Market Power in Philippine Agricultural Markets

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Abstract

Market power in markets are distortions that limit the efficient allocation in an economy. Measuring these distortions is nowhere more important than in agricultural markets. In this paper, we use the production function method to measure market power. Using available establishment level surveys for agricultural suppliers from 2012 to 2018, we estimate a PSIC 5-digit national average markup parameter through an extension of standard neoclassical Total Factor Productivity (TFP) regressions pioneered by Hall (1988). Prior work in measuring markups in the Philippines rely on estimating average variable profit directly from survey or financial disclosures data. We estimate both a returns to scale parameter and a national markup parameter. We find modest markups and constant or modest increasing returns to scale. These estimates are consistent with the relationship between markups, profits and returns to scale.

Introduction

The goal of efficiency in agricultural markets is of paramount importance to deliver food downstream while sustain agricultural activities upstream. This is especially true in developing countries where most of the population relies on agriculture for income and food security. In the Philippines, despite having a lower GDP share than the services and industry sectors (PSA 2020), agriculture remains a major source of employment, employing one-quarter of the total workforce. (PSA 2021) Therefore, ensuring the sector's long-term growth is a top priority for the government to achieve its goals of food security and poverty reduction.

One of the challenges that affects agriculture are market distortions which limit productivity and welfare. One of these distortions is market power. Recently, there has been a resurgence on interest in market power in the macroeconomy (De Loecker, Eeckhout, and Unger 2020a), and the efficiency of agricultural value chains (Crespi and MacDonald 2022). Measuring market distortions are a key first step to public policy interventions or antitrust investigations in specific markets. As we will see in the literature review below, while there is a growing literature on market power in developing countries, and in the Philippine specifically, very few have been able to test for or measure market power directly.

In this paper, we use the production function method to estimate markups using comprehensive agricultural producer survey data in the Philippines. We find markups in the range of 8%

on average over 2012 to 2018. This is also consistent with a modest economies of scale in the range of 2% to 3%. Previous work measuring Philippine markups, is work on manufacturing – including food manufacturing – from Medalla, Quimba, and Rosellon (2020a). They give 12% to 13% over 2014 to 2006, and implicitly assume constant returns to scale. Our estimates are consistent with keeping the sample only to firms observed for 6 or 7 years in the sample. The restricted sample' average firm size is in the order of 10 times larger than firms observed fewer times. We can interpret our results as a national level **aggregated** markups for agriculture. We will now turn to a brief review of the extant literature on market power in developing country agricultural markets, and then describe the theoretical machinery that motivates our regression work.

Literature Review

This paper attempts to measure market power in agricultural markets in a developing country setting. The direct evidence for market power is scant, in part due to the enduring notion that because there are many sellers or low concentration in agricultural markets, competition is not a concern. However, there is evidence that pockets of market power exists within the agricultural value chain(Dillon and Dambro 2017). Bellemare, Bloem, and Lim (2022), in their review of the literature on agricultural value chains in low-income countries, finds that competitiveness among crop markets in sub-Saharan Africa are mixed and country specific. Common factors cited in literature reviews that contribute to market power are remoteness and trade costs (Barrett et al. 2022).

Many papers look for price non-integration as evidence for market power. Recent vintages of price integration studies that feature domestic trade costs to explain non-integration, such as in Moser, Barrett, and Minten (2009) or Allen (2014). Porteous (2019) uses a structural model of production, trade, and storage to estimate trade costs in sub-Saharan Africa. By including information on the direction of trade and product level data allows for the estimation of geographic pass-through estimates which allows a indirect measure of the influence of market power the lack of price integration over space.(Atkin and Donaldson 2015) These pass-through methods are complementary to our attempt to test for and measure the size of the market power inefficiency in general agricultural industries. Our establishment survey data has geographical location of the enterprise, but not the breadth of its geographical activities.

Other papers look at market power in specific markets within the value chain using structural econometric models which includes econometrically estimating demand. In the upstream portion of the chain, market power has been found in the rubber intermediaries in Indonesia (Kopp and Sexton 2021), where farmers receive 20% less in crop prices due to monopsony. Dhingra (2016), Zavala (2014) and Rubens (2021) find that farmers' exposure to processors with market power lowers their income. The integration of experimental methods and structural estimation have also been used to measure market power of Kenyan traders (Bergquist and Dinerstein 2020). In contrast with the mentioned literature, our paper follows the production function estimation tradition that allows the estimation of market power without estimating demand.

Philippine Market Power Research

Before discussing the literature on markup estimation using the production function, we first turn to summarizing the work done on measuring market power in Philippine agricultural markets. There have been only a few papers on market power and market integration in agricultural markets in the Philippines. Like studies in other developing country contexts, these studies on market power and integration in agricultural markets rely on testing price series for price integration or asymmetric price transmission.[1] These use inter-province or inter-region price differences, or vertical price adjustment or integration, i.e. from farmgate to wholesale to retail prices. Their argument is that perfectly competitive markets would mean either full price transmission or at least symmetric price transmission.

Many of these price tests are conducted in rice markets, the largest agricultural commodity produced in the Philippines by value. There has been work on intra-province geographic price integration (Silvapulle and Jayasuriya 1994) and national vs international price cointegration (Roehlano Briones 2019). As for vertical price integration – or market integration across the supply chain, many studies (see Umali and Duff (1992), Reeder, M. (2000), Digal (2011)) look at asymmetric price transmission. Broadly, the results are conflicting, finding either symmetric or asymmetric price transmission, possibly due to varying modelling techniques or time periods. Arguably, the most comprehensive is by Intal, Cu, and Illescas (2012) that extends Umali's analysis to post-2000's, and finds the same results of weak market integration.[2] A relatively recent contribution to price tests on Philippine market integration is Allen (2014), who uses direction of trade data for Philippine agricultural commodities to measure trade costs and information frictions from differences in inter-regional commodity prices.

There are very few papers that deal with structural estimation methods in specific markets, principally because of data constraints. One set of work in this vein used industry surveys in computing for concentration measures. Recently, Medalla, Quimba, and Rosellon (2020b) updated Aldaba (2005) which calculated market concentration measures Herfendahl Index (HHI), Four-Firm Concentration Ratio (CR4) and profit rates from the Philippine manufacturing firm censuses to screen for market power. Concentration measures are attractive because they are relatively easy to compute given market shares, and as such, is a major tool to screen for market power by competition agencies. A problem with focusing on these measures is that they may not be directly connected to market power. A decrease in costs may increase market share and increase measured concentration but would not be related to an increase in market power. Methods that directly measure the size of market power are preferable to measuring HHI or CR4.

More recently, there has been survey research on profits and markups at different levels of the supply chain. Mataia et al. (2020) were able to construct estimates of the costs and revenues for the 2014-2015 rice producing season. This research has been able to quantify this marketing margin along different legs of the supply chain and compared it to Vietnam and Indone-

[1] Although these Philippine papers are of an older vintage, as this review makes clear.

[2] Another strand in the literature, which is the real focus of (Intal, Cu, and Illescas 2012), is to examine the role and effectiveness of the National Food Authority to stabilize farmgate prices. In this paper, and in (Santos, Clemente, and Gabriel 2018), the finding has been that the NFA has been largely ineffective because of its small participation in the market.

sia as benchmarks. In addition to Mataia et al., Bordey et al. (2018) conducted a survey of traders, miller and wholesalers and looked at the gross marketing margin, the difference between wholesale and farmgate prices, and compared them across ASEAN countries. They found that the Philippines' gross marketing margin is significantly larger than the next largest margin of Indonesia's with Php 9.06 vs Php 5.61.

This paper contributes to the Philippine literature on the efficiency of agricultural markets. It is the first paper to test for the presence of, and measure the extent of market power in Philippine agricultural markets using structural methods. Our approach is complementary to the direct measurement of average profits and margins. First, there is a theoretical link between profits, markups and returns to scale that we will highlight in our results. The inefficiency of market power is directly related to price-cost markups, and welfare considerations of such market power are informed by the extent of scale economies. Second, relating to value chain survey descriptive studies specifically. our data focuses on agricultural producers which situates our enterprises at the upstream side of the value chain.

Market Power Research using Production Function Methods

In this paper we will use production function techniques initiated by Hall (1988), which is a generalization of Solow's (1957) classic growth model. In this framework with constant returns to scale, imperfect competition can be detected when input growth is associated with disproportionate growth in output. All of these production function papers rely on the insight that the elasticity of output should equal the revenue share of the input under perfect competition. This insight can be applied econometrically using production function or cost function estimation.

First, Hall (1990) extended his method to include estimating returns to scale with the markup. Roeger (1995) uses the dual relationship between production and costs to use the cost function TFP (TFP as a residual to Cost and Input prices), to eliminate the TFP terms residual which could be a source of endogeneity. Crepon, Desplatz, and Mairesse (2005), Dobbelaere (2005) and Amador and Soares (2013) present a model that extends Hall's framework to make it applicable to measuring labor's bargaining power using panel data methods. Hall's insight has also been used in testing theories on how imports affect markups in work by Levinsohn (1993) and Abegaz and Basu (2011). A recent extension of Hall is work by De Loecker, Eeckhout, and Unger (2020a) – and a family of related papers released since – which uses firm-level data to estimate time varying output elasticities by industry using advanced control function techniques. A stochastic frontier production function method was used by Lopez, He, and Azzam (2018) to find markups in the 20% range for for US agricultural enterprises. This paper applies these techniques to Philippine Agricultural enterprises. In our preferred regression specifications, we find small markups of up to 8% and constant or modest increasing returns to scale. These results are robust to restricting the sample to enterprises samples most often by the Philippine Statistical Authority.

Theoretical Framework

Markups are a wedge between price and marginal cost, usually modeled as price divided by marginal cost or $\mu = P/MC$. This paper uses the production function approach to estimate markups, as first posited by Hall (1998). To present our theoretical framework, we assume an establishment level Cobb-Douglass production function with two inputs, capital and labor. An assumption of constant return to scale in two inputs, labor and capital, gives technological progress as a residual of output and inputs' growth rates:

$$\Delta q_{i,t} - \alpha \Delta n_{i,t} - (1-\alpha)\Delta k_{i,t} = A_{i,t} \tag{1}$$

where α is the cost share of labor. Technological growth as a residual $A_{i,t}$ is called the Solow residual. Under perfect competition, this share of labor is also equal to the output elasticity with respect to labor. Allowing the possibility of market power, the output elasticity of labor is a function of the markup and the share of labor: $\varepsilon_N^Q = \alpha\mu$.Thus the above equation (1.1) can be rewritten more generally as:

$$\Delta q_{i,t} = \mu\alpha \Delta n_{i,t} + \mu(1-\alpha)\Delta k_{i,t} + A_{i,t} \tag{2}$$

Some basic manipulations lead us to a simpler estimation equation:

$$\Delta q_{i,t} - \Delta k_{i,t} = \mu\alpha \left(\Delta n_{i,t} - \Delta k_{i,t}\right) + A_{i,t} \tag{3}$$

We can adapt equation (3) for our regression estimation, controlling for time-variation in technology by including year dummies and an i.i.d. error term. A key assumption underlying these derivations is that these inputs where we focus our attention are flexibly set by the firm. If they are flexible, then they will embody the cost minimization first order condition reflected in $\varepsilon_X^Q = \mu\alpha$, where X is the flexible input.

We also investigate an extension to this regression, by allowing for economies of scale. Under economies of scale, firms should impose a mark-up to finance fixed costs. From the production theory, we have that $\varepsilon_N^Q + \varepsilon_K^Q = \lambda$. If there are increasing returns to scale, we have $\lambda > 1$. Given this change, our estimable equation becomes:

$$\Delta q_{i,t} - \Delta k_{i,t} = \mu\alpha \left(\Delta n_{i,t} - \Delta k_{i,t}\right) + (\lambda - 1)\,\Delta k_{i,t} + A_{i,t} \tag{4}$$

In our estimation equation, we will expand our specification to include materials expenditure $m_{i,t}$:

$$\Delta q_{i,t} - \Delta k_{i,t} = \mu\alpha_L \left(\Delta n_{i,t} - \Delta k_{i,t}\right) + \mu\alpha_M \left(\Delta m_{i,t} - \Delta k_{i,t}\right) + (\lambda - 1)\,\Delta k_{i,t} + A_{i,t} \tag{5}$$

We note that given the a Cobb-Douglass Production function, we can also estimate this model in log-levels and with different market power distortions for material and labor. With labor, materials and capital as factors of production, we can write our model in logs as:

$$q_{i,t} - k_{i,t} = \varepsilon_L \left(n_{i,t} - k_{i,t}\right) + \varepsilon_M \left(m_{i,t} - k_{i,t}\right) + (\lambda - 1)\, k_{i,t} + A_{i,t} \tag{6}$$

We now have $\varepsilon_L = \frac{dY}{dL}\frac{L}{Y}$ and $\varepsilon_M = \frac{dY}{dM}\frac{M}{Y}$ as the elasticity of output with respect to labor and materials respectively. If we allow for non-constant returns to scale, the sum of these elasticities are equal to scale parameter $\sum \varepsilon_X = \lambda$. We note that this specification allows separate estimation of the labor and materials markup. Econometrically, this flexibility will likely lead to better estimates of the elasticities of output.

In our analysis in the paper, we will be focusing on the markup from materials as in (Crepon, Desplatz, and Mairesse 2005) because labor will likely not be as flexible an input as materials. Further, we can confirm if the markup is greater than one per factor, and if at least one is greater than one, then we can get a ratio where we can check if the distortions in either input are not the same magnitude: $\frac{\varepsilon_{X1}}{\alpha_{X1}} / \frac{\varepsilon_{X2}}{\alpha_{X2}} = \tilde{\mu} \neq 1$ This will allow us to say if the inefficiencies facing labor is greater or less than the inefficiencies faced by the more flexible input market for materials.

Establishment Data Analysis

We discuss information on the survey of establishments from 2018 to 2010.[3] We use the annual establishment survey data from the PSA, called the Census of Philippine Business and Industry or the Annual Survey of Philippine Business and Industry. These establishment surveys are a key input to generating Philippine economics statistics and they survey agriculture, services and manufacturing establishments. In this paper, we will be using Module A, which contains revenue, cost and other information on producers and support services suppliers in Agriculture, Forestry and Fishing. What are not here are wholesalers and food manufacturers (including millers), who are in the wholesaler and manufacturing modules respectively. Hence, we focus on producers higher up the supply chain.

We first look at the structure of revenue and costs for our agricultural establishments. Revenue structure could give us insight into where in the supply chain these establishments are located. Cost structure would give us information on how these establishments produce their output. Both of these should inform our empirical approach and interpretation of market power.

The technical documentation of the CPBI and ASPBI indicate that the sampling is confined to formal industry, and an establishment is defined as an economic unit which engages in a "predominantly" one kind of economic activity at a fixed physical location.[4] What is not clear is whether their activity is limited to that geographic location. The sampling frame for these

[3]There is no 2011 Survey, due to budgetary issues. The electronic available pre-2010 is also spotty for module A.

[4]Technical Notes on CPBI from https://psa.gov.ph/sites/default/files/attachments/itsd/specialrelease/Explanatory%20Notes_3.pdf

establishment survey's comes from a regularly updated *List of Establishments* curated by the Philippine Statistical Authority. The CPBI takes as a sampling frame all of the formal establishments in the *List of Establishments*, which is approximately 40% of establishments in the list.[5] All formal establishments with total employment of 20 of more are selected as respondents with 100% certainty, while smaller establishments are sampled randomly.

We combined the CPBI and ASPBI establishment surveys from 2018 to 2010 in our full dataset. The combined dataset's variables pertinent for this exercise are responses for employment size (annual average), expenditure on employment, expenditure on materials, the book value for capital, income from various sources and other descriptive variables. The response rates are high, and for the most recent year of 2018, the response rate is 88%. For Module A specifically, the response rate is 90%.

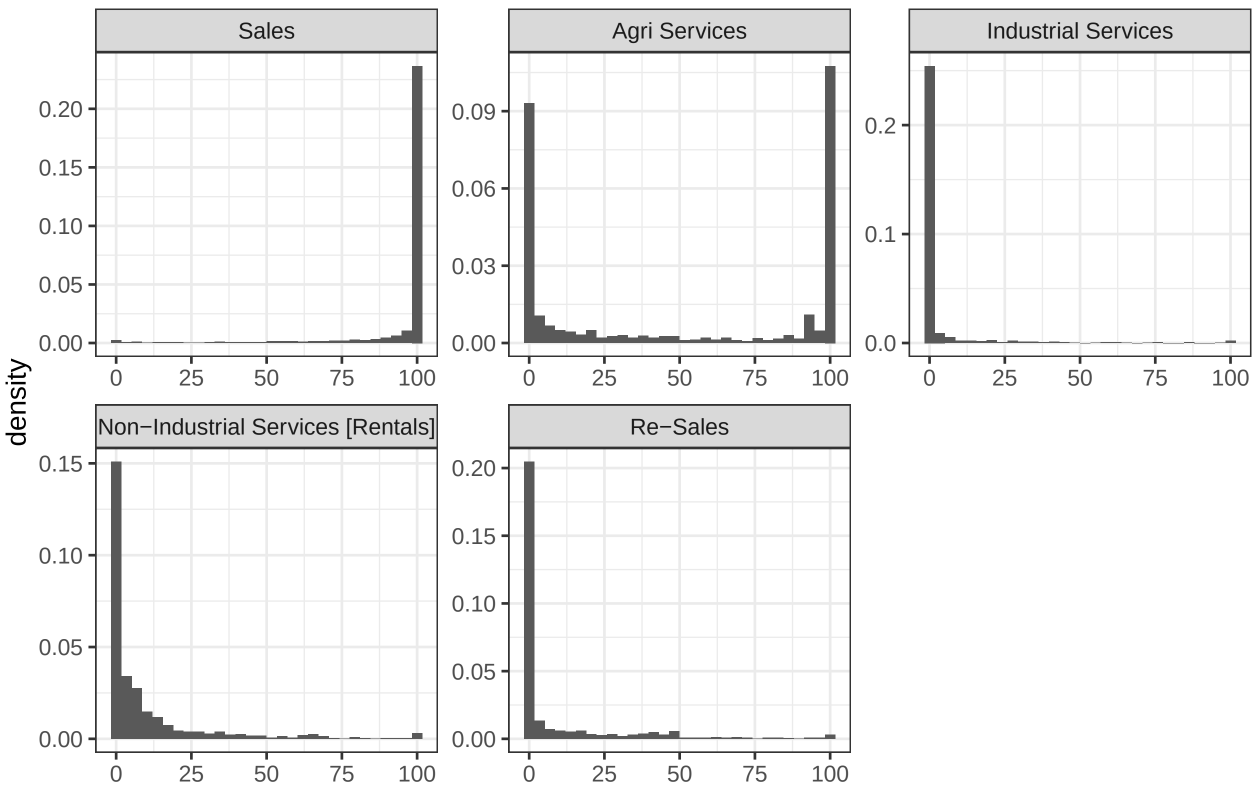

Figure 1: Agricultural Establishments' Revenue Structure (2018-2010)

Revenue and Cost Structure

There are two main issues to consider in the construction of this dataset: issues on the revenue side and the cost side. On the revenue side, the establishment survey records sales from sales of products among many other sources of income. Most of the establishments have sources of income to be sales of products. But there is a non-negligible source of income stemming from non-sales, what the questionnaire classifies as rendering agricultural services.

[5]The rest, 60%, being informal establishments.

First, we share the revenue structure of the establishments in the sample. We note that there are several possible sources of income, from sales of products to service provision. We plot the distribution of the different revenue sources as share of total revenue below in Figure 1

We can see that most establishments earn revenue through sales of products, but there is a sizeable count that primarily sell agricultural services. For our empirical work, we would like to separate these service oriented establishments from our main regression. Our purpose in focusing on establishments that sell goods within PSIC-5 industries is to ensure that the production function within these industries are fairly similar and that they occupy the same position in their respective supply chains.

We present some statistics on the cost structure of our establishments. First, we note that there is a change in how costs structure is measured in the datasets. Post 2010, the cost structure is divided into Cost-of-Goods Sold (COGS) and General Administrative Expenditure. Under either, there are entries for outsourced services (which are Industrial and Non-Industrial Service), labor and materials. There are separate entries for re-sale of goods, Agricultural Services done by others, and a miscellaneous category consisting of financial expense items such as interest, royalties and depreciation. For surveys prior to 2010, there is no longer any distinction between COGS and General Administrative Expenditure but they kept the sub-entries for Labor, Materials, Industrial Services by Others, Non-Industrial Service by Others, and Re-Sale. So all of these categories should be considered the sum of COGS and General Administrative Expenditures. In work by De Loecker, Eeckhout, and Unger (2020a), General Administrative Expenditures is considered as fixed costs and contributes to increasing returns to scale. We will see evidence that fixed costs as a share of total costs have risen late in the sample. Unfortunately, while we can divide total labor expense between COGS and General Administrative Expenditure, we cannot divide labor employment into similar categories. The survey has information on average total employment only for the year. Hence, running a regreession based on COGS-based labor only is not possible. In our regression work, we will focus on all total labor and materials expenses initially. However, we will focus on materials coefficient in our investigation on markups. We will find that there is no difference in our results if we use COGS based materials expenses and Total Materials Expenses. We prefer to use the total expenditure on materials because many establishments chose to input only total expenditure instead of separating their materis expenditure into COGS and General Administrative Expenditure. The average total materials cost between COGS-materials expense is practically the same; over the entire sample, average materials costs is 46 million pesos (nominal) for either category. Finally, conceptually speaking, its unclear what General Administrative Expenditure for materials means for the individual establishments, while the same classification for labor and other forms of overhead makes sense.

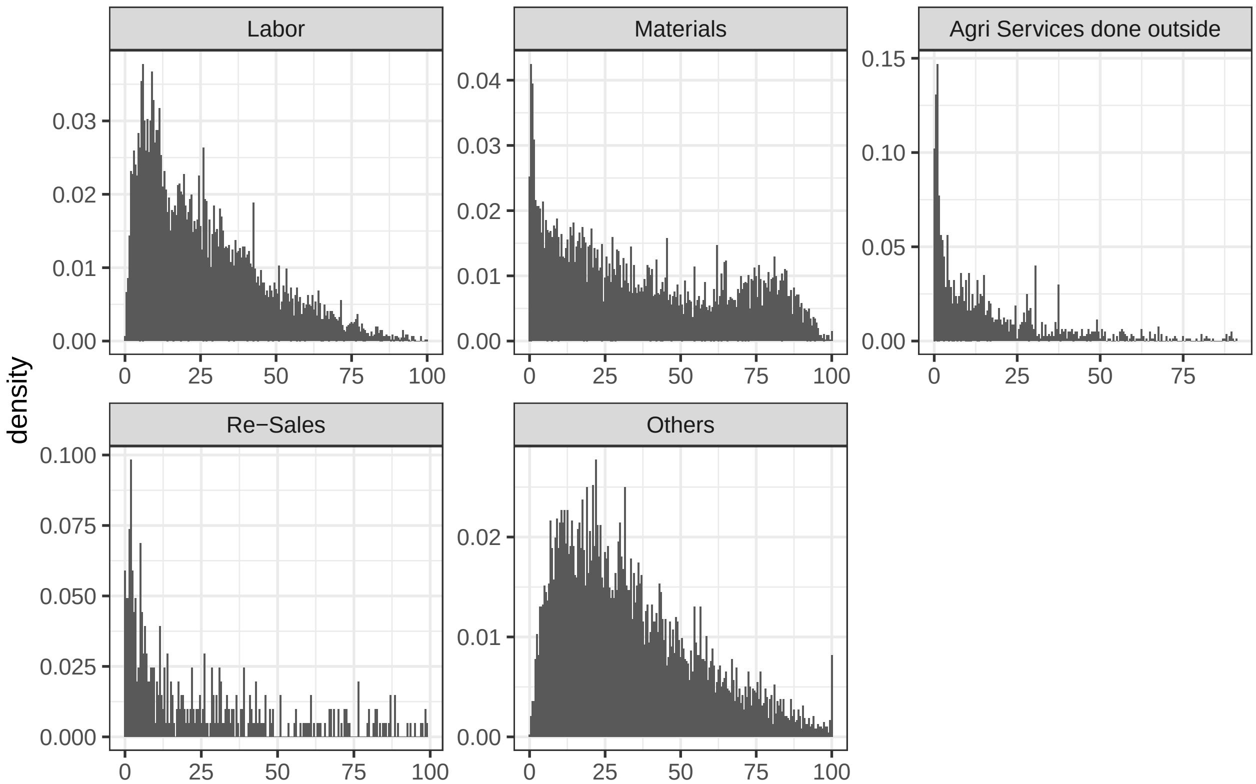

Figure 2: Agricultural Establishments' Cost Structure (2018-2010)

Given these restrictions, to maximize our sample we look at the total expenditure for labor, materials, Agricultural Services and "others" in Figure 2. Agricultural Services and Resale costs are also important for a few establishments. Notably however, there are businesses without any labor and/or any materials. Focusing on these businesses (without labor or materials), what cost item emerges? There are 435 observations that have either no labor or materials, and 42 without both. However, with a total establishment count of 9538, these are quantitatively small. In our empirical work, we would like to capture establishments which use labor and materials to produce products, instead of using establishments which rely on re-sale or outsourced agricultural services. This is in keeping with the arguments made previously regarding similarity in production processes, and the position on the supply chain. Finally, because there is no 2011 survey year, we restrict our attention to year 2012 up through 2018.

We summarize our data preparation steps here. First we calculate the total cost and revenue shares of labor and materials at the establishment level. We then filter for establishments with most of their income from sales (at least 80%), filter out establishments which do not report labor or materials costs. We then calculate PSIC-5 digit level weighted averages, using survey weights. Using weights allow us to interpret these estmates as nationally representative representative. Finally, we get the log change of our continuous variables and smooth out the labor and materials expenditure shares by calculating their averages over neighboring years. In our initial regressions below, we include the two types of shares; share of total costs and share of total revenue. We include some summary statistics for our regression variables in Table 2 below. These are all in first log differences, except for the share variables.

Table 1: Cost Structure for Agricultural Establishments

Post 2010 Cost Structure	2010 and before
COGS	Materials
Labor	Labor
Material	Industrial Service by Others
OverHead	Non-Industrial Service by Others
Industrial Service by others	ReSale
Non-Industrial Service by others	Others
Agricultural Services	
Re-Sale Goods	
General Admin Expense	
Labor	
Material	
Industrial Service by others	
Non-Industrial Service by others	
Others	
Others	

Table 2: "Five Digit PSIC Weighted Averages"

Variable	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Total Income	319	0.094	0.943	−3.509	−0.270	0.454	4.672
Sales Income	319	0.090	0.947	−3.509	−0.276	0.434	4.692
Total Labor	319	−0.021	0.738	−3.701	−0.246	0.245	3.899
Labor Share of Total Income	319	25.460	12.320	0.564	15.469	33.707	79.815
Labor Share of Sales	317	21.853	11.121	1.656	12.652	29.119	72.636
Total Labor Exp.	319	0.032	1.097	−4.597	−0.276	0.359	6.787
Materials Share of Total Income	319	36.299	17.322	0.297	23.084	47.037	81.679
Materials Share of Sales	318	35.930	17.461	0.068	23.197	46.235	90.218
Total Material Exp.	319	0.041	1.250	−5.972	−0.446	0.503	6.512
Total Capital	319	0.013	1.042	−3.389	−0.462	0.361	5.743

Note: All continous variables in log differences, except for shares.

Estimation

Based on Equation (5), we present our OLS regression results here, with heteroscedasticity robust standard errors in **Table 3**. All the variables here are deflated with the matched PPI Agricultural Index. The PPI Agriculture indices are not mapped to PSIC classifications; instead they are thematically assigned (i.e. Fisheries, Cereals, etc.). I include two definitions of inputs shares in Table 3. The first are deflated variables where we use the assigned PPI per year and total revenue share for the labor and material inputs. The second is when we use total expenditure as a share of costs for the inputs. We filter for establishments with sales as a share total income is greater than 80% on average, and for firms with a income share of each input is less than 100 and greater than zero. Furthermore, the bottom 1% and top 99% of the observed value of our regressors and dependent variable are removed prior to estimation.

In **Table 3**, we find that either specification will result in the markup estimate of greater than one and significantly different from zero. We note that cost share has a lower markup value, consistent with the results of De Loecker, Eeckhout, and Unger (2020a), which also present similar results using US data. We have two specifications, one including a scale economies parameter $\lambda - 1$, and one that assumes that $\lambda = 1$. The scale economy term of $\lambda - 1$ is insignificantly different from zero. Hence, on average, these industries' technology is consistent with constant returns to scale, but is also consistent with a slight increasing returns to scale of 4%. We shall see that a modest returns to scale is consistent with the overall results. The markup value is either $\mu = 1.39$ or $\mu = 1.34$ under these revenue share OLS results using equation (5)'s specification.

Table 3: OLS Regression, Aggregated PSIC-5

	Revenue Share		Cost Share	
	(1)	(2)	(3)	(4)
$\alpha\,(\Delta X - \Delta k)$	1.34^{***}	1.39^{***}	1.22^{***}	1.24^{***}
	(0.08)	(0.11)	(0.08)	(0.09)
Δk		0.04		0.02
		(0.06)		(0.06)
R^2	0.63	0.63	0.62	0.63
Adj. R^2	0.63	0.63	0.62	0.62
Num. obs.	319	319	319	319

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

We noted in our theoretical framework that the model can also be assessed using the levels of the inputs and assessing the corresponding elasticities of output ε_L and ε_M, as written in Equation (6). We note that this specification may be preferable because it can more flexibly estimate the elasticities of inputs as an average over PSIC-5s. We are interested in particular with the estimate of the elasticity of output with respect to material inputs because it is likely to be the most flexible input [(Dobbelaere and Mairesse 2008), (Levinsohn and Petrin 2003)] which is most consistent with our framework.

We estimate the OLS, Fixed Effects, Random Effects and First Differences models for the production function in levels without scale terms in **Table 4**. Not including the scale term imposes constant returns to scale. The pooled model has the highest coefficients for materials, the next is random effects, and then fixed effects and first differences. Staying with the pooled model estimate of 0.52, and noting that the formula for markups is $\mu = \varepsilon_M/\alpha_M$. Given the revenue share of materials is 0.363, the formula indicates that 1.43 is approximately the same as the OLS results in Table 3.

For fixed effects and first differences, the coefficients for labor and capital are also similar in magnitude.The Hausman test for fixed versus random effects has a p-value far less than 0.05 which is evidence leaning toward the consistent fixed effects coefficients over random effects. We run the same set of models, but including log capital stock in **Table 5**. With the scale economies as a free parameter, we find that the fixed effects estimates have the lowest value for materials output elasticity and has decreasing returns to scale as a point estimate, but remains consistent with constant returns to scale due to large standard errors. Compared to first differences, the coefficient on labor is smaller. We note that fixed effects estimation has a tendency to find decreasing returns to scale (Griliches and Mairesse 1995). Similar to Table 4, the null on the Hausman test is soundly rejected. Comparing these two tables, we consider the *first differences* model as the favored specification. Broadly, the coefficients we have so far are consistent with $\lambda = 1$, or modest increasing returns to scale. In the Appendix Table A1, we present the analog to Equation (6) but using the COGS based materials expenditure. Our results our similar but noisier likely because some establishments chose to input only total expenditure instead of dividing it into COGS and General Administrative Expenditure. Thus we will continue to use the total expenditure based materials expenditure.

Table 4: Panel Data Models using Equation 6, Aggregated PSIC-5

	OLS	FE	RE	First Diff
$n-k$	0.26^{***}	0.38^{***}	0.31^{***}	0.38^{***}
	(0.04)	(0.07)	(0.04)	(0.07)
$m-k$	0.52^{***}	0.39^{***}	0.48^{***}	0.39^{***}
	(0.04)	(0.10)	(0.06)	(0.06)
R^2	0.73	0.58	0.66	0.59
Adj. R^2	0.73	0.47	0.66	0.58
Num. obs.	319	319	319	319

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

The panel data models for the aggregated dataset in levels are designed to deal with unobservables in this relatively short unbalanced panel. Differencing would also eliminate the fixed unobservables in the error term. In addition to fixed effects and first differencing, another method which has been used extensively in production function estimation is the IV-General Method of Moments. In this establishment averaged panel dataset, we are concerned with endogeneity in that the factor usage is brought about by a shock unobserved by the econometrician which also affects the dependent variable directly. Our contemporaneous quasi-differenced factor $\alpha(dX - dk)$ variable or the differenced capital Δk might be biased and inconsistent. To address this, we implemented a Generalized Method of Moments (GMM) to the quasi-differenced specification in Equation (5). Panel data GMM was production function estimation context in Blundell and Bond (2000), and is widely used in panels with short time periods but many cross-sectional units.

Under the assumption that past changes in the independent variable are uncorrelated with current values of the independent variable, we can use lags of the independent variable as instru-

Table 5: Panel Regression Levels including Scale term using Equation 6, Aggregated PSIC-5

	OLS	FE	RE	First Diff
$n-k$	0.25^{***}	0.23^{*}	0.23^{**}	0.36^{***}
	(0.05)	(0.11)	(0.07)	(0.05)
$m-k$	0.52^{***}	0.39^{***}	0.47^{***}	0.37^{***}
	(0.05)	(0.09)	(0.06)	(0.03)
k	−0.01	−0.19	−0.10	−0.04
	(0.06)	(0.12)	(0.08)	(0.05)
R^2	0.73	0.60	0.66	0.61
Adj. R^2	0.73	0.49	0.66	0.61
Num. obs.	319	319	319	250

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

ments. Under a panel data implementation, GMM-instruments can be numerous. For the time t observation, it can have instruments from values $t-s \geq 0$ for all lags $s = 2, 3...t$. The number of instruments rises quickly with the number of time periods, hence the number of moment conditions to be minimized also increases

As is usual with Panel-GMM, we present post-estimation model specification checks using the Sargan-Hansen **overidentification** test for each GMM. This test tests the appropriateness of the instruments in the model by testing the alternative hypothesis that the instruments are correlated with the error term. In addition, testing for autocorrelation in the errors are also standard.

Instrument proliferation in the panel-GMM case can lead to under-rejection of the Sargan Overidentification test by overfitting the instrumented variables (Roodman 2009). A response to this concern is to cap the number of lags for the dynamic panel instruments, and to use standard instruments (or collapsing the dynamic panel instruments). The other way to limit the number of instruments is to use "collapsed" instruments, that is to deal with it as if they are normal instruments that might be used in IV application via 2SLS. In this paper's regression tables, we use collapsed instruments from lags 2 through 4. We experimented with using panel-GMM type instruments which we capped the lagged value from $(t-2)$ until $(t-3)$. The results are similar.[6].

We ran the GMM for Equation (5) with and without scale economies in **Table 6**. Both specifications have Sargan-Hansen Overidentification pvalues greater than 0.05. The estimated coefficients for the markup are appreciably smaller, however the standard errors are much larger. These estimates are consistent with a very small markup term.

In Table 7, we also estimate the model in Equation (6) via IV-GMM, with the coefficients interpreted as elasticities of output. We perform both difference and system GMM estimation, two panel data methods popularized papers like (Arellano and Bond 1991) and (Blundell and Bond

[6]We used level log values of the inputs because this specification already has the main model in differenced form. All GMM estimations use two-step method for calculating standard errors. We also experimented with capping the lag values and using Panel GMM instruments. The results are similar.

Table 6: GMM Estimates PSIC-5 Aggregation based on Equation 5

	(1)	(2)
$\alpha\,(\Delta X - \Delta k)$	1.176^{***}	0.782^{***}
	(0.313)	(0.296)
Δk		-0.064
		(0.171)
Observations	319	243
R^2		
Over-ID p-values	0.271	0.456

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

2000). The difference GMM model takes Equation (6) and gets first differences, and uses levels of past values of inputs as instruments to estimate the GMM Difference coefficients. Hence we can think of it as the instrumental variable version of the first differences model wa have already estimated. We used the lags of 2 through 4, and these includes time dummies as well. The difference GMM coefficients are the first two columns, and they are not too dissimilar to the first difference panel regression, except the standard errors are at least twice as large. This is especially true for the specification which includes the scale economies term. The magnitude of the markup term is similar, and hence our conclusion has not changed.

System GMM takes the differenced equation and adds the original level equation and estimates it as a system of equations. The level equation is instrumented by lagged differences of the endogenous variables, while the differenced equation is instrumented by lagged levels of the endogenous variables. It was was created because lagged levels of the endogenous variables may be weakly correlated to its first differences in the difference-GMM IV. Columns 3 and 4 of Table 7 present the System GMM estimates. Its estimated coefficients are larger for materials, but its still not too different from first differences or with the Difference GMM model. Unfortunately, their standard errors are quite large. Each of these models have passed the Sargan-Handen Overidentification test. Taking the results of Table 7 in its totallity, we find that the coefficient on materials output elasticity is fairly constant and that our data is consistent with a scale economies term of one, constant returns to scale, or a modest economies or diseconomies of scale.

Robustness Regressions

To investigate the robustness of our results, we restrict our PSIC-5 averages to those establishments that have been sampled for six years or more. There are establishment identifiers in the dataset, and we can tally the number of years each establishment is observed. The counts are shown in Appendix A1. Most establishments are surveyed only once, but a sizeable number are observed 6 or 7 times.

To motivate this restriction, we document characteristics of the frequently repeated observations of establishments in our sample. We look at the characteristics of firms that are observed

Table 7: GMM Panel Regression Levels based on Equation 6, Aggregated PSIC-5

	Diff	Diff	Sys	Sys
$n-k$	0.35^{**}	0.18	0.26	0.21
	(0.12)	(0.50)	(0.21)	(0.26)
$m-k$	0.36^{*}	0.20	0.31	0.32
	(0.15)	(0.12)	(0.22)	(0.22)
k		−0.19		−0.07
		(0.43)		(0.35)
n	69	69	69	69
T	6	6	6	6
Num. obs.	319	319	319	319
Num. obs. used	195	195	464	464
Sargan Test: chisq	0.99	5.21	10.23	10.51
Sargan Test: df	4.00	6.00	10.00	9.00
Sargan Test: p-value	0.91	0.52	0.42	0.31
Wald Test Coefficients: chisq	14.07	10.49	15.95	15.85
Wald Test Coefficients: df	2	3	2	3
Wald Test Coefficients: p-value	0.00	0.01	0.00	0.00
Wald Test Time Dummies: chisq	6.78	4.19	7.83	8.15
Wald Test Time Dummies: df	4	4	4	4
Wald Test Time Dummies: p-value	0.15	0.38	0.10	0.09

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

more often in **Table 8** below. We can see that firms that are observed more in the same are larger and spend more on inputs than those that are observed only once or twice. This comports with interviews at the PSA and the survey's technical notes which state that the large firms are the ones always included in the sampling frame.

Table 8: Average Real Income and Costs by Agricultural Producers (2012-2018)

Yrs5	Total Income	Total Cost	Labor Cost	Total Labor	Material Cost	Capital Book Value
Less Than 6	27,955,455	26,823,553	3,394,624	30	14,757,055	18,168,537
6 Years or More	234,091,509	238,012,641	47,082,494	240	92,214,505	248,042,343

Our first analysis of the agriculture markets is to repeat the regressions we have estimated so far for the restricted sample of 6 years and over, aggregated to the PSIC-5 level. The goal is to check if the results are unchanged as when we restrict the sample to establishments which are always present. That is, if the results are driven by the entry and exit of establishments over the sample.

Moreoever, we have documented a significant difference between PSIC-5 averages for frequently observed firms and less frequently sampled firms in their size. Aggregating to the national level (for these formal-sector firms) would require calculating the revenue share weighted markup, in the manner advised by De Loecker, Eeckhout, and Unger (2020b) where they write that aggregate markups are $\mu = \sum_i m_{i,t}\mu_{i,t}$. This revenue share weighed markup, aggregated over the entire economy, measures national level markup levels. While we cannot do that in this aggregated framework, we note that firms of 6 years or more is 10 times larger based on income and cost from Table 8. To the extent that the full sample is not too dissimilar to the restricted dataset, we can reach similar findings to the average markup at the national level.

We run the regression model regression results for this restricted sample, in **Table 9**. The data preparation is the same, except we first filter on establishments which have six or seven years in our sample before we aggregate to the PSIC-5 level. Similar patterns between Table 9 and Table 3 hold; indeed their coefficients are quite similar. The only exception is the returns to scale term which is negative; which suggests diminishing returns to scale. However, the coefficient's error is large, and is not distinguishable from zero, or constant returns to scale.

Table 9: OLS Regression based on Equation 5, Aggregated PSIC-5 sample from firms observed 6 or 7 years

	Revenue Share		Cost Share	
	(1)	(2)	(3)	(4)
$\alpha\Delta X - \Delta k$	1.35^{***}	1.24^{***}	1.27^{***}	1.17^{***}
	(0.09)	(0.16)	(0.08)	(0.14)
Δk		-0.13		-0.12
		(0.12)		(0.11)
R^2	0.66	0.67	0.68	0.69
Adj. R^2	0.66	0.67	0.68	0.68
Num. obs.	230	230	230	230

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

We further run our preferred specifications using the levels of output and inputs, estimating fixed effects, random effects and first differences for specifications that do not include and includes the free scale parameter in Tables 10 and 11. The coefficients for inputs labor and materials are similar to the estimates when the dataset includes all of the establishments. Similarly to Table 9, we have a fairly large negative coefficient, but is not significant. This likely reflects the large size of capital by these larger companies.

Estimated Mark-ups, Aggregate Profit Rates and Input Wedges

We now look at determining average markups. First, we find that the GMM estimates of Equation (5) finds that the markup is 17%, but the errors are large to as to not allow a cleaner determination of the average markup. We will rely on the model in levels in Equation (6) which allows

Table 10: Panel Data Models, Aggregated PSIC-5 over firms 6 or 7 years

	OLS	FE	RE	First Diff
$n-k$	0.27^{***}	0.42^{***}	0.33^{***}	0.43^{***}
	(0.07)	(0.11)	(0.08)	(0.10)
$m-k$	0.49^{***}	0.33^{**}	0.38^{***}	0.37^{***}
	(0.06)	(0.11)	(0.09)	(0.08)
R^2	0.68	0.53	0.57	0.57
Adj. R^2	0.68	0.43	0.57	0.57
Num. obs.	230	230	230	230

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 11: Panel Regression Levels including Scale term, Aggregated PSIC-5 for firms observed 6 or 7 years

	OLS	FE	RE	First Diff
$n-k$	0.24^{*}	0.12	0.19	0.29^{*}
	(0.10)	(0.17)	(0.11)	(0.12)
$m-k$	0.49^{***}	0.35^{***}	0.38^{***}	0.37^{***}
	(0.06)	(0.10)	(0.09)	(0.08)
k	-0.03	-0.33^{*}	-0.15	-0.20
	(0.07)	(0.15)	(0.09)	(0.12)
R^2	0.68	0.58	0.58	0.63
Adj. R^2	0.68	0.49	0.58	0.63
Num. obs.	230	230	230	230

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

us to freely determine the elasticites of output with respect to labor and materials. We argue, similar to Dobbelaere and Mairesse (2008) and other work, that materials input is likely to be the most freely determined and is therefore most likely to have the most consistent estimate of the markup. We find that the ε_M ranges from .32 (from the System GMM) to 0.37. Our estimate of the markup now depends on the average value of materials in revenue, which is 34%. The our point estimate for the markup ranges from 0.936 to 1.082.

De Loecker, Eeckhout, and Unger (2020a) argues that aggregate profit rates can be calculated by measuring the *revenue weighted* average profit rate, or $\mu = \sum_i m_{i,t}\mu_{i,t}$. They note that aggregate profit rates can be related to scale economies and markup as follows: $\Pi(Q) = \frac{PQ-TC(Q)}{PQ} = 1 - \frac{MC}{P}\frac{AC}{MC}$. This expression puts the profit rate as a function of the markup and a measure of economies of scale $\frac{AC(Q)}{MC(Q)}$ (See also Basu (2019)). In this estimation exercise, the term $\hat{\lambda}$ is our measure of economies of scale and $\hat{\mu}$ is our markup. This relation explains what accompanies high markups. When markup rates are high, this will be accompanies by either: a high profit rate, or economies of scale (AC is above MC), or both. Alternatively, a measure of markups and economies of scale should correspond to 'implied' profit rates, or $\tilde{\pi}$. In our application, we can use our measure of $\hat{\lambda}$ to include returns to scale as a factor in determining profit rates and compare the implied average profit rate from the estimation to the average profit rate in the data.

In our application using aggregated PSIC-5 industries as observations, we can calculate the average profit rate at the PSIC-5 level as $\frac{\hat{\lambda}}{\hat{\mu}}$. This term is total revenue divided by total costs, and is closely related to the above definition of the profit rate We draw the probability density function for this statistic in Figure 3 below. Included in the figure are our estimates profit rates implied from the estimated values, using $\lambda = 1$. First, we use the OLS results which has the free returns to scale in Table 3, and from the estimation in levels in Table 5. We call these *OLS Model 1* and *OLS Model 2*. Second, we use the preferred estimates using the Equation 6, in Tables 4 and 5, from the first differences results. Last, we use the GMM System estimation using the results from Table 7. We use the estimate based on materials output elasticity with the formula $\mu = \frac{\varepsilon_M}{\alpha_M}$, with the exception of OLS Model 1. The revenue weighted and simple arithmetic mean are also presented in Figure 3.

The relationship between profit rates, returns to scale and markups should be consistent, and the first difference model is the closest to revenue weighted average profit rates. We also note that increasing returns pushes estimated profit rates $\left(\frac{\hat{\lambda}}{\hat{\mu}}\right)$ closer to the measured revenue weighted profit rates. For the first difference specification, to exactly match the average seen in the data, $\hat{\lambda}$ should be 1.02, which is well within one standard deviation of $\hat{\lambda}$.

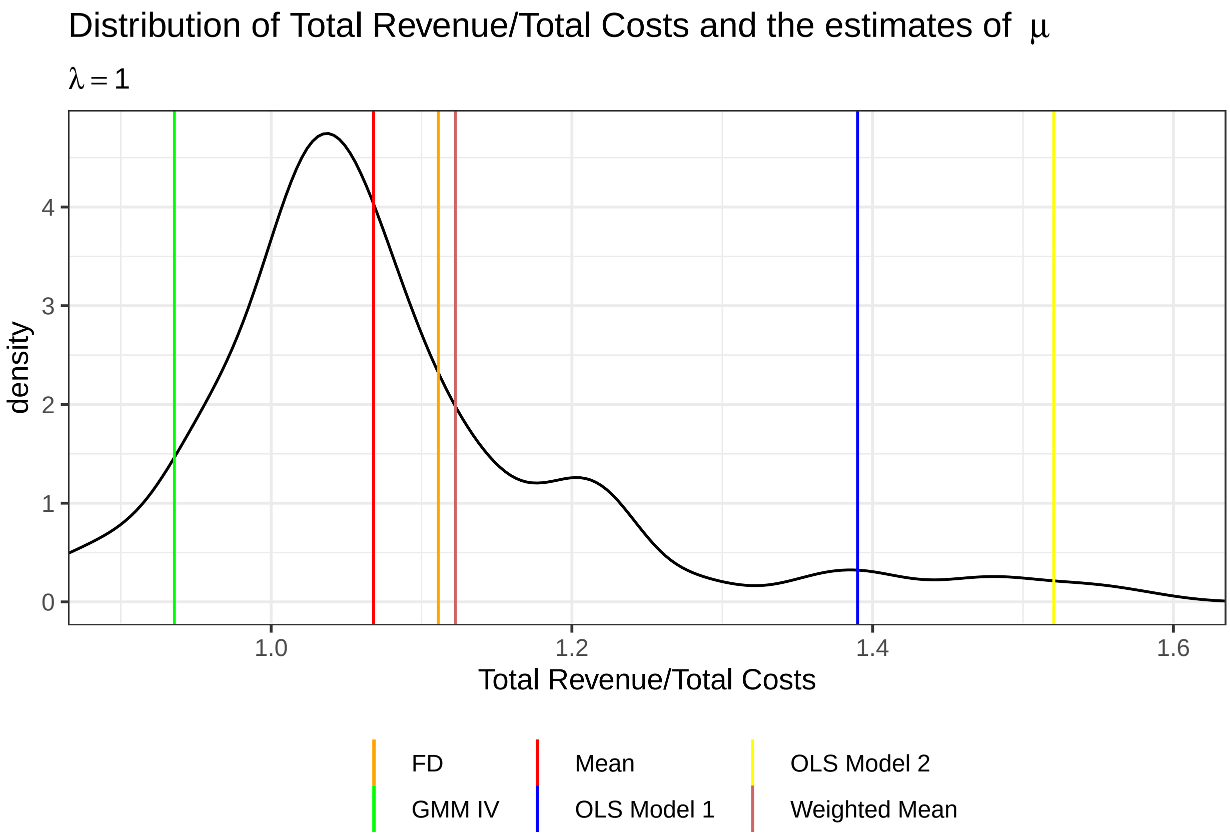

Figure 3: Profit Rate Density Function and Model Estimates

We look at the evolution of fixed costs and profits rates over time in Figure 4. Fixed costs will contribute to increasing returns to scale in the production function. We measure fixed costs as the "General Administrative Expenses" portion of total costs. The same plot features *revenue* weighted profit rates by PSIC-5. While (simple) average profit rates have been rising slightly from 1.5 to 1.10, **revenue weighted** profit rates have been falling. These two series tell us that returns to scale have been somewhat rising while revenue weighted profit rates have been falling, which shows us that that aggregate *markup* rates have not been rising as much.

We finally note that our estimation based on elasticity of output with respect to income allows us to consider the frictions based on labor against materials. Similarly to materials, we note that the wedge for labor is determined by $\frac{\varepsilon_L}{\alpha_L}$. For our preferred estimates, we have that the wedge for labor is higher than for materials because the revenue share for labor is only 25%. The ratio between the two is between $\frac{\varepsilon_L}{\alpha_L} / \frac{\varepsilon_M}{\alpha_M}$ =1.32 and $\frac{\varepsilon_L}{\alpha_L} / \frac{\varepsilon_M}{\alpha_M}$ =1.06[7]. This ratio is often related to a markdown in wages. In a model with monopsony power, this ratio will be equal to $\frac{e_L^S+1}{e_L^S}$. We can back out the elasticity of labor supply with our coefficients, which is e_L^S=3.12 on the low end and 15.7 on the high end. In the Philippine context however, its not entirely clear if this is due to monopsony power because agricultural daily wage rates are regulated. This mark-down

[7]The coefficient for labor in the sample restricted first difference regression is 0.29 while it is .37 in the full sample first difference regression.

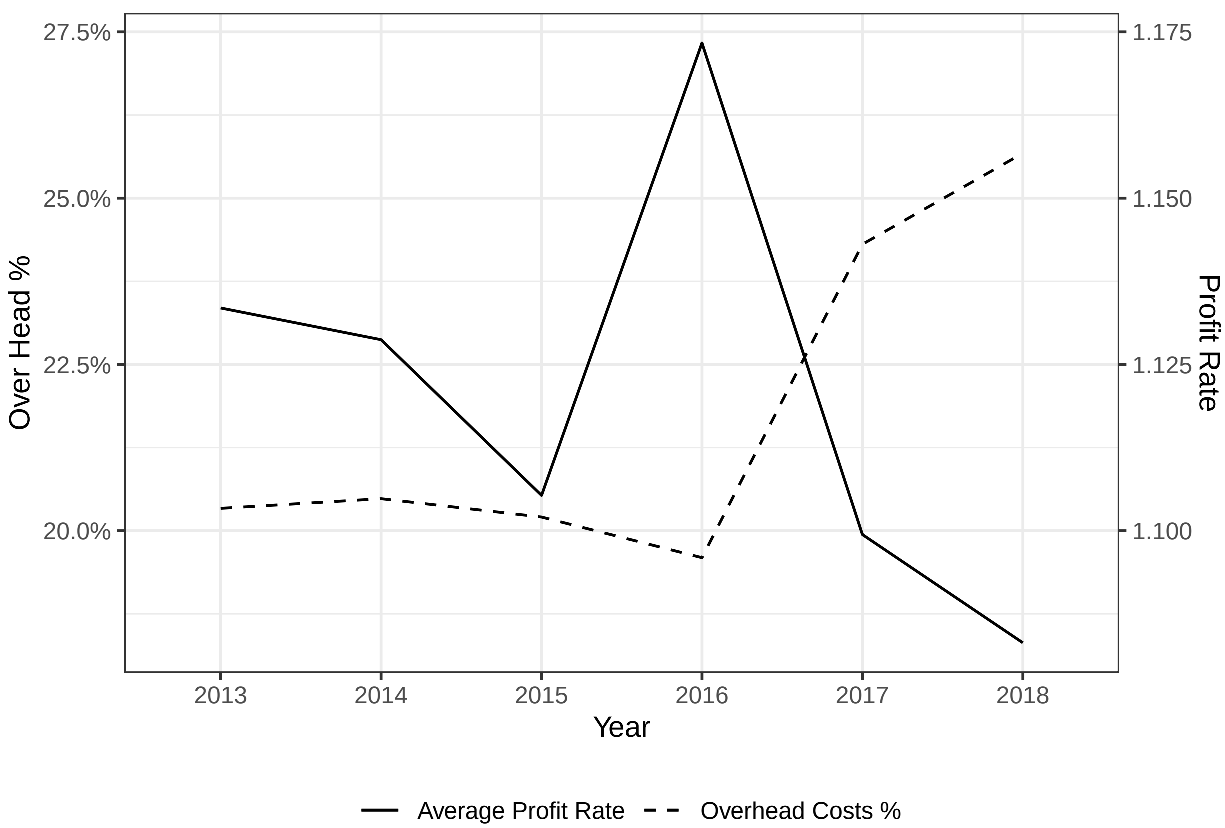

Figure 4: Profit Rates and Overhead as % of Revenue

could simply be an artifact of minimum wages. This is an fruitful avenue for future research in agricultural labor markets.

Conclusions

We collected establishment data on formal agricultural suppliers in the Philippines for a seven year period from 2012 to 2018. We use the production function method to estimate national average industry-level markups in agricultural supplier markets. Using the fact that output elasticities of flexible inputs are naturally related to mark-ups, we estimated output elasticities for labor and for materials and a returns to scale parameter. Our first differences and GMM IV estimates of output elasticities of materials have markup point estimates from ran -0.08 to +0.08 and returns to scale consistent with constant or modest returns to scale. These estimates are robust to using only establishments that appear 6 or 7 years which are also the largest agricultural suppliers. We compare these to industry level aggragated profit rates and find that these markup and returns to scale estimates are consistent with these revenue weighted average profit rates. We note that these agricultural suppliers are high up the agricultural supply chain. Measuring the share of overhead costs, as well as revenue weighted profit rates over time, we find that overhead costs share is rising while **revenue** weighted profit rates are falling. These markup rates are modest and not rising. Hence, recent concerns on market power's role in agricultural price inflation are likely to be caused by downstream establishments. Our results also point to larger distortions in the labor market, pushing real wages down. We show the utility of using the production function method in measuring markups and returns to scale to assess market power related inefficiencies in agricultural markets in the Philippines. Further work in applying these methods to other parts of the supply chain will fill in remaining gaps in our knowledge.

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Appendix

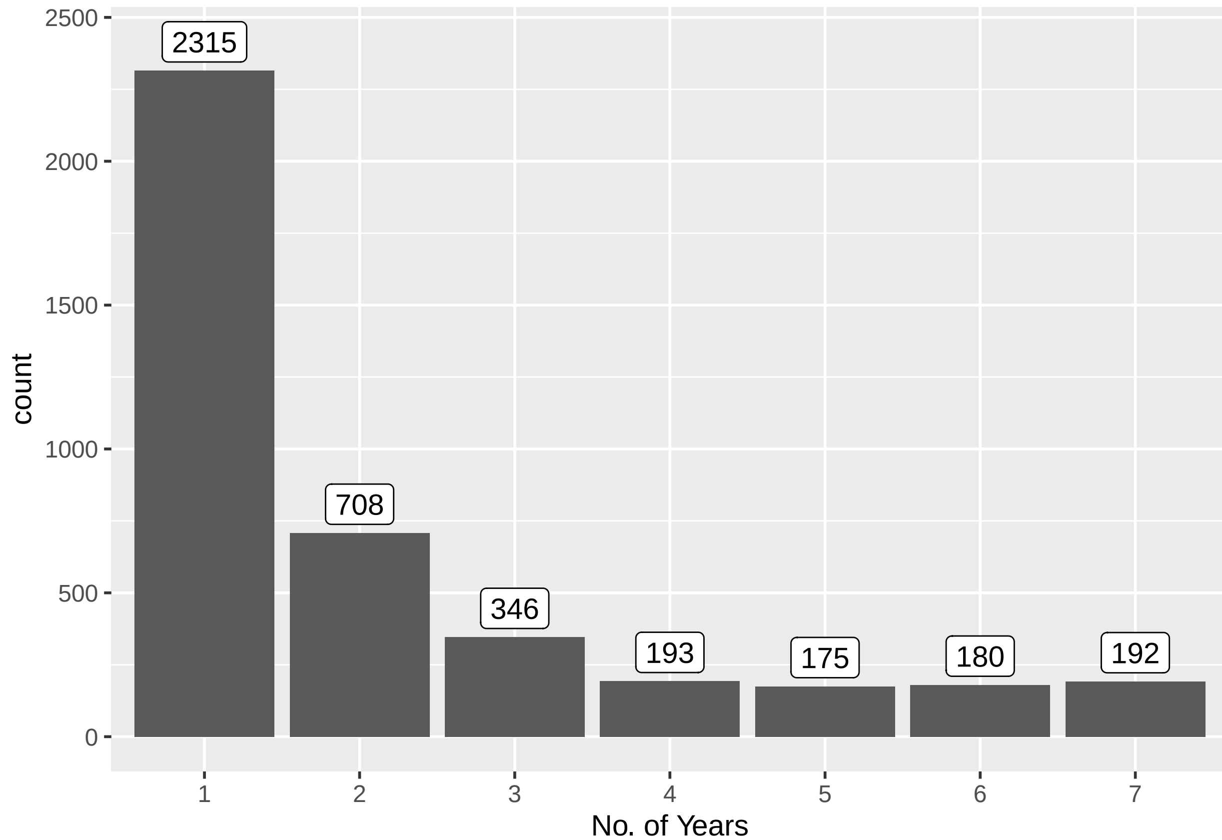

Figure A1: Count of Establishments by No. of Years

	First Diff	Fixed Effects
$n-k$	0.39^{***}	0.40^{***}
	(0.07)	(0.08)
$m-k$	0.36^{***}	0.30^{*}
	(0.06)	(0.13)
R^2	0.56	0.51
Adj. R^2	0.56	0.38
Num. obs.	318	318

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table A1: Panel Data Models, Aggregated PSIC-5 with COGS Materials Expenditure Full Sample