications designed to foster the sustainable production of commodities.[35] 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. For coffee – the largest product in the Fair Trade market – less than 40% of available quantity is certified. In my analysis, I abstract from the non-monetary benefits and costs of selection.[36]

Outside of bananas and flowers, Fair Trade is not prevalent in Ecuador. I model Fair Trade by introducing a perfectly competitive exporter in each market. In addition to being tractable, this flexibly captures the many ways Fair Trade works in practice (Podhorsky 2015). The Fair Trade exporter faces the same supply curve as other exporters, but pays farmers their marginal revenue product. One reason the Fair Trade exporter is able to pay higher prices is that it has access to buyers who are willing to pay a premium for Fair Trade branded products (Hainmueller, Hiscox, and Sequeira 2015). Alternatively, the Fair Trade exporter can represent a cooperative that allows farmers to export directly (Bacon, Mendez, and Stuart 2008). Since farmers own the cooperative, they internalize markdowns.[37]

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 12 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 14%.[38] As the new exporter becomes among

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

[36] 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).

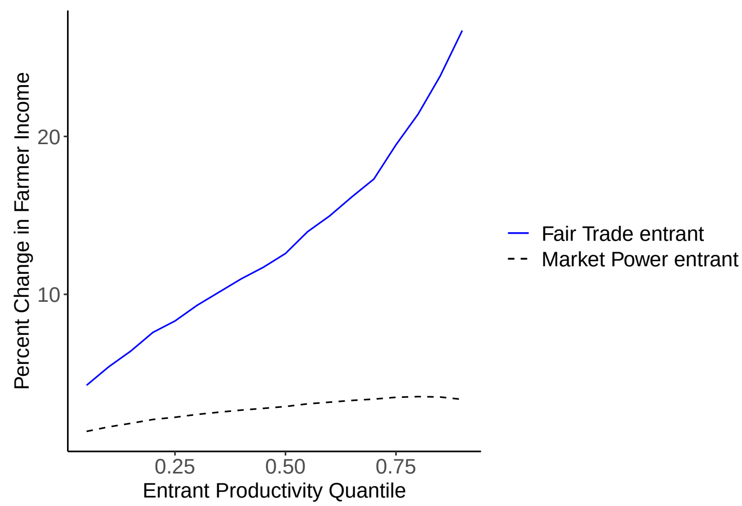
[37] In addition to paying higher prices, buyers provide access to credit in order to overcome the fixed costs of exporting.

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

the most productive in the economy, the gains increase to 34%, or about half of the gains from perfect competition in Table 10. 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 much broader range of products.

To get a sense of the indirect and directs 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 12: 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 has market power. The solid blue line indicates the Fair Trade counterfactual in which the exporter is perfectly competitive.

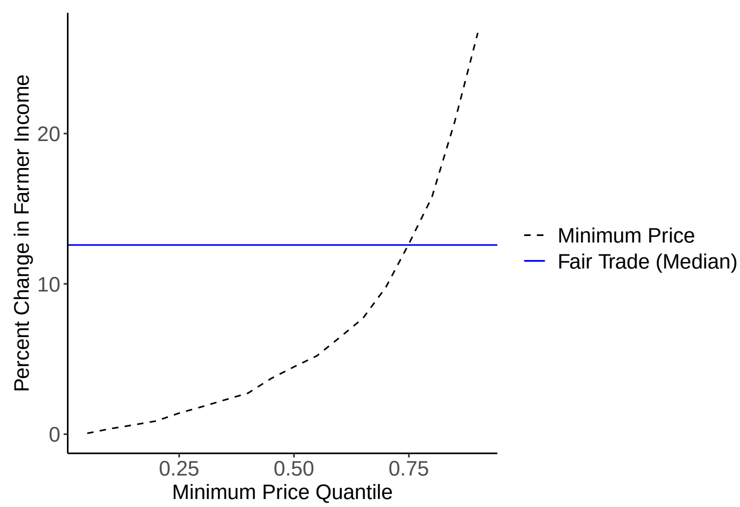
5.2 Minimum prices

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 relatively cheap to implement, but create more distortions.

To illustrate how price floors affect the equilibrium, 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.[39] As the minimum price becomes too high, no exporters can afford to pay, and demand contracts so much that farmers may be worse off.

Figure 13 summarizes how the increase in farmer income varies with how high the floor is relative to the distribution of prices. The blue solid line shows the gains from a Fair Trade exporter with the median productivity level. The dashed black line implies that in order for a price floor to achieve the same gains, it would have to be above the 75th percentile of the price distribution – an extraordinarily high value. Fair Trade implements a price floor without distorting the behavior of smaller exporters (Podhorsky 2015), making it more effective for raising farmer income.

Figure 13: Effect of price floor on farmer income



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 price floor. The solid blue line indicates the Fair Trade counterfactual in which the exporter has median productivity (See Figure 12).

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

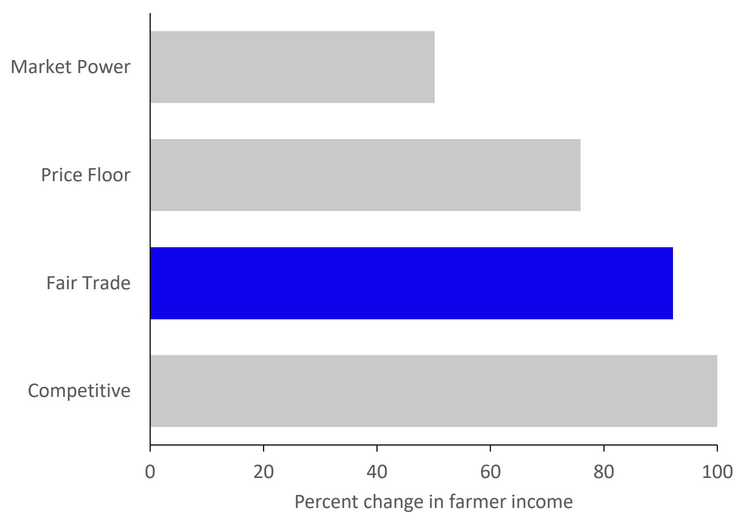
5.3 Do farmers share in future gains?

So far, I have only considered differences in farmer income between very different equilibria, comparing scenarios with perfectly competitive intermediaries, Fair Trade entrants, and mandated minimum prices against the baseline model with unrestricted market power. Now, I fix an equilibrium and ask what happens to farmer income as international demand changes. For each counterfactual equilibrium – perfect competition, Fair Trade, minimum price – I begin with the simulated cross-section from the corresponding section above. Then, I draw shocks from the distribution of international price changes (Table 5) and solve the model again to create a simulated panel. For the equilibrium with market power, I use the actual data.

Figure 14 shows the percent increase in farmer income following a doubling in the foreign price. There are several key takeaways. First, farmer income increases by only 50% in the baseline with market power. Farmers receive more if there is a price floor, and still more if there is a Fair Trade exporter. This is consistent with Fair Trade reducing exporter market power more than minimum prices.

These results highlight a trade-off inherent to agricultural support policies, complicating the conclusions of the previous sections. Farmer income is lower on average when exporters have market power, but it is also less responsive to changes in international demand. Farmers benefit less from future gains, but they also suffer less from future losses. Fair Trade reduces the insurance provided by exporter market power, increasing farmer income on average but potentially leaving them more vulnerable to future shocks.

Figure 14: Pass-through of demand shock to farmer income



Notes: Figure shows percent change in farmer income following a 100% increase in international prices. "Market Power" refers to the data. "Competitive" refers to the model in Section 4.6. "Fair Trade" refers to the model in Section 5.1, with exporter productivity equal to the median productivity from the data. "PriceFloor" refers to the model in Section 5.2, with price floor equal to the median price from the data.

6 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 offers millions of farmers a path out of poverty. I have shown 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 more common policies like minimum support prices. A back-of-the-envelope calculation suggests that even a modest Fair Trade program implemented across the agricultural sector in Ecuador could raise 22% of poor farmers out of poverty.[40] However, increasing farmer income today may make farmers more vulnerable to economic shocks tomorrow. Further research is needed to understand the tradeoffs between greater prosperity and higher uncertainty.

[40] See appendix for details.

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A Appendices

A.1 Data Appendix

A.1.1 Additional summary statistics

Table 6 summarizes the network of exporters and farmers across 2-digit products.

Table 6: 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.1.2 Robustness of stylized facts

Table 7 shows a linear specification of the stylized fact in Table 3. Given the unweighted average farmer share of around 0.2, the coefficient of -0.104 in Column 3 is consistent with the 53% lower farmer shares among large exporters reported in Table 3.

Table 7: Farmer shares and exporter concentration

	Farmer Share	Farmer Share	Farmer Share	Farmer Share
	(1)	(2)	(3)	(4)
Relative Exporter Size	-0.101	-0.108	-0.104	-0.109
	(0.016)	(0.019)	(0.018)	(0.021)
FE	No	Yes	Yes	Yes
Controls	No	No	Yes	Yes
Weights	No	No	No	Yes
Observations	1,923	1,923	1,923	1,923
R^2	0.021	0.325	0.418	0.585

Notes: Column 1 shows regression of farmer shares on relative exporter size. Column 2 adds product-year fixed effects. Column 3 adds time-varying controls described in text. Column 4 weights each observation by the share of total exports. Clustered standard errors are shown in parentheses.

A.2 Theory Appendix

A.2.1 Derivation of CES supply curve

The farmer maximizes $y_{ij} = \log p_{ij} + \log q_f + \frac{\nu^1_{fj}}{1+\theta} + \frac{\nu^2_{fij}}{1+\eta}$ 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:

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

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

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

Substituting above yields the CES supply system for crops

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

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

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

Using these definitions and the fact that $q_j = p_j^{\theta} X = p_j^{\theta}\Big(\sum_j p_j^{1+\theta}\Big)^{-1} Y$, 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 Pass-through of international price changes

Let export revenue $y_{ij} = p_j^x z_{ij} q_{ij}^{\alpha} m_{ij}^{\beta}$, where $\alpha + \beta \neq 1$. Normalizing the price of other inputs m_{ij} to 1, we have the following first order condition for crops q_{ij}

$$[1 + \tfrac{1}{\eta}(1 - s_{ij}) + \tfrac{1}{\theta} s_{ij}] p_{ij} = \tfrac{\alpha}{1-\beta}[\beta^{\beta} z_{ij} p_j^x]^{\frac{1}{1-\beta}} q_{ij}^{\frac{\alpha}{1-\beta}-1}$$

Substituting the CES supply system and collecting constants, we have

$$[1 + \tfrac{1}{\eta}(1 - s_{ij}) + \tfrac{1}{\theta} s_{ij}] p_{ij} = \kappa_{ij} (p_j^x)^{\frac{1}{1-\beta}} [p_{ij}^{\eta} p_j^{\theta-\eta}]^{\frac{\alpha+\beta-1}{1-\beta}}$$

where $\kappa_{ij} = [\beta^{\beta} z_{ij}]^{\frac{1}{1-\beta}} [(\sum_j p_j^{1+\theta})^{-1} Y]^{\frac{\alpha+\beta-1}{1-\beta}}$.

Taking derivatives with respect to p_j^x and doing some heavy algebra, we have

$$\frac{\partial \log p_{ij}}{\partial \log p_j^x} = \frac{1}{1-\beta} \times \left[1 + \frac{1-\alpha-\beta}{1-\beta}\Big(\eta(1-s_{ij}) + \theta s_{ij}\Big) + \frac{(\frac{1}{\theta} - \frac{1}{\eta}) s_{ij}(1-s_{ij})(1+\eta)}{1 + \frac{1}{\eta}(1-s_{ij}) + \frac{1}{\theta} s_{ij}}\right]^{-1} \tag{11}$$

Under constant returns to scale, $\alpha + \beta = 1$, and Equation 11 simplifies to

$$\frac{\partial \log p_{ij}}{\partial \log p_j^x} = \frac{1}{\alpha} \times \frac{1+\frac{1}{\eta}(1-s_{ij})+\frac{1}{\theta}s_{ij}}{1+\frac{1}{\eta}(1-s_{ij})+\frac{1}{\theta}s_{ij}+(\frac{1}{\theta}-\frac{1}{\eta})s_{ij}(1-s_{ij})(1+\eta)}$$

One can show that as long as η is sufficiently larger than θ, the pass-through is strictly decreasing in the exporter's market share. In addition, the further apart are η and θ, the more steeply that pass-through decreases.

Similarly,

$$\frac{\partial \log q_{ij}}{\partial \log p_j^x} = \frac{1}{\alpha} \times \frac{\Big(1+\frac{1}{\eta}(1-s_{ij})+\frac{1}{\theta}s_{ij}\Big)\Big(\frac{1}{\eta}(1-s_{ij})+\frac{1}{\theta}s_{ij}\Big)^{-1}}{1+\frac{1}{\eta}(1-s_{ij})+\frac{1}{\theta}s_{ij}+(\frac{1}{\theta}-\frac{1}{\eta})s_{ij}(1-s_{ij})(1+\eta)}$$

A.2.3 Pass-through of value added changes

Lamadon et al. (2019) use the pass-through of value added to wages in order to estimate market power in the context of labor markets. Berger et al. (2019) use the same pass-through to validate their estimates of market power. Although the mapping of value added to farmgate prices is less straightforward than the mapping of value added to wages, I show that this is equivalent to my approach.

In my setting, exporter value added relative to farmer output can be written as follows:

$$VA_{ij} = \frac{p_{ij}q_{ij}}{\alpha}\left[1-\alpha+\frac{1}{\eta}\Big(1-s_{ij}\Big)+\frac{1}{\theta}s_{ij}\right]$$

Taking logs, taking the derivative with respect to $\log p_{ij}$, using the expression for $\frac{\partial \log p_{ij}}{\partial \log q_{ij}}$, and rearranging, we have

$$\frac{\partial \log VA_{ij}}{\partial \log p_{ij}} = 1 + \frac{1}{\frac{1}{\eta}(1-s_{ij})+\frac{1}{\theta}s_{ij}} + \frac{(1+\eta)(\frac{1}{\theta}-\frac{1}{\eta})(1-s_{ij})s_{ij}}{1-\alpha+\frac{1}{\eta}(1-s_{ij})+\frac{1}{\theta}s_{ij}}$$

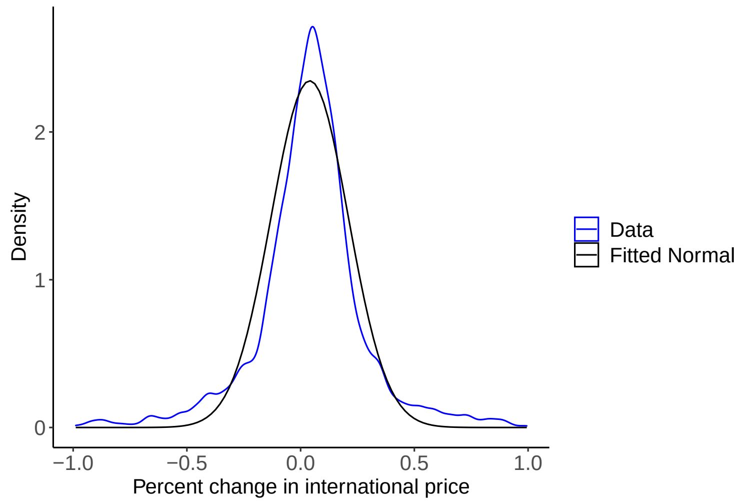
Letting $s_{ij} \to 0$, we have $\frac{\partial \log p_{ij}}{\partial \log VA_{ij}} = \frac{1}{1+\eta}$ and letting $s_{ij} \to 1$, we have $\frac{\partial \log p_{ij}}{\partial \log VA_{ij}} = \frac{1}{1+\theta}$. Therefore, changes in farmgate prices in response to changes in value added among small exporters identify η, while changes among large exporters identify θ. In my model, changes in international prices induce changes in value added, so this is equivalent to my approach.

A.3 Estimation Appendix

A.3.1 Specification of demand shocks

Figure 15 plots the distribution of trade shocks described in Section 4.2 and used in the estimation. It is well-approximated by a normal distribution with mean 0.04 and standard deviation 0.17.

Figure 15: Percent change in international prices



Notes: Blue line plots density of percent change in international prices. Black line plots density of fitted normal distribution.

A.3.2 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. Finaly, 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 $\hat{p}_{ij} = (\alpha \frac{\epsilon_{ij}}{1+\epsilon_{ij}} z_{ij} s_{ij}^{-\frac{\eta-\theta}{1+\eta}})^{1+\theta}$
  - 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.3.3 Simulated Method of Moments

I calibrate $(\mu_z, \sigma_z^2, \mu_d, \sigma_d^2)$ and 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

$$\Delta \log p_{ijt} = \gamma_0^S + \gamma_1^S s_{ij,t-1} + \gamma_2^S \Delta \log p_{ijt}^x + \gamma_3^S s_{ij,t-1} \times \Delta \log p_{ijt}^x + \varepsilon_{ijt}^S$$

- Estimate regressions in the real data

$$\Delta \log p_{ijt} q_{ijt} - \Delta \log x_{ijt} = \gamma_0^D + \gamma_1^D s_{ij,t-1} + \gamma_2^D \Delta \log p_{ijt}^x + \gamma_3^D s_{ij,t-1} \times \Delta \log p_{ijt}^x + \varepsilon_{ijt}^D$$

- Calculate farmer shares in the simulate data

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

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

- Pick (η, θ, α) to minimize $\Big|\Big|\gamma_2^D - \gamma_2^S(\alpha, \eta, \theta)\Big|\Big| + \Big|\Big|\gamma_3^D - \gamma_3^S(\alpha, \eta, \theta)\Big|\Big| + \Big|\Big|\phi^D - \phi^S(\alpha, \eta, \theta)\Big|\Big|$.

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.4 Measurement appendix

A.4.1 Relating θ to the literature

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 $\hat{\theta} = 0.34$ corresponds to a shape parameter of 1.34 for the distribution of land heterogeneity. The following table reports this estimate, along with those from a selection of papers.

Table 8: Sources for Figure 6

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.4.1
Gouel and Laborde 2018	1.2	Section 6.2

A.4.2 Relating η to the literature

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 iceberg 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 $\eta = 1.32$ yields a mean of 1.56. 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 9: Sources for Figure 7

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.4.2
Sotelo 2020	2.34	Reported in Table 4

A.4.3 Relating markdowns to the literature

In Section 4.5, I calculate the average markdown of farmer prices relative to marginal revenue products implied by the estimated model and data on exporter sizes. The following table reports this estimate, along with those from a selection of papers.

Table 10: Sources for Figure 9

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 4.5
Rubens 2020	0.35	Section 4

A.4.4 Estimating η and θ from relative pass-through to prices and quantities

Taking the ratio of pass-through to crop prices and quantities above yields the crop supply elasticity:

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

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 $\rho(s_{ij}) \equiv \frac{d \log p_{ij} / d \log p_j^x}{d \log q_{ij} / d \log p_j^x}$, match between the model and the data. I proceed in several steps: (1) estimate $\hat{\rho}(s_{ij})$ in the data, (2) simulate $\rho(s_{ij})$ in the model, (3) form moments from $\hat{\rho}(s_{ij})$ and $\rho(s_{ij})$, (4) minimize the distance between the moments.

I estimate the following regressions:

$$\Delta \log p_{ijt} q_{ijt} = \gamma_0 + \gamma_1 s_{ij,t-1} + \gamma_2 \Delta \log p^x_{jt} + \gamma_3 s_{ij,t-1} \times \Delta \log p^x_{jt} + \varepsilon_{ijt} \tag{12}$$

$$\Delta \log x_{ijt} = \delta_0 + \delta_1 s_{ij,t-1} + \delta_2 \Delta \log p^x_{jt} + \delta_3 s_{ij,t-1} \times \Delta \log p^x_{jt} + \varepsilon^x_{ijt} \tag{13}$$

where γ_2 and δ_2 measure how exporters adjust crop expenditures and export quantities in response to demand shocks, and γ_3 and δ_3 measure how those responses vary with the relative size of the exporter. I expect $\gamma_2 > 0$ and $\delta_2 > 0$, while $\gamma_3 < 0$ and $\delta_3 < 0$. Intuitively, exporters expand production in response to meet greater demand, but relatively large exporters respond less because their costs rise more quickly due to market power. Given estimates of Equations 12 and 13, I calculate the crop supply elasticity $\hat{\rho}(s)$ as follows:

$$\hat{\rho}(s) = \frac{\hat{\gamma}_2 + \hat{\gamma}_3 s}{\hat{\delta}_2 + \hat{\delta}_3 s} - 1 \tag{14}$$

Table 11 displays the regression results. The estimated coefficients are consistent with my hypothesis. The last two rows of Table 11 report the supply elasticities implied by these estimates at relatively small exporters ($s = 0$) and relatively large exporters ($s = 1$). Relatively larger exporters face steepr supply curve, consistent with the discussion in Section 4.2.

Table 11: Exporter responses to demand 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 12. Column 2 shows estimates of Equation 13. $\hat{\rho}(0)$ and $\hat{\rho}(1)$ were calculated using Equation 14. Both specifications include exporter fixed effects. Clustered standard errors are shown in parentheses.

In order to simulate $\rho(s)$ in the model, I proceed in several steps. First, I draw the productitivty of each exporter from a distribution chose to match the distribution of exports in the data. For each guess of η, θ, and the other parameters, I solve the model by finding the vector of relative exporter sizes that satisfy the definition of equilibrium in Section 3.4 (see Appendix A.3.2 for further details). The solution becomes period $t = 1$ of simulated data. Next, I shock the model with demand shocks drawn from a distribution matching the one in the actual data. I solve it again, treating the solution as period $t = 2$ of simulated data. Third, I estimate Equations 12 and 13 using the simulated data. Finally, I calculate the crop supply elasticity $\rho(s)$ using Equation 14.

The crop supply leasticity 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 $\rho(0)$ and $\rho(1)$ generated by the model match the elasticities $\hat{\rho}(0)$ and $\hat{\rho}(1)$ estimated in the data and reported in Table 11:

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

A.4.5 Aggregate welfare calculation

In order to compare aggregate welfare (rather than just farmer welfare) between the baseline economy with market power and the counterfactual economy with perfect competition, I make two important modifications. First, I include exporter profits in aggregate consumption, since the rents from the economy must be spent somewhere. Second, I convert the quantity of crops produced into labor disutility units, creating a trade-off between higher consumption and higher disutility of production. I follow Berger et al. (2019) and choose the following specification for aggregate utility:

$$U = u\left(C - \frac{1}{\Omega^{\frac{1}{\omega}}} \frac{Q^{1+\frac{1}{\omega}}}{1+\frac{1}{\omega}}\right)$$

where $C = \Pi + PQ$ is aggregate income including exporter profits, ω is the Frisch elasticity, Ω is a shifter which converts crop units into labor units, and u is utility function with standard properties. I calibrate ω to a value of 0.2 and set Ω to 0.832, so that total farm income matches between the model and the data. The welfare gain λ is the percent subsidy to consumption that equalizes aggregate utility between market power and perfect competition:

$$u\left(C_{MP}(1+\lambda) - \frac{1}{\Omega^{\frac{1}{\omega}}} \frac{Q_{MP}^{1+\frac{1}{\omega}}}{1+\frac{1}{\omega}}\right) = u\left(C_{PC} - \frac{1}{\Omega^{\frac{1}{\omega}}} \frac{Q_{PC}^{1+\frac{1}{\omega}}}{1+\frac{1}{\omega}}\right)$$

Plugging in the values from the simulated data yields $\lambda = 0.029$, so that aggregate welfare is 2.9% higher under perfect competition. The increase in welfare is low because increases in farmer income are offset by decreases in exporter profits and increases in farmer disutility from producing more.[41]

A.4.6 Back-of-the-envelope calculation

My back-of-the-envelope calculation combines estimates from this paper with external data from 2019.

Total agricultural exports were about 10B USD. The estimated farmer share is 0.34. The estimated effect of Fair Trade on farmer income is 0.14. Multiplying these, we have an increase in farmer income of 476M USD.

The labor force is approximately 9M people. The agricultural employment share is 0.3, and the poverty rate in agriculture is 0.4. The annual income at the poverty line in Ecuador is about 2000 USD. Multiplying these, we have that the amount need to raise all poor farmers above the poverty line is 2.16B USD.

Dividing the increase in farmer income due from Fair Trade by the amount needed to raise all farmers out of poverty, we have that Fair Trade would raise $100 \times \frac{476\text{M}}{2160\text{M}} = 22\%$ of farmers out of poverty.

[41] With higher Frisch elasticities, welfare gain is even lower, because not only do exporters have lower profits, but farmers have higher disutility for farming.

A.5 Production Function Appendix

For an alternative approach to estimating η and θ, re-write Equation 2 as follows

$$\frac{\alpha}{\phi_{ij}} = \frac{1}{\psi_{ij}} = 1 + \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij}$$

Suppose we have an estimate of the output elasticity of crops, α, and data on the farmer share, ϕ_{ij}. This equation implies that we can infer η and θ by projecting the ratio $\frac{\alpha}{\phi_{ij}}$ onto exporter market shares s_{ij}.[42]

A vast body of work[43] addresses the fundamental concern with estimating α: that low input quantities could imply either low output elasticity or high productivity. Here, I summarize two canonical approaches. The first, popularized by Syverson (2004), infers output elasticities from the share of each input in total costs, bypassing the productivity issue. However, it assumes perfect competition in input markets.

The other approach uses a control function for unobserved productivity, together with appropriate instruments, to estimate the production function (Levinsohn and Petrin 2003; Olley and Pakes 1996). Although this approach has become the gold standard, it imposes significant data requirements. At a minimum, it requires data on input quantities.

A.5.1 Cost shares approach

Assuming the market for other inputs such as labor is perfectly competitive, their first order condition is

$$\frac{p_j^m m_{ij}}{p_j^x x_{ij}} = 1 - \alpha$$

The share of export revenue paid to farmers reflects both the output elasticity α and the markdown ψ. The share paid to other inputs, however, reflects only the output elasticity $1 - \alpha$. Subtracting the other input share from 1, we can therefore measure α.[44] This approach is sensitive to the measurement of input costs – any missed costs will bias α upward. To reduce the influence of measurement error, the literature uses the share of *costs* paid to other inputs rather than the share of revenues (Foster, Haltiwanger, and Syverson 2008; Syverson 2004).

$$1 - \alpha = \frac{p_j^m m_{ij}}{p_j^m m_{ij} + p_{ij} q_{ij}}$$

With perfect competition in input markets, cost shares deliver the same estimate of $1 - \alpha$ as revenue shares. With market power in crop markets, cost shares overestimate $1 - \alpha$ and therefore *underestimate* α.

[42] If exporter i is very small, so that $s_{ij} \to 0$, this implies that the wedge will be very close to one plus the (inverse) elasticity of substitution across exporters, $\frac{1}{\eta}$. On the other hand, if the exporter is very large, so that $s_{ij} \to 1$, it will be very close to one plus the (inverse) elasticity of substitution across crops, $\frac{1}{\theta}$. The wedge between output elasticities and farmer shares for small exporters identifies η, while the wedge for large exporters identifies θ.

[43] See De Loecker and Goldberg (2014) for a comprehensive survey.

[44] Note that if other inputs are also marked down, then this measurement will be an upper bound on α, and the associated wedge will be a *lower* bound on crop market power.

This approach is popular for measuring market power in industries with relatively homogeneous production processes, as is the case here. In the data, there is almost twice as much variation in farmer shares compared with other input shares within products, suggesting that the assumption of constant shares for other inputs is reasonable.

Of course, there is still some variation in cost shares across firms, which implies different output elasticities for each firm. The literature aggregates cost shares within groups of firms assumed to the have the same output elasticities, e.g. by calculating the median within an industry. In our setting, we consider three groupings: HS 2-digit, 4-digit, and 6-digit products. Within each group, exporters use the same technology for exporting. For example, a box of bananas requires roughly the same amount of cardboard across exporters. We aggregate cost shares in three ways: the median, the mean, and the sales-weighted mean.

There are several different ways to measure expenditures on other inputs, $p_j^m m_{ij}$. First, I identify non-crop purchases in the firm-to-firm data. These are added to wage bills for my first measure of $p_j^m m_{ij}$. Second, since some exporters purchase crops through domestic intermediaries, I add payments to intermediaries (net of payments to farmers) for my second measure. Finally, since exporters report the value of capital annually, I add payments to capital for my third measure. I follow Morlacco (2019) and assume a common user cost of capital of 20%. Note that if the firm-to-firm data include flow payments to capital (Kikkawa et al. 2019), this will lead to double-counting.

This table summarizes the estimated output elasticities for my preferred specification: 2-digit product grouping, aggregation by weighted average, and other inputs including payments to workers and intermediaries. The results are broadly consistent with the idea that crops that require more processing before being exported have higher output elasticities $1-\alpha$. This holds both across products at the 2-digit level (prepared fish has a higher elasticity than raw fish) and at lower levels of disaggregation (frozen raw fish has a higher elasticity than fresh raw fish). Note that this table implies α is indeed lower than in the main estimation, consistent with the cost share approach underestimating α in the presence of market power in crop markets. However, it is most similar to the main estimate in the largest products, fish and fruit.

Table 12: Output elasticities, cost share approach

2-digit Product	$1-\alpha$
Live animals	0.60
Fish and crustaceans	0.44
Dairy produce	0.70
Other animal products	0.98
Live plants	0.84
Vegetables	0.57
Fruit and nuts	0.42
Coffee, tea, spices	0.75
Cereals	0.80
Mill products	0.97
Oil seeds	0.88
Vegetable extracts	1.00
Other vegetable products	0.95
Animal or vegetable fats and oils	0.53
Meat and fish preparations	0.68
Sugars and sugar confectionery	0.95
Cocoa and cocoa preparations	0.80
Cereal preparations	0.96
Vegetable and fruit preparations	0.69
Other preparations	0.89
Beverages	0.96
Waste from the food industries	0.80
Tobacco products	0.78

Notes: Table shows estimates of $1-\alpha$ by product following the cost shares approach discussed in the text.