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Competition in Global Value Chains

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Abstract

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I show that exporter market power reduces the benefits of international trade for farmers. Using microdata from Ecuador, I link exporters to the farmers who supply them across the universe of cash crops. I document that farmers earn significantly less when they sell crops in export markets that are highly concentrated. I propose a model in which farmers choose a crop to produce and an exporter to supply. Exporter market power is driven by two key elasticities, which govern heterogeneity in farmer costs of switching crops and switching exporters. I develop a method to estimate them using exporter responses to international price shocks. The estimates imply that farmers earn only 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.

Competition in Global Value Chains

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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 substitution 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 25%.

To highlight the effectiveness of Fair Trade, I consider 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 additional 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

[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).

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, 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 substitution 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 estimated 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 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

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

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 and validate it. In Section 5, I use the estimated model to measure the market power faced by farmers. In Section 6, I conduct counterfactual analyses of Fair Trade and other agricultural support policies. I conclude in Section 7 by discussing the limitations of the current study and the directions for future research.

2 Data

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

2.1 Ecuador: an ideal setting

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

Despite its small size, Ecuador is an important producer of cash crops such as cocoa,

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

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

A disproportionate share of the poor work in agriculture, both in Ecuador and across developing countries (Townsend 2015). Income gains in the agricultural sector are therefore crucial for reducing poverty. Ecuador offers an ideal setting for studying an important barrier to such gains: the lack of competition among exporters.[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

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

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 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.

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

[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.

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 liability 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 Section 4.

Table 1: Farmer and exporter statistics

(a) Exporters

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

(b) Farmers

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

Notes: Panel A shows summary statistics across exporters. Panel B shows summary statistics across farmers. Rows 1-4 show medians. Rows 5-6 show means.

A second concern is that the data may not be capturing small family farms, but rather large factory farms. The median farm does not report any employees or wages, consistent with the high rate of self-employment. 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

[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.

[11] Adao et al. (2019) follow this approach for manufacturing industries in Ecuador.

themselves. To avoid distributing farm sales among employees and owners and arbitrarily deciding who is a farmer, I measure farmer income as sales and make no distinction between farms and farmers. This is equivalent to assuming that all farm sales are paid to farmers, which will overestimate farmer income (since not all workers and owners are farmers). At the same time, this underestimates the number of farmers (since even small family farms contain multiple 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,

[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.

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.

Table 2: Exporter-farmer networks

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

Notes: Table summarizes exporter-farmer 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 the median number of farmers supplying each exporter (indegree). Column 6 shows the median number of exporters supplied by each farmer (outdegree).

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.

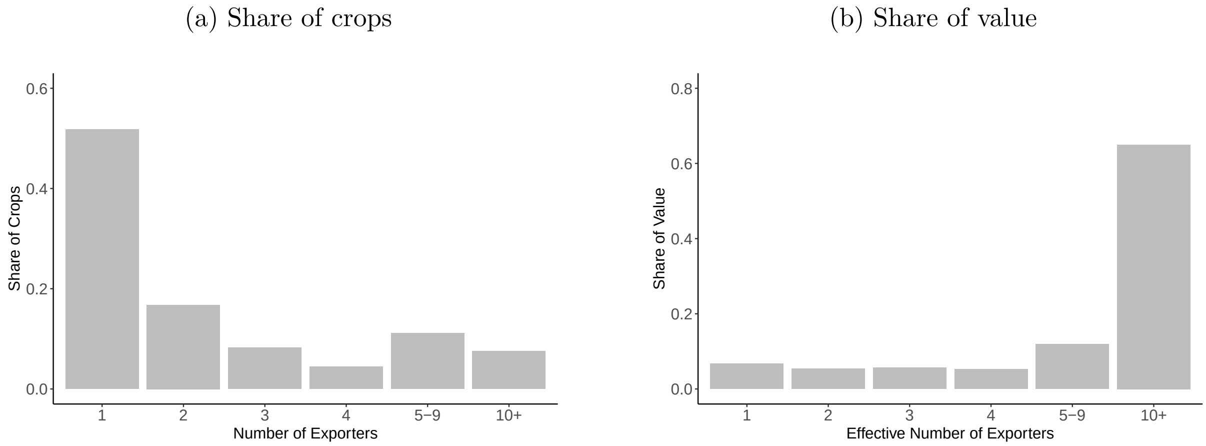
2.3.1 Crop markets are highly concentrated

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 a 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 required 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:

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

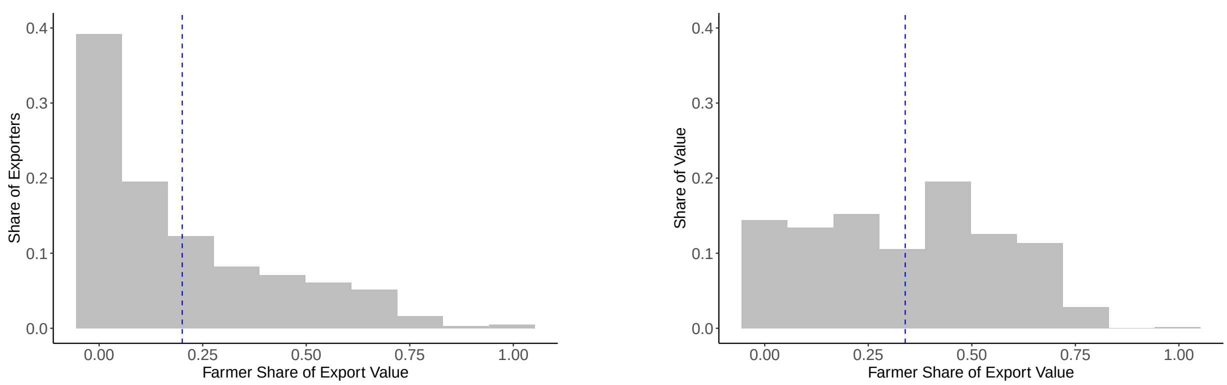
Panel A of Figure 2 shows the distribution of the farmer share across all exporters. The blue line indicates an average farmer share of around 0.25, meaning that for every dollar of agricultural products exported from Ecuador, farmers earn 25 cents. Many exporters have farmer shares lower than 10%, while 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 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 a substantial share of cocoa is grown to the coastal port of Guayaquil. In my dataset, this could appear as wages or payments to suppliers who are *not* classified as farmers. I exploit this dimension of the data to establish the next fact, and use the model to definitively distinguish between value added and market power.

Figure 2: Farmer share of export value

(a) Share of exporters (b) Share of 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.

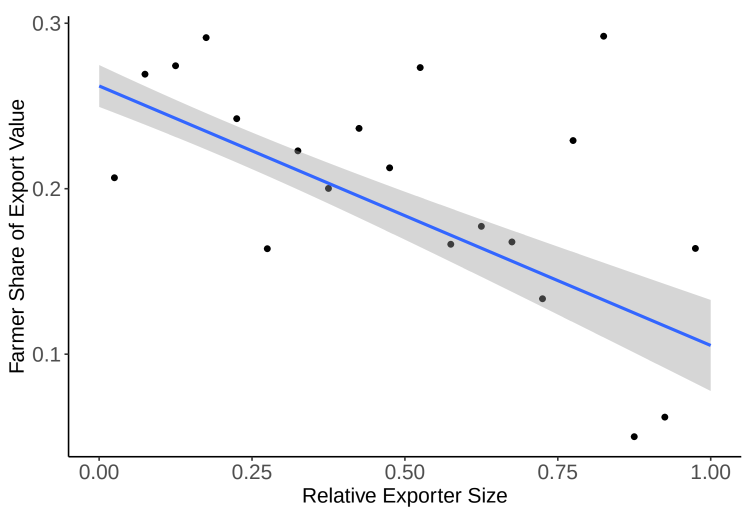
2.3.3 The farmer share is lower when exporters are more concentrated

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.

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

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

Figure 3: Farmer shares and exporter concentration



Notes: Figure plots 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 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, log export prices, 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.

[14] Alternative specifications are shown in the appendix.

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

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

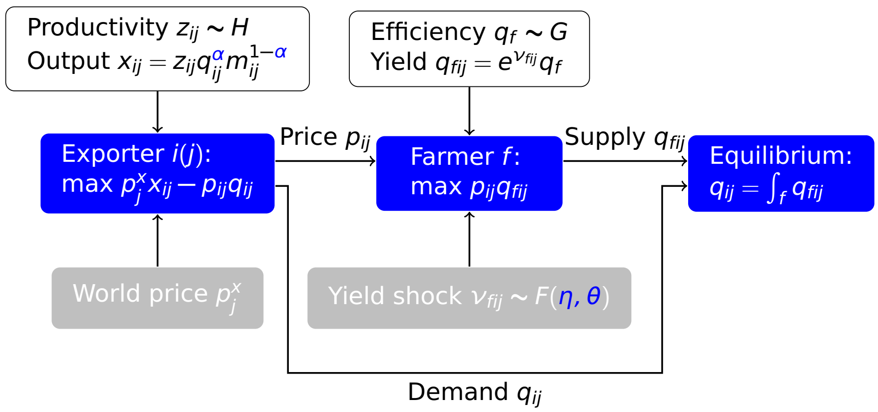
In this section, I develop a model of imperfect competition among exporters in the market for crops. Farmers choose a crop to produce and sell to exporters, who have market power. The concentration of exporters, and hence their market power, differs across and within crops and impacts farmer well-being. 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] Figure 4 summarizes the structure of the model.

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

Figure 4: Model structure



Notes: Endowments and technologies shown in white boxes. Model shocks shown in grey boxes. Optimization and market clearing conditions shown in blue boxes. Black arrows denote optimization results. Blue text denotes model parameters. See text for variable descriptions.

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 heterogeneity 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_{fj}^c for producing each crop j and an idiosyncratic shock $\nu_{fi(j)}^e$ for supplying each exporter $i(j)$. Since each exporter buys and sells a single crop, $i(j)$ uniquely identifies an exporter. For convenience, I drop the parentheses in subscripts, so that ν_{fij}^e becomes shorthand for $\nu_{fi(j)}^e$.

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

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

where η and θ are two key elasticities discussed in detail below. The idiosyncratic shocks determine her yield: the higher are ν_{fj}^c and ν_{fij}^e, the more she can supply if she chooses crop j and exporter i. In this sense, ν^c_{fj} models the land's suitability for growing crop j in a stochastic way, while ν^e_{fij} models 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 prohibitively low. If the farmer chooses crop j and exporter i, she earns profits $p_{ij}q_{fij}$. She chooses a crop and exporter by solving:

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

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

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

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

[17] See the appendix for a proof.

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

depends on how large the price index of crop j (numerator) is relative to the overall price index (denominator), which is a CES aggregate of price indexes across crops.

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

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

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

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

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

where $q_j = \left(\sum_{i(j)} q_{ij}^{\frac{1+\eta}{\eta}}\right)^{\frac{\eta}{1+\eta}}$ is the quantity index for crop j and $Q = \left(\sum_j q_j^{\frac{1+\theta}{\theta}}\right)^{\frac{\theta}{1+\theta}}$ is the overall quantity index.[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 4.3, I relate my estimates of θ to a large literature that estimates this heterogeneity directly. Finally, θ is the elasticity of substitution across crops in the CES supply function. The higher is θ, the more substitutable are different crops from the point of view of farmers. In a dynamic setting, higher substitutability would correspond to higher rates of farmer switching across crops.

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

[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 substitutable within crops than across crops from the point of view of farmers. These are reasonable interpretations.

3.4 Exporter price setting

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

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

where $z_{ij} \sim H$ is an idiosyncratic productivity term. This is the only source of ex-ante heterogeneity across exporters within a given product.[21]

Exporters of product j exert market power over farmers, which I model as Cournot or Bertrand competition for crops. When deciding what quantity to purchase (Cournot) or what price to offer (Bertrand) for a crop, exporters form expectations about how farmers respond. In other words, they internalize the upward sloping crop supply curve in Equations 2 (Cournot) and 1 (Bertrand): each additional unit they purchase increases the price of every other unit. Because Cournot competition yields intuitive expressions for farmer shares at the crop level (see Equation 7), I present the equilibrium under Cournot competition here and show the equilibrium under Bertrand competition in the appendix. However, I will estimate the model and perform measurement exercises under both forms of competition.

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

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

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

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

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

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

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

3.5 Exporter market power in equilibrium

Given Cournot competition between exporters trying to procure crop j[22] and the supply curve in Equation 2, the supply elasticity has the following closed form:

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

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

where $s_{ij} = \frac{p_{ij}q_{ij}}{\sum_{i(j)} p_{ij}q_{ij}}$ is the relative size of exporter i in crop j as defined in Section 2.3.3. In other words, the supply elasticity, ϵ_{ij}, is the weighted harmonic mean of the elasticity of substitution across crops, θ, and across exporters, η, where the relative sizes of exporters form the weights.[23] Substituting into Equation 3, the equilibrium farmer share is:

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

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

To make the connection between theory and data more explicit, take logs on both sides of Equation 5. In addition, let the log output elasticity vary by 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:

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

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. In Section 4.2, I discuss how the model allows me to estimate them separately. Furthermore, I will show that my estimates of η and θ, together with Equation 6, are consistent with the coefficients in Table 3.

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

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

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

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 controls 1%, $HHI_j^{-1} = 1.02$, so that the market is *effectively* a monopsony. Equation 7 implies that the lower the effective number of exporters for a given crop, the lower the crop-level farmer share. This further links the theory to the data: the number of exporters is low in Figure 1, while the 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 2) and exporter optimization (Equation 5).

3.6 Special case: symmetric markets

To provide intuition on how market power operates in this setting, I consider the case of symmetric exporters.[24] 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 7:

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

$$\text{farmer share}_j = \alpha \times \left(1 + \frac{1}{\epsilon_j}\right)^{-1} = \alpha \times \left[1 + \frac{1}{\eta}\left(1 - \frac{1}{N_j}\right) + \frac{1}{\theta}\frac{1}{N_j}\right]^{-1} \tag{8}$$

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 8 then implies that the crop-level farmer 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 8 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 the stylized fact from Section 2, and externally, by comparing my estimates to values of η and θ implied by the agricultural trade literature.

4.1 Identification using pass-through of demand shocks

Consider what happens when there is a sudden increase in the international price 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.[25]

To see this more formally, log-linearize around the equilibrium in Equation 5:

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

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:

$$\Delta \log p_{ij} = \underbrace{\left[1 + \frac{(\frac{1}{\theta}-\frac{1}{\eta})(1+\eta)s_{ij}(1-s_{ij})}{1+\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})s_{ij}}\right]^{-1}}_{\rho(s_{ij})} \times (\Delta \log p^x_j + \Delta \log z_{ij}) \tag{9}$$

Clearly, $\eta > \theta$ implies that $\rho < 1$, so that pass-through is incomplete under market power. In the appendix, I show that ρ is also decreasing in s_{ij} under this condition. Equation 9 implies that for a given change in international prices, $\Delta \log p^x_j$, the corresponding change in crop price, $\Delta \log p_{ij}$, will be smaller for relatively large exporters, provided that international price shocks are orthogonal to exporter productivity shocks, $\Delta \log z_{ij}$. This reflects the intuition that pass-through declines with relative exporter size and forms the basis of my estimation procedure.

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

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

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 9, e.g. using Nonlinear Least Squares, will yield biased results.

4.2 Estimation in the presence of strategic interaction

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

4.2.1 Estimating η and θ

In order to take Equation 9 to the data, I estimate the following pass-through regression:

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

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

I proceed in several steps: (1) estimate Equation 10 in the actual data, (2) simulate Equation 10 in the model, (3) pick η and θ so that the coefficients γ and ζ from the model match their counterparts in the data.[26] 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 10 in the data, I first construct the demand shocks. I follow a standard Bartik specification combining exporter trade shares from my microdata with international prices from COMTRADE:

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

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

[26] 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.

Table 4: Exporter responses to price shocks

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

Notes: Column 1 shows estimates of pass-through regressions (Equation 10). 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 10 in the model, I proceed in several steps (see Appendix A.3.1 for further details). First, I draw the productivity of each exporter from the productivity distribution described below. For each guess of η, θ, and the other parameters, I solve the model. Next, I shock the model by drawing from the trade shock distribution described below. I solve the model again to create a simulated panel. Finally, I estimate Equation 10 using the simulated panel. The resulting pass-through coefficients, denoted $\gamma(\eta, \theta)$ and $\zeta(\eta, \theta)$, are functions of η and θ.

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

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

4.2.2 Estimating α

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 7:

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

where HHI_j is taken from the simulated data. Let $\phi(\alpha)$ denote the average farmer share. I pick α so that $\phi(\alpha)$ matches its counterpart in the data, denoted $\hat{\phi}$ and reported in Figure 2:

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

4.2.3 Other parameters

I assume that (log) exporter productivity, $\log z$, and price shocks, $\Delta \log p^x$, follow normal distributions:[27]

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

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

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

4.2.4 Parameter estimates

Table 5 summarizes the baseline estimated model under Cournot competition.[28] The elasticities of substitution across exporters, η, and across crops, θ, are small, indicating that exporters face steep supply curves and exercise market power over farmers. The output elasticity of crops, α, is large relative to the farmer share, further indicating a high degree of market power. I explore the economic meaning of these estimates in detail below.

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

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

Table 5: Parameter estimates

Parameter	Estimate	Moment	Value
(a) Key parameters			
η	1.72	Baseline pass-through, $\hat{\gamma}$	0.35
θ	0.35	Decline in pass-through with size, $\hat{\zeta}$	-0.23
α	0.51	Average farmer share, $\hat{\phi}$	0.24
(b) Other parameters			
μ_z	13.98	Terciles of log exporter revenue	
σ_z	2.27		
μ_d	0.02	Terciles of log price changes	
σ_d	0.11		
M	157	Number of crops	
N_j	1-10	Number of exporters per crop	

4.3 Model validation

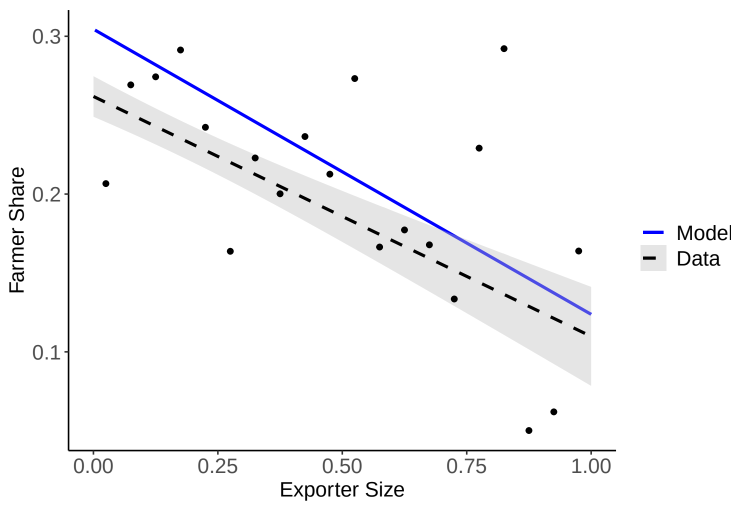
I validate the model in several ways: internally, by comparing moments not targeted in the estimation procedure between the model and the data; and externally, by comparing the heterogeneity in production and transport costs implied by the model with estimates from the agricultural trade literature.

4.3.1 Internal validation

Figure 5 plots the negative relationship between farmer share and relative exporter size, in the model and in the data. The latter was first documented in Figure 3. The relationship in the model, which is influenced by 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 6 and compare the results to Column 1 of Table 3. The coefficient on relative exporter size is slightly more negative at -0.87, but not statistically distinguishable. In the appendix, I estimate an overidentified version of the model which matches this coefficient in addition to the coefficients from the pass-through regression, and obtain similar results.

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

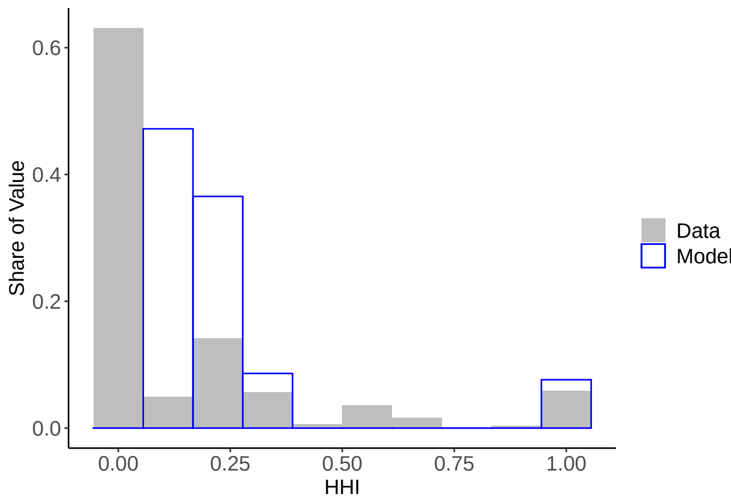


Notes: Figure plots relative exporter size on the x-axis and farmer shares of export value on the y-axis. Solid blue line indicates predictions from the model. Dashed black line indicates predictions from the data. Grey area indicates a 95% confidence interval.

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 6 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* have 4-5 exporters per crop.[29]

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

Figure 6: Crop market concentration, model vs. data

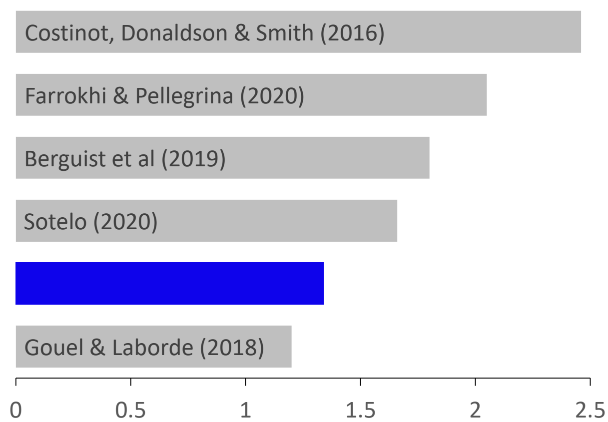


Notes: Figure plots the distribution of HHI across crops, weighted by the share of exports in each bin. Blue bars indicate the model. Grey bars indicate the data.

4.3.2 External validation

I validate the model externally by comparing my estimates of θ and η to those implied by the literature on agricultural production and trade in developing countries. Recall the interpretation of θ in Section 3.3 as a measure of land heterogeneity: the higher is θ, the less heterogeneous is the land, and the more suitable it is for producing 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 7 compares this value to those from the literature. They are generally larger than my estimate of 1.35, indicating a smaller degree of heterogeneity than in my setting. Importantly, I include the largest number of distinct products, which may explain why I find more heterogeneity. Consistent with this explanation, Gouel and Laborde 2018 is both the only other study to include animal products and the only study to find lower heterogeneity. Sotelo 2020 finds a value similar to mine in Peru, the most agroclimactically similar country to Ecuador among those studied.

Figure 7: Estimates of land heterogeneity from the literature

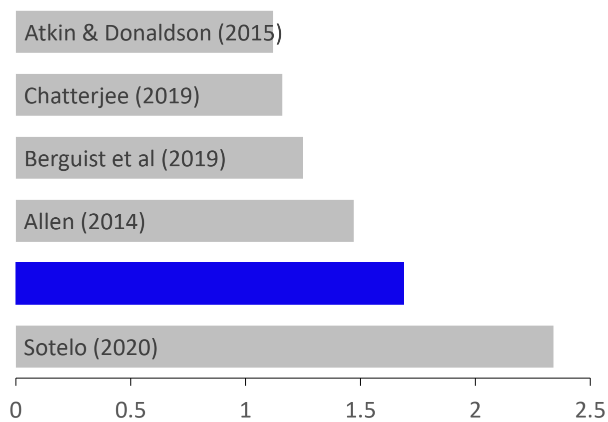


Notes: Figure plots estimates of land heterogeneity from selected papers in grey, and the corresponding value implied by $\hat{\theta}$ in blue. See text of Appendix A.3.8 for conversion details. See Table 13 for source details.

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 8 shows the average estimated trade cost for several studies that focus on agriculture in developing countries. They are generally smaller than my estimate, indicating lower trade costs on average. The most comparable study is Chatterjee 2019, where trade costs allow local intermediaries in India to exercise market power over farmers. Lacking the kind of spatial data he uses to define each geographic market, I define a single market for each crop, which may explain why my estimates are larger. On the other hand, my estimates are *smaller* than in Sotelo 2020, which uses spatial data from Peru, the country most geographically similar to Ecuador among those studied.[30]

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

Figure 8: 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.3.7 for conversion details. See Table 12 for source details.

5 Measurement

Armed with estimates of η and θ, I turn to interpreting them in my empirical context. First, I use the actual data to calculate the implied markdowns faced by farmers in Ecuador. Second, I conduct simulations to compare the level of farmer income between the estimated model and a counterfactual in which exporters behave competitively, rather than strategically. Finally, I decompose the aggregate effect of market power into different channels and examine heterogeneity across crops.[31]

[31]Throughout this section, I use parameters estimated using the relative pass-through to prices vs. quantities. See the appendix for estimation details and parameter values. These specfications yield the highest estimates of market power (Cournot) and lowest estimates of market power (Bertrand). The other three specifications – baseline Cournot, overidentified Cournot, and overidentified Bertrand – yield estimates in between.

5.1 Measuring crop markdowns in Ecuador

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

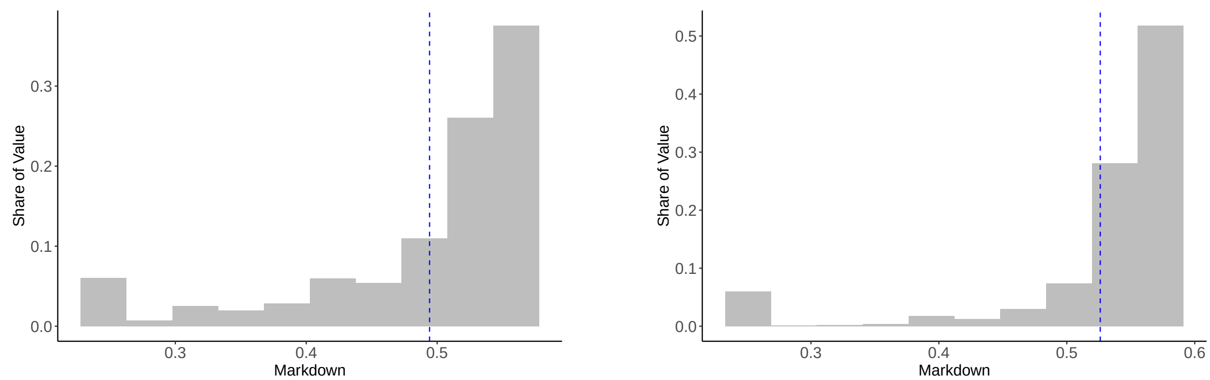
$$\text{markdown}_{ij} = \left[1 + \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij}\right]^{-1} \tag{11}$$

Panel A of Figure 9 plots the distribution of markdowns under Cournot competition, obtained by plugging in the estimated η and θ and observed s_{ij} into Equation 11. The weighted average is 0.49, implying that farmers receive around half of their marginal revenue product. While the majority of exporters pay farmers 50-60% of their marginal product, some exporters, including of important crops like coffee and palm, pay less than 30%.

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

Figure 9: Distribution of markdowns

(a) Cournot competition (b) Bertrand competition



Notes: Figure plots the distribution of markdowns across exporters, weighted by the share of exports in each bin. The dashed blue line depicts the average. Panel A assumes Cournot competition, and Panel B assumes Bertrand competition.

5.2 What if markets were perfectly competitive?

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

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

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

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

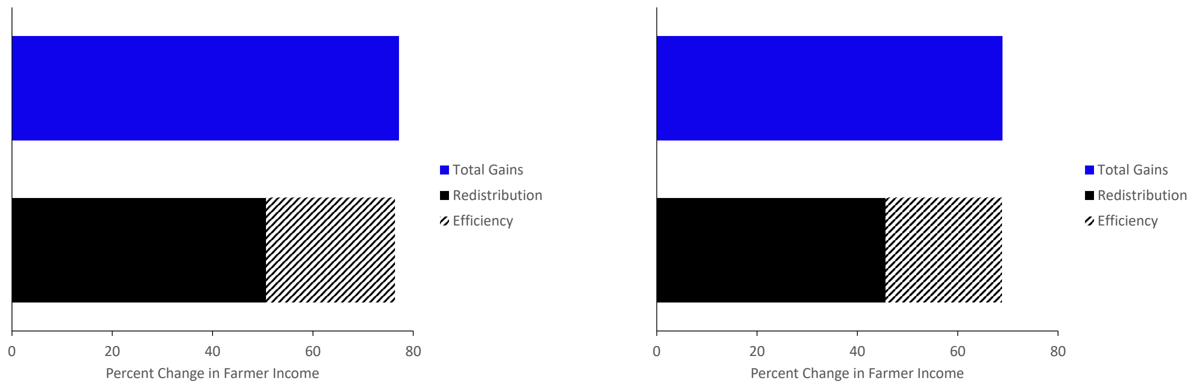
where the superscript MP denotes the baseline with market power and PC denotes the counterfactual with perfect competition.

Figure 10 displays the results of the decomposition. In Panel A, I assume Cournot competition and find that farmer income would be 77.1% higher in the absence of market power. Redistribution from exporters to farmers increases income by 50.7%, accounting for almost two thirds of the gains.[32] Greater efficiency accounts for the remaining third, a 25.6% increase in farmer income. In Panel B, I assume Bertrand competition. As expected, the overall gains (66.1%) from perfect competition are lower, but the breakdown between redistribution (43.4%) and efficiency (21.9%) is similar.

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

Figure 10: Farmer income gains from perfect competition

(a) Cournot competition (b) Bertrand competition

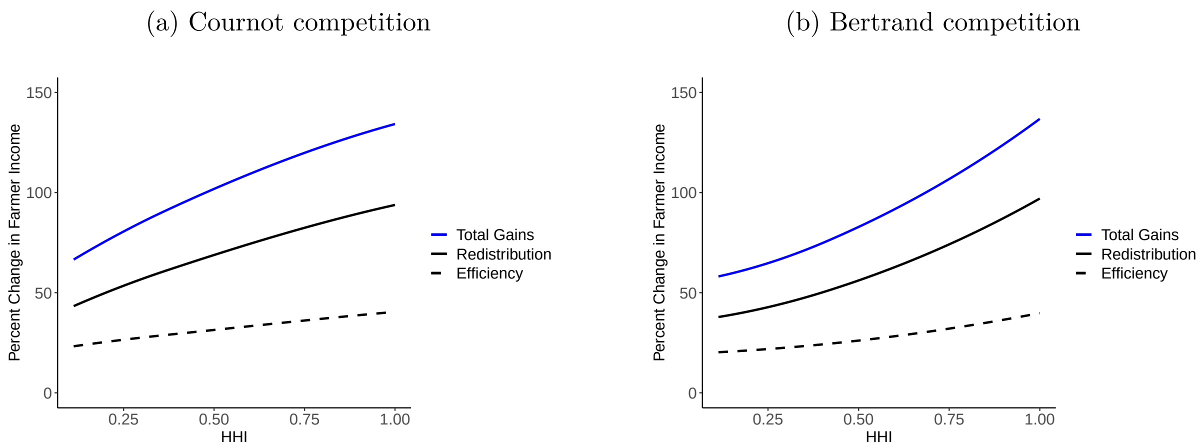


Notes: Figure shows percent increase in farmer income between model with market power and model with perfect competition. Decomposition is described in text. Panel A assumes Cournot competition among exporters. Panel B assumes Bertrand competition.

Although all farmers gain from perfect competition, the gains are not equally shared. Panel A of Figure 11 shows how increases in farmer income vary with the baseline level of crop market concentration, HHI_j, under Cournot competition. Gains range from around 67% in relatively competitive crops, such as bananas, to 134% in the least competitive crops, including cocoa. Both redistribution and efficiency gains increase with crop market concentration, but redistribution increases proportionally more.

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

Figure 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. Panel A assumes Cournot competition, and Panel B assumes Bertrand competition.

6 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.[33]

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

6.1 Fair Trade

Fair Trade is a series of product certifications designed to foster the sustainable production of commodities.[34] 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.[35]

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.[36]

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

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

[35]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).

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

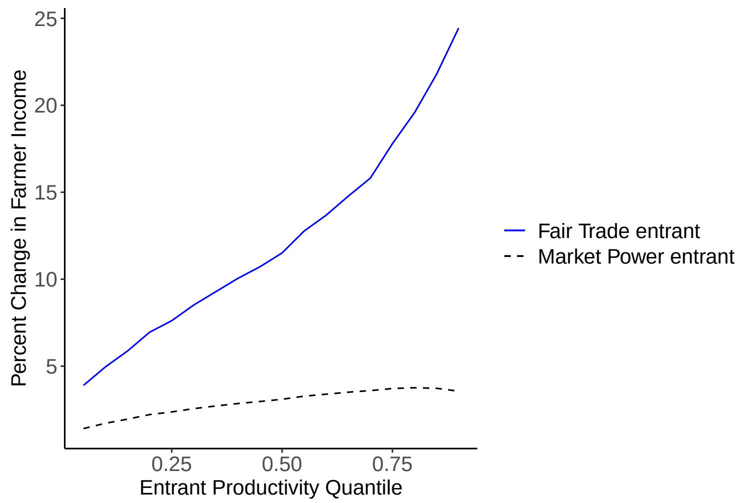
a higher price conditional on his productivity, further raises prices. Fair Trade therefore has a positive direct and indirect effect on prices. These effects reflect the primary goals of Fair Trade: increasing prices and improving bargaining power among farmers. Furthermore, their importance has been 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 12%.[37] As the new exporter becomes among the most productive in the economy, the gains increase to 25%, or about one third of the gains from perfect competition in Figure 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 direct effects of the Fair Trade exporter, I estimate how farmer income would change if the new exporter behaved strategically. The dashed black line indicates that the gains from Fair Trade are driven by the direct effect on participating farmers.

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

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.

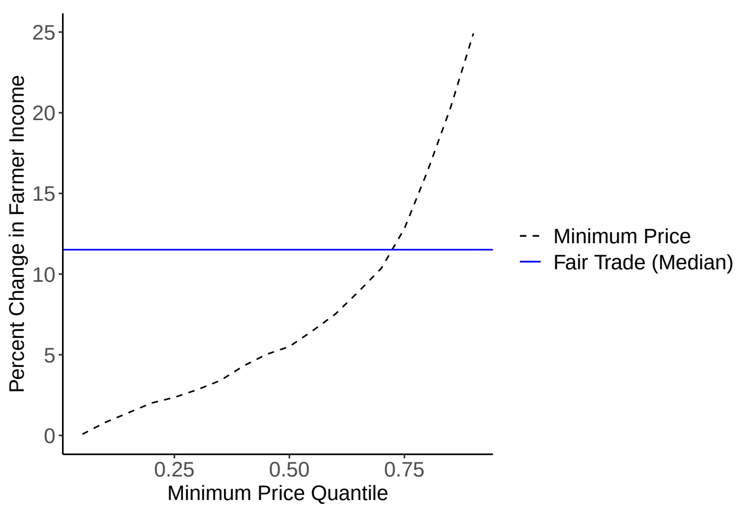
6.2 Minimum prices

A common alternative to Fair Trade is for governments to set a price floor across *all* exporters of a given product. In Ecuador, bananas and palm are the only exported products with price floors (Cunha et al. 2019). Minimum price support is growing, especially for exported commodities in developing countries (Anderson 2009). Compared to conditional subsidies, these policies are 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.[38] 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 near 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).

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

6.3 Do farmers benefit from globalization?

So far, I have only discussed differences in farmer income across 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 prices change. 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

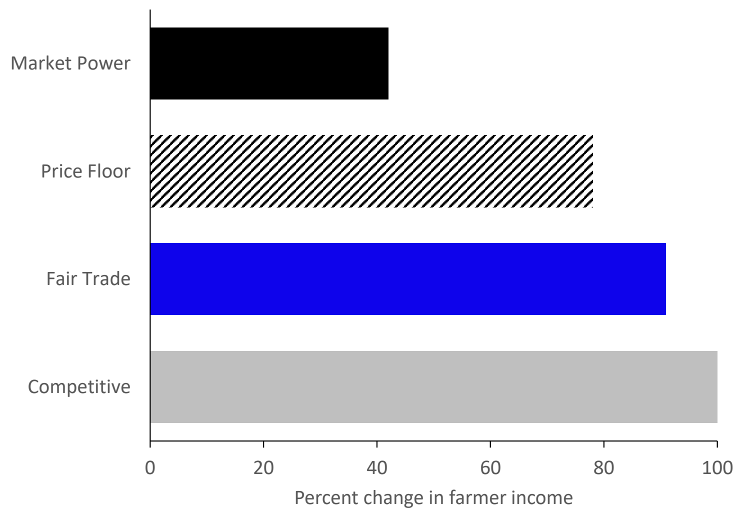
Figure 14 shows the percent increase in farmer income following a 100% increase in the international price. There are several key takeaways. First, farmer income increases by less than 50% in the baseline with market power. Farmer income increases less under Fair Trade and less still when under a price floor. This is consistent with Fair Trade reducing exporter market power more than minimum prices. Finally, pass-through is perfect when exporters are competitive, so that farmer income increases 1 for 1 with international prices.

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

The model allows me to quantify how risk averse farmers would have to be to prefer the lower income and lower risk they face under minimum prices. In Figure 13, farmer income is approximately 6% higher when the minimum price equals the median from the baseline model, and 12% higher when there is a Fair Trade exporter with the median productivity level from the baseline model. In Figure 14, the pass-through of an international price shock to farmer income is 78% with a minimum price and 91% with Fair Trade. In the appendix, I show that these numbers imply a coefficient of relative risk aversion around 2. This is within the range of estimates from a large sample of developing countries (Gandelman and Hernandez-Murillo, 2014).

In contrast, farmers would have to be unreasonably risk averse to prefer the baseline with market power. The pass-through of an international price shock to farmer income is only 42% with market power. At the same time, farmer income is 69% higher under Fair Trade. This implies a coefficient of relative risk aversion of almost 5.5, which is high even among experimental estimates of risk aversion among farmers in Ethiopia (Yesuf and Bluffstone, 2009).

Figure 14: Pass-through of price shocks to farmer income



Notes: Figure shows average percent change in farmer income following a 100% increase in international prices. "Market Power" refers to the data in Section 4.2. "Competitive" refers to the model in Section 5.2. "Fair Trade" refers to the model in Section 6.1, with exporter productivity equal to the median productivity from the data. "Price Floor" refers to the model in Section 6.2, with price floor equal to the median price from the data.

7 Conclusion

Recent decades have seen the rise of both concentration and globalization. Understanding the consequences of concentration is especially important in the agricultural sector in emerging economies, where globalization offers millions of farmers a path out of poverty. I show that these consequences are large in the context of export value chains in Ecuador.

To overcome the challenge of measuring inequality in value chains, I link three administrative data sources. Customs microdata capture exporter revenue, VAT microdata capture exporter payments to suppliers, and firm registry data identify which suppliers are farmers. I exploit the unique network structure of my dataset to document that farmers earn significantly less if they sell to an exporter who dominates the market for a crop.

To quantify the importance of market power, I develop a model in which farmers choose a crop to produce and an exporter to supply. The more costly it is for farmers to switch crops or switch exporters within a crop, the more that farmer shares fall with exporter size. The elasticities of substitution across crops and across exporters within a crop are therefore crucial to measuring market power. I develop a method to estimate them using exporter responses to international price shocks. The estimated model implies that farmers in products as diverse as fruit and fish receive a fraction of their marginal revenue products.

Despite the prevalence of market power, globalization can still provide farmers a path out of poverty. Fair Trade increases farmer income substantially while avoiding the distortions created by 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 13% of poor farmers out of poverty.[39] 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.

[39] See the appendix for details.

7.1 Future work

This dissertation provides a blueprint for bringing high resolution tax data to bear on the study of imperfect competition. The increasing availability of such data worldwide, especially in emerging economies, will allow researchers to examine the division of surplus between buyers and sellers in many other markets. In ongoing work, I use linked employer-employee data and buyer-supplier data to simultaneously measure the market power of large firms over workers and suppliers. The balance between these two types of market power determines whether antitrust policy or labor market regulations will be more effective for fighting inequality.

The methods I develop in this dissertation connect cutting edge models of imperfect competition and agricultural production, opening the door for future work at the intersection of these fields. The elasticities of substitution I estimated from variation in pass-through line up with those estimated by others from geospatial and agroclimactic variation. Together with the distribution of exporter market shares, they are sufficient for measuring markdowns. In another project, I combine estimates of the former (from the FAO) with data on the latter (from the World Bank) to measure market power at a micro level across more than 50 developing countries.

This dissertation leaves open the crucial question of why export markets are so concentrated in the first place. Non-Tariff Barriers (NTBs) to trade, such as quality standards for agricultural products, change the structure of international markets by forcing some buyers and sellers to exit. In joint work with researchers at the World Bank and United Nations, I combine microdata on the universe of exporters and importers across seven Latin American countries with data on all NTBs implemented in Latin America over 20 years. Together, these data allow me to observe both sides of international markets, as well as the most important restrictions affecting those markets, for the first time ever.

Preliminary results suggest that following the implementation of a new NTB, the number of exporters in a market falls relative to the number of importers, and import prices rise. These differences persist for years, potentially increasing exporter bargaining power in addition to product quality. Going forward, I will exploit the firm-level richness of the data to distinguish between these two channels, shedding futher light on the forces that shape competition in global value chains.

A Appendices

A.1 Data appendix

A.1.1 Additional network 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 (1)	Farmer Share (2)	Farmer Share (3)	Farmer Share (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 $y_{ij} = \log p_{ij} + \log q_f + \frac{\nu^c_{fj}}{1+\theta} + \frac{\nu^e_{fij}}{1+\eta}$ across i and j. The maximum satisfies $y_{ij} > y_{kl}$ for all k and l. For any k and l, the terms $\log q_f$ on both sides of the inequality cancel, so that the maximum is independent of farmer capacity.

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

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

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

Define the crop-level price and quantity indexes

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

Substituting above yields the CES supply system for crops

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

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

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

Finally, define the aggregate price and quantity indexes

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

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

A.2.2 Bertrand competition

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

$$\epsilon_{ij} = \eta(1 - s_{ij}) + \theta s_{ij} \tag{12}$$

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

$$\text{farmer share}_{ij} = \alpha \times \left[1 + \frac{1}{\eta(1 - s_{ij}) + \theta s_{ij}}\right]^{-1} \tag{13}$$

Since $\eta > \theta$, Equation 13 implies a negative relationship between the farmer share and the relative size of the exporter, just like Equation 5. Aggregating across exporters yields the crop-level farmer share:

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

This equation is analogous to 7, but difficult to interpret without an analog to the HHI.

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

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

is greater than the markdown under Cournot competition:

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

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

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

A.2.3 Pass-through of international price changes

Taking the derivative with respect to p_j^x of the log-linearized equilibrium in equation 9 and rearranging yields an expression for the *partial equilibrium* pass-through:

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

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

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

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

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

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

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

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

The first term is the price pass-through, which is less than 1 and declines with exporter size. The term in parentheses can be greater or less than 1, so there is no clear prediction for average quantity pass-through. However, since $\eta > \theta$, this term increases with exporter size, so that quantity pass-through unambiguously declines with size.

I test the predictions for quantity pass-through by estimating the following regression:

$$\Delta \log x_{ijt} = \delta_{jt} + \beta s_{ij,t-1} + \gamma \Delta \log p^x_{ijt} + \zeta s_{ij,t-1} \times \Delta \log p^x_{ijt} + \varepsilon_{ijt} \tag{15}$$

where the terms are defined as in Equation 10. Table 8 displays the results of different specifications analogous to those of Table 4. As predicted by the theory, quantity pass-through decreases significantly with size. Furthermore, quantity pass-through is substantially lower than price pass-through. The positive correlation between price responses in Table 4 and quantity responses in Table 8 support the interpretation of international price shocks as demand shocks for exporters. By shifting the demand curve for exporters, these shocks trace out their supply curves and identify buyer market power.

Table 8: Quantity responses to price shocks

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

Notes: Column 1 shows estimates of pass-through regressions (Equation 15). Column 2 adds product and year fixed effects. Column 3 adds time-varying controls described in text. Clustered standard errors are shown in parentheses.

A.3 Estimation appendix

A.3.1 Solving the model

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

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

A.3.2 Simulated Method of Moments

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

- Guess (η, θ, α). Draw productivities $\log z_{ij} \sim N(\mu_z, \sigma_z^2)$. Solve model and treat as data with $t = 1$.

- Draw shocks $\Delta \log p^x_{ijt} \sim N(\mu_p, \sigma_p^2)$. Solve model again and treat as data with $t = 2$.

- Estimate regressions in the simulated data

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

- Estimate regressions in the real data

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

- Calculate farmer shares in the simulated data

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

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

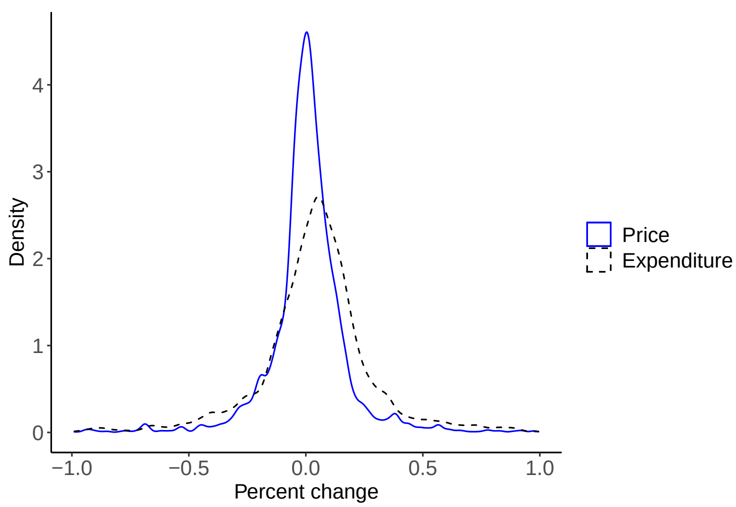
- Pick (η, θ, α) to minimize $\Big|\Big|\hat{\gamma} - \gamma(\alpha, \eta, \theta)\Big|\Big| + \Big|\Big|\hat{\zeta} - \zeta(\alpha, \eta, \theta)\Big|\Big| + \Big|\Big|\hat{\phi} - \phi(\alpha, \eta, \theta)\Big|\Big|$.

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.3.3 Specifying demand shocks

Figure 15 plots the distributions of demand shocks under two different specifications of the shift-share design described in Section 4.2. Both specifications use shares of export revenue by destination. The first, shown in blue, uses shifts in import prices at the destination (excluding imports from Ecuador). It is well-approximated by a normal distribution with mean 0.02 and standard deviation 0.11. The second, shown in black, uses shifts in import *expenditures* at the destination (again excluding imports from Ecuador). This generates substantially more dispersion in demand shocks, and is well-approximated by a normal distribution with mean 0.05 and standard deviation 0.15. When solving the model, I can draw price shocks directly from the distributions in the data. For the sake of reproducibility, I draw from the fitted normal distributions instead.

Figure 15: Percent change in international prices



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

A.3.4 Recovering exporter productivities

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

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

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

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

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

A.3.5 Overidentified model

In this section, I estimate an overidentified version of the model under both Cournot and Bertrand competition. I proceed as in Section 4.2, with one important modification. In addition to matching the baseline pass-through (γ in Equation 10), the decline in pass-through with exporter size (ζ in Equation 10), and the average farmer share, I match the decline in farmer share with exporter size (β in Equation 6). The theory implies that this coefficient is a function of η and θ, as discussed in Section 3.5. Furthermore, it is precisely estimated in Table 3, unlike the coefficient on the interaction term in Table 4. This will be particularly helpful for estimating θ.

To estimate the model under Bertrand competition, I make two modifications to the estimation procedure in Section 4.2. First, I compute the optimal farm price using the Bertrand supply elasticity (Equation 12) rather than the Cournot supply elasticity (Equation 4). Second, I choose the output elasticity α to match the Bertrand farmer share (Equation 14) rather than the Cournot farmer share (Equation 7).

Table 9 presents estimates of the key parameters. The overidentified model features stronger potential market power than the baseline model in the form of lower elasticities of substitution η and θ. However, the actual market power implied by the output elasticity α is similar to that of the baseline model. Note that the Cournot model matches all moments well, despite being overidentified. However, the Bertrand model struggles to generate both the steep decline in pass-through and the steep decline in farmer shares as a function of exporter size.

Table 9: Key parameters, overidentified model

Parameter	Cournot	Bertrand	Moment	Value (Data)	Value (Cournot)	Value (Bertrand)
η	1.68	1.26	$\hat{\gamma}$	0.35	0.36	0.44
θ	0.37	0.30	$(\hat{\zeta}, \hat{\beta})$	(-0.23,-0.82)	(-0.22,-0.83)	(-0.16,-0.89)
α	0.51	0.51	$\hat{\phi}$	0.24	0.24	0.24

A.3.6 Estimating η and θ from relative pass-through

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

$$\frac{\partial \log p_{ij}/\partial \log p^x_j}{\partial \log q_{ij}/\partial \log p^x_j} = \frac{1}{\eta}(1 - s_{ij}) + \frac{1}{\theta} s_{ij} \tag{16}$$

Letting $s_{ij} \to 0$, we have that the supply elasticity of small exporters identifies η. Letting $s_{ij} \to 1$, we have that the supply elasticity of large exporters identifies θ. Following Berger et al. (2019), I pick η and θ so that exporter responses to shocks as a function of relative size, denoted by $\xi(s_{ij}) \equiv \frac{d \log p_{ij}/d \log p^x_j}{d \log q_{ij}/d \log p^x_j}$, match between the model and the data. I proceed in several steps: (1) estimate $\hat{\xi}(s)$ in the data, (2) simulate $\xi(s)$ in the model, (3) form moments from $\hat{\xi}(s)$ and $\xi(s)$, (4) minimize the distance between the moments.

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

$$\Delta \log p_{ijt} q_{ijt} = \delta^v_{jt} + \beta^v s_{ij,t-1} + \gamma^v \Delta \log p^x_{ijt} + \zeta^v s_{ij,t-1} \times \Delta \log p^x_{ijt} + \varepsilon^v_{ijt} \tag{17}$$

$$\Delta \log x_{ijt} = \delta^q_{jt} + \beta^q s_{ij,t-1} + \gamma^q \Delta \log p^x_{ijt} + \zeta^q s_{ij,t-1} \times \Delta \log p^x_{ijt} + \varepsilon^q_{ijt} \tag{18}$$

where v stands for "value" and q stands for "quantity." All other terms are defined as in Equation 10. Equation 17 represents the expenditure response to international price shocks, while Equation 18 represents the quantity response. I use Equation 17 rather than Equation 10 to avoid including quantity responses in both dependent variables. When constructing demand shocks following the shift-share design in Section 4.2, I use the log change in import expenditures at the destination rather than the log change in import prices.

Given estimates of Equations 17 and 18, I calculate the crop supply elasticity $\hat{\xi}(s)$ as follows:

$$\hat{\xi}(s) = \frac{\hat{\gamma}^v + \hat{\zeta}^v s}{\hat{\gamma}^q + \hat{\zeta}^q s} - 1 \tag{19}$$

Table 10 displays the regression results. As above, the estimated coefficients imply that (a) pass-through is imperfect, (b) pass-through declines with exporter size, and (c) shocks shift the demand curve and trace out the supply curve. The last two rows of Table 10 report the supply elasticities implied by the estimates for relatively small exporters, $\hat{\xi}(0)$, and relatively large exporters, $\hat{\xi}(1)$. Notice that larger exporters indeed face steeper supply curves.

Table 10: Exporter responses to expenditure shocks

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

Notes: Column 1 shows estimates of Equation 17. Column 2 shows estimates of Equation 18. $\hat{\xi}(0)$ and $\hat{\xi}(1)$ were calculated using Equation 19. Both specifications include product and year fixed effects. Clustered standard errors are shown in parentheses.

To simulate $\xi(s)$ in the model, I proceed as above, guessing η and θ, solving the model, shocking the model, solving again, estimating Equations 17 and 18 in the simulated data, and calculating $\xi(s;\eta,\theta)$ using Equation 19. Notice that the supply elasticity in the model depends on η and θ.

The crop supply elasticity faced by relatively small exporters identifies η,while the supply elasticity faced by relatively large exporters identifies θ. Therefore, I pick η and θ so that the elasticities $\xi(0;\eta,\theta)$ and $\xi(1;\eta,\theta)$ generated by the model match the elasticities $\hat{\xi}(0)$ and $\hat{\xi}(1)$ estimated from the data and reported in Table 10:

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

Table 11 reports the three key parameters of the model estimated using the relative pass-through of demand shocks, which I will call the Berger-Herkenhoff-Mongey procedure. Notice that this procedure implies *higher* market power than the procedure in the main text: the estimated η and θ are lower, while the estimated α is higher.

Table 11: Key parameters, Berger-Herkenhoff-Mongey procedure

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

A.3.7 External validation of η

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

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

Table 12: Sources for Figure 8

Reference	Iceberg trade cost	Source
Atkin and Donaldson 2015	1.12	Section 4.3
Chatterjee 2019	1.16	Section 6.1.1
Bergquist et al. 2019	1.25	Section 4
Allen 2014	1.47	Table 7
This paper	1.69	Section A.3.7
Sotelo 2020	2.34	Reported in Table 4

A.3.8 External validation of θ

To compare crop-specific productivity shocks in my model to those in the agricultural trade literature, assume there is a single exporter for each crop, so that the only relevant shock is $\frac{\nu_{fj}}{1+\theta}$. A farmer with efficiency q_f now produces $e^{\frac{\nu_{fj}}{1+\theta}}q_f = e^x q_f$ units of crop j, where x follows a Gumbel distribution with scale parameter $\frac{1}{1+\theta}$. In the literature, land heterogeneity typically follows a Frechet distribution with shape parameter $\tilde{\theta}$. It remains to convert the cost shock to a productivity shock, and the Gumbel parameter to the associated Frechet parameter.

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

Table 13: Sources for Figure 7

Reference	Land heterogeneity	Source
Costinot et al. 2016	2.46	Table 2
Farrokhi and Pellegrina 2020	2.05	Table 2
Bergquist et al. 2019	1.80	Section 4
Sotelo 2020	1.66	Section 5
This paper	1.34	Section A.3.8
Gouel and Laborde 2018	1.2	Section 6.2

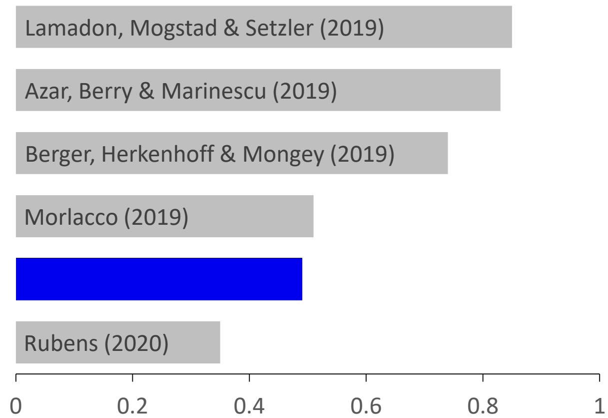
A.4 Measurement appendix

A.4.1 External validation of markdowns

Figure 14 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,[40] they all employ markdowns as a measure of market power. Most of these studies estimate considerably higher markdowns, meaning that buyers have *less* market power than in my setting. However, the most directly comparable study, Rubens (2020), which estimates the market power of cigarette manufacturers over tobacco farmers in China, finds *lower* markdowns. Moreover, several of these studies focus on workers in US labor markets (Lamadon et al. 2019; Berger et al. 2019; Azar et al. 2019), who are likely more mobile than farmers in Ecuador.

[40]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 16: Estimates of markdowns from the literature



Notes: Figure plots average markdown from selected papers in grey, and my average markdown under Cournot competition in blue. See Table 14 for source details.

In Section 5.1, 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 14: Sources for Figure 16

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

A.5 Policy appendix

A.5.1 Risk aversion calculation

Given a lognormal income process with mean μ and variance σ^2, the relative risk premium π for a farmer with Constant Relative Risk Aversion (CRRA) preferences and parameter γ implies:

$$1 - \pi = e^{-\frac{\sigma^2\gamma}{2}}$$

In a one-period model, this equation answers the question: what fraction of her income would a farmer give up to eliminate the risk of her income process? Recall from above that log changes in international prices are approximately normally distributed with variance 0.11. Given a pass-through rate of ρ, log changes in farmer income *conditional on an equilibrium* are normally distributed with variance $\sigma^2 = 0.11\rho^2$. Letting Y denote total farmer income in an equilibrium, the dollar amount a farmer would give up to eliminate her risk is:

$$Y \times (1 - \pi) = Ye^{-\frac{0.11\rho^2\gamma}{2}}$$

A farmer is indifferent between equilibria i and j if the amount of money she would give up to eliminate her risk is equal. Substituting above, we have:

$$Y_i e^{-\frac{0.11\sigma_i^2\gamma}{2}} = Y_j e^{-\frac{0.11\sigma_j^2\gamma}{2}}$$

Solving this equation for γ yields:

$$\gamma = \frac{2\log(Y_i/Y_j)}{0.11(\rho_i^2 - \rho_j^2)}$$

Plugging in the estimated pass-through rates and relative incomes across equilibria yield the results in the text.

A.5.2 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 0.24. The estimated effect of Fair Trade on farmer income is 0.12. Multiplying these, we have an increase in farmer income of 408M 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 under Fair Trade by the amount needed to raise all farmers out of poverty, we have that Fair Trade would raise $100 \times \frac{288\text{M}}{2160\text{M}} = 13\%$ of farmers out of poverty.

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