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TRADERS IN THE FOOD DISTRIBUTION CHAIN: ESTIMATING TRADE COSTS AND MARKUPS FROM PRICE DATA[*]

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Abstract

Out of a wide gap between price of commodity paid by final consumers and the one obtained by farmers some part is attributed to cost of transportation, and the remaining is the markup that traders keep for themselves. Previous literature can explain part of the price difference between the origin and the destination of a good using the observed components of a market, but they still leave an unexplained part of the gap open to being driven by either the trade costs or the markups. Our paper proposes a new method, which allows us to estimate trade costs and markups separately using only price data. The method explores the idea that the markups along the distribution chain of a good are shaped by the same final demand, and, therefore, respond similarly to a reduction in the price of a good at the initial point of the chain.

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1   Introduction

In developing countries, there are wide gaps between the price of food paid by consumers
and the one obtained by farmers. These gaps are attributed to two potential factors: the
high costs of trading goods and the lack of competition between traders, which allows them
to put high markups on their services. Measuring these factors correctly can be of immense
help to policymakers since each of them tends to be addressed with different investments.
However, doing so is challenging and we still have limited knowledge about their relative
importance to price gaps.

The reason why it is challenging to separately measure trade costs and markups is because
trade costs are not fully observed (see, e.g., Anderson and Wincoop (2004)).[1] If trade
costs were observed, then the portion of the price gap unexplained by trade costs could be
attributed to markups an vice versa. To measure trade costs, the current methods assume
perfect competition between traders (see, e.g., Fackler and Goodwin (2001)), which implies
that markups are equal to zero and that all the price gaps come from trade costs.

This paper proposes a method that explores the variation in price gaps *within the distri-
bution chain of a good* to recover trade costs and markups from price data. Our method is
based on two steps. First, we estimate the difference in trade costs between two segments of
a chain. To do so, we estimate how much a reduction in the price of a good at the beginning
of a chain is passed along by traders and how much they keep for themselves in the form of
markups. We use these estimates to infer the difference in the price gap between two seg-
ments of a chain that comes from differences in markups, which then allow us to attribute
the remaining difference to differences in trade costs.[2] Second, we fully recover the level
of trade costs. To do so, we combine our measure of the difference in trade costs between
segments with assumptions about trade costs between crops to fully recover the level of trade

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[1]For example, even if data on the transportation cost of a good is available, information on the insurance
paid by traders may not be.

[2]In particular, under the demand assumptions used in Atkin and Donaldson (2015), markups in different
segments of the chain are proportional to each other and price variations within the distribution chain of a
good contains information on this proportionality.

costs in each segment.

To illustrate our method, consider the case of a distribution chain with two segments, a downstream and an upstream market, which is what we use in our model. In the upstream stage, wholesale traders pay a price P_o for goods at an origin wholesale market and move them to a destination wholesale market to sell them for P_w. In the downstream stage, retail traders pay P_w and sell goods to the final consumer by P_r. As an illustrtive example, imaginge the following: one dollar decrease in P_o leads to 80 cents decrease in P_w and 70 cents decrease in P_r. Therefore, the traders at the wholesale stage get 20 cents and the ones at the retail stage get 10, with the remaining 70 cents being passed to the final customer. In this case, markups in the wholesale stage are twice the markup in the retail one.

To understand how we can recover trade costs consider the following set of equation

$$P_w - P_o = \tau_w + \mu_w, \tag{1}$$

$$P_r - P_w = \tau_r + \mu_r. \tag{2}$$

The first equation is the decomposition of the price difference between wholesale market and origin market into trade cost and traders' markups. The second equation is the same decomposition between retail and wholesale markets at the origin. τ_w and τ_r are the trade costs and μ_w and μ_r are the markups in each segment. Define $\alpha = \frac{\mu_w}{\mu_r}$. In the example above $\alpha = 2$. In the paper we show that α can be recovered using variation in the price data in much more general settings. More specificaly, it can be constructed using estimates of how a price change in the starting point of a segment pass-through to the next ones.

Once we have an estimate for α, we can combine equations (1) and (2) by multiplying equation (2) to α and subtracting equation (1) from it, which gives us

$$\alpha(P_r - P_w) - (P_w - P_o) = \alpha\tau_r - \tau_w. \tag{3}$$

This equation is the fundamental contribution of our method. Notice, that it contains

only prices, transportation costs, and the coefficient that can be estimated using prices.

Armed with equation (3), we can recover the levels of trade costs by exploring price different for other chains where the trade costs are the same. For two different commodities with two different α but the same trade costs, we can notice that τ_r and τ_w are recoverable just by solving a system of two equations with two unknowns. In our case, we extend the method to allow for different crops.

Before applying the estimator to the data we study its theoretical properties using Monte-Carlo simulations. We conclude that our estimator behaves the best if there is a significant variability in competition structure across commodities (in particular, α's are different from each other), and there is a significant degree of monopolization for both retail traders sector and wholesale traders sector. We notice that estimators behave much worse if one of the sectors is close to perfect competition.

As an application we use our method for a few selected markets in Ghana, however, for the majority of cases we were not able to reject the hypothesis of perfect competition in the retail sector in Ghana.

Our work draws from Atkin and Donaldson (2015), who develop a method to estimate the impact of distance on trade costs in the presence of imperfect competition between traders. We use two key ingredients from their model. First, the fact that the pass-through rates, which can more easily be estimated in the data, serves as a sufficient statistic for the effect of competition between traders. Second, the Bulow-Pfleidered demand structure (see (Bulow & Pfleiderer, 1983)), which provides tractable equations that we can use to treat the price differences. The key distinguishing feature of our paper is that, since they use price variation across space, they do not separately identify unobserved shocks to the demand from shocks to the trade costs. They control for these shocks by interacting fixed effects with estimates of the pass-through, which would jointly capture the effects.

This paper contributes to research in international economics measuring trade costs (Anderson & Wincoop, 2004). More recently, this literature has emphasized the importance

of the intra-national trade costs for the welfare gains from trade (Costinot & Donaldson, 2014; Ramondo, Rodriguez-Clare, & Saborio-Rodriguez, 2016; Sotelo, 2018). This literature has largely focused on the estimation of trade costs between two points in a market, the origin and the destination of a good. Here, we estimate trade costs along the distribution chain of a good. Besides the potential policy interest in decomposing the importance of trade costs in different stages of the distribution chain, we show that by focusing on variation within the distribution chain we can give a step further and recover the markups in each segment.

The remainder of this paper proceeds as following. Section 2 outlines the theoretical model. Section 3 provides methodology for it to be applied to data. In section 4 we do simulations and apply the method to the simulated data. In section 5 we provide an empirical example from markets in Ghana and section 6 concludes.

2 The Model

In this section, we first describe a version of the model with one origin and destination for a good following Atkin and Donaldson (2015) to discuss the intuition behind our identification. We then present a model of the supply distribution chain of a good where traders in each stage of the chain enjoy some market power. We describe a simple model with one good and one origin and solve for the equilibrium of this model using a generic demand function. We introduce the parametrization of the demand function to obtain the equations used to identify the trade costs, and introduce several origin and crops together with the additional assumption that we use to take the model to the data.

2.1 Intuition for identification

The contribution of our paper as well as the paper by Atkin and Donaldson (2015), is that the complex parameters can be identified from the data using only price data. This is especially important for developing countries where quantity data is usually unavailable while price

data of a very good quality is in abundance (see, for example, (Arshavskiy, Dave, & Nyarko, 2018)).

The intuition for why price data alone can be enough to identify complex parameter of competition structure can be easily seen from the following analysis (see Figure 1).
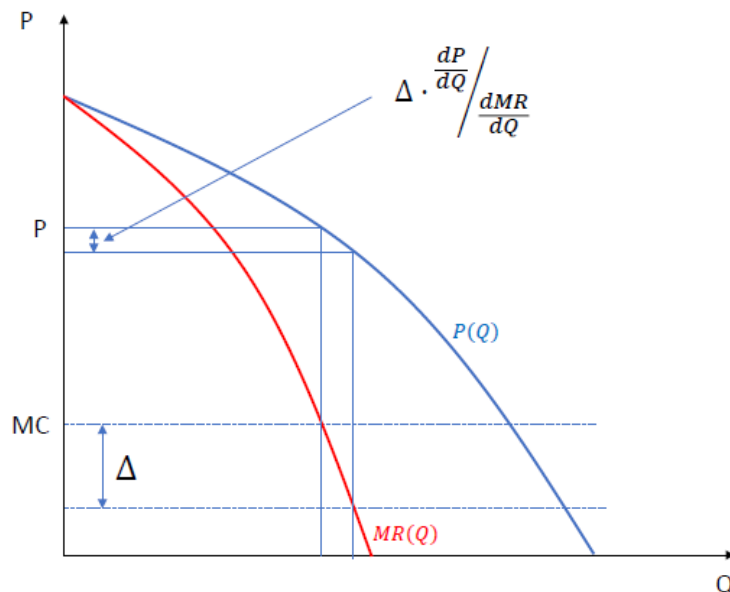
Figure 1: Simple example

Consider a standard profit-maximizing monopolist on a single market. She faces demand function $P(Q)$, and has marginal revenue $MR(Q)$. Assume marginal costs are constant and equal to MC. We are analyzing the reaction of equilibrium price to a reduction in marginal cost.

If marginal cost drops by Δ, price will go down by $\Delta \cdot \frac{\frac{dP}{dQ}}{\frac{dMR}{dQ}}$, which, with some math can be expressed as $\Delta \cdot \frac{1}{2+\epsilon}$, where $\epsilon = \frac{\frac{d^2 P}{dQ^2}}{\frac{dP}{dQ}} \cdot Q$ is the slope elasticity of demand.

Next, if we assume that the slope elasticity of demand is constant, and we know how the price reacts to a change in the marginal cost, we can compute the slope elasticity of demand.

In relation to our settings, marginal cost is a combination of origin market price and transportation cost, the reaction of the price to the change in the marginal cost close to the pass-through rate and the slope elasticity of demand contains information regarding

competition and market structure.

Consider a model as the one described in Atkin and Donaldson (2015), where the price gap between the final destination of a good at the retail market and its price at the origin can be written as

$$P_r - P_o = \tau + \mu(c, \phi, D),$$

where P_r is the price at the retail market, P_o is the price at the origin, τ is the trade cost and μ is the markup, which is a function of the marginal costs of traders c, the competitiveness environment ϕ and the demand conditions D. The change in the price gap given by a change in trade cost in this case is given by

$$
\begin{aligned}
\frac{d(P_r - P_o)}{d\tau} &= \frac{\partial \mu}{\partial c}\frac{\partial c}{\partial \tau} + \frac{\partial \mu}{\partial \phi}\frac{\partial \phi}{\partial \tau} + \frac{\partial \mu}{\partial D}\frac{\partial D}{\partial \tau} \\
&= \rho + \frac{\partial \mu}{\partial \phi}\frac{\partial \phi}{\partial \tau} + \frac{\partial \mu}{\partial D}\frac{\partial D}{\partial \tau}
\end{aligned}
$$

Here, $\rho = \frac{\partial \mu}{\partial c}$ is the pass-through rate. The equation above shows the challenges of separating trade costs from markups. When we assume perfect competition between traders. The pass-through rate is equal to 1, and the second and third term disappears, since the markups are always equal to zero. Any change in trade costs translate directly into price gaps in the data. In this case, trade costs are identified. However, under imperfect competition, one has to adresses a number of issues. First, the increase in trade costs does not translate directly into an increase in price gap. The pass-through controls this transmission of the shock on trade costs. Second, increasing trade costs can be associated with changes in the competition environment as captured by the second term on the right hand side, as well as changes in the demand. The key intuition in our identification comes from the fact that, by looking within the distribution chain of a good, we can assume that the price gap between two segments, which is associated with an increase in τ, has no effect on the demand so that the third term disappears. Also, the second term can be recovered from the data with the measures of pass-through.

Next, we present the model where we extend the current framework to include a middle stage in the distribution chain of a good, the wholesale market.

2.2 Modelling the distribution chain of a good

2.2.1 Setup

Timing. Now, we consider a distribution chain of a single product that contains two stages before reaching the final consumer. Traders in each stage of the market play an oligopolistic game with the following timing. First, there is an upstream stage where wholesale traders purchase goods at an origin city from farmers for an exogenous price P_o and transport them to the outskirts of a destination city where wholesale markets are located. Traders at this stage set their prices based on the competition with other traders and their conjectures about the demand of retail traders for goods from wholesale traders. Second, there is a downstream stage where retail traders purchase the goods from the outskirts of the destination city for P_w and take them into retail markets inside the city where final consumers are located. Retail traders set the price for final consumers P_r based on the competition with other traders and the actual aggregate demand for goods at the retail market.
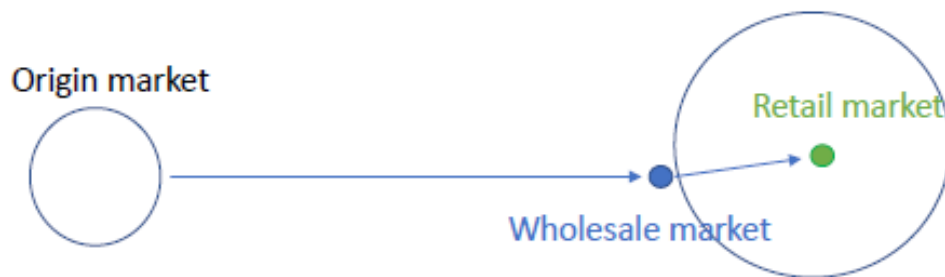

Figure 2: Supply chain

Upstream stage: the wholesale market. A commodity is produced around a single origin city. Goods are sold at a wholesale market at the outskirts of this city for price P_o per one unit. We assume P_o is exogenous. The marginal cost of transporting them to the destination wholesale market is constant and equal to τ_w per one unit. We assume that

there is an exogenous number of traders m_w in this stage. Each trader chooses quantity q_w, with total quantity being equal to Q_w, based on a relationship between the price P_w and the potential demand for their product at that price in the wholesale market at the destination that is taken as given,

$$P_w = P_w(Q_w). \tag{4}$$

The relation $P_w = P_w(Q_w)$ in (4) is interpreted as the conjectures of the wholesalers as to what is the relationship between aggregate sales and prices in the wholesale market. We construct the equilibrium so that these conjectures will be borne out.

With the assumptions above, we can define the following profit function that is maximized by farmers [3]

$$\Pi_w \equiv P_w(Q_w)q_w - (P_o + \tau_w)q_w. \tag{5}$$

The first order condition gives us

$$\frac{\partial P_w(Q_w)}{\partial Q_w} \cdot \frac{\partial Q_w}{\partial q_w} \cdot q_w + P_w(Q_w) - P_0 - \tau_w = 0. \tag{6}$$

Downstream stage: the retail market. The final consumers in the retail market have a demand function $P_r = P_r(Q_r)$, which retail traders use in their profit function. Traders in the retail market take the upstream price P_w as given. Under various market structure assumptions, we will determine the market equilibrum output Q_r at the retail stage as a function of the given upstream price P_w. Later on we will use this relationship to create the conjections of wholesalers in equation (4), which in turn will enable us to solve for the equilibrium of our two stage model.

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[3] Our results remain the same if we consider that traders have a fixed cost of F_w to operate.

Each trader chooses an output level q_r by maximizing the following profit function

$$\Pi_r \equiv P_r q_r - (\tau_r + P_w) q_r \tag{7}$$

where q_r is the quantity sold individually by the retail trader and τ_w is the marginal trade cost of taking the product from wholesale market at the outskirts of the city into the retail market inside it. From the first order conditions, we obtain

$$P_r = P_w + \tau_r - \frac{\partial P_r}{\partial Q_r} \cdot \frac{\partial Q_r}{\partial q_r} \cdot q_r.$$

Now, we assume that there are m_r identical traders and that the effect of each individual trader on total quantity Q_r is constant and equal to $\theta_r \equiv \frac{dQ_r}{dq_r}$. We also define a competitiveness index of the market as $\phi_r \equiv \frac{m_r}{\theta_r}$, where m_r is the number of traders in the market. Using these definitions, we can write the first order condition as

$$P_r = P_w + \tau_r - \frac{1}{\phi_r} \frac{\partial P_r}{\partial Q_r} Q_r \tag{8}$$

Note that equation (8) captures the effect of the marginal cost $(P_w + \tau_r)$ and a markup term $\left(-\frac{1}{\phi_r} \frac{\partial P_r}{\partial Q_r} Q_r\right)$ on the retail price P_r.

The above oligopoly model for the retail market took as fixed a value of the P_w. The solution to (8) will result in an optimal aggregate quantity in the retail stage which is a function of P_w, $Q_r = Q_r^*(P_w)$. Upon inverting we can write this as

$$P_w = P_w^*(Q_r). \tag{9}$$

2.2.2 Equilibrium

Now, we need to specify the conjectures that the wholesale traders have regarding the relationship between their quantities and the prices they receive, $P_w = P_w(Q_w)$ in equation (4). The wholesale traders upstream take as given the reaction function of traders in the retail

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market as we have just described and, in particular, take as given the relation $P_w = P_w^*(Q_r)$ in (9). Traders in the wholesale market believe that the relationship between total output in their market Q_w and the price in their market P_w is given by the equation(9) with $Q_w = Q_r$, or $P_w = P_w^*(Q_w)$.

We can now go back to the maximization problem of the wholesale traders (5)

$$\Pi_w = P_w^*(Q_w)q_w - (P_o + \tau_w)q_w.$$

The first order condition in (6) can now be written as

$$\frac{\partial P_w^*(Q_w)}{\partial Q_w} \cdot \frac{\partial Q_w}{\partial q_w} \cdot q_w + P_w^*(Q_w) - P_0 - \tau_w = 0.$$

Note here that $\frac{\partial Q_w}{\partial q_w}$ is determined by the conjectures the traders have about the response of their fellow traders to their own individual change in quantity. The expressions $P_w^*(Q_w)$ and $\frac{\partial P_w^*(Q_w)}{\partial Q_w}$ are obtained from (9) the reaction functions of traders in the retail market.

Defining $\phi_w = \frac{m_w}{\theta_w}$, recalling that $Q_w = m_w q_w$, and rearranging (6) we get:

$$P_w = P_0 + \tau_w - \frac{1}{\phi_w}\frac{\partial P_w}{\partial Q_w}Q_w \tag{10}$$

$Q_w = Q_r$ since Q_w is the total quantity that has been brought and sold to the retail traders (equation (5), revenue of the wholesale traders), and Q_r is the total quantity that has been bought by the retail traders (7). We can define $Q \equiv Q_r = Q_w$. Therefore, $P_w(Q_w) = P_w(Q_r) = P_w(Q)$ (equation (9)), and we can use Q everywhere instead of Q_w and Q_r.

Equation (10) becomes

$$P_w = P_0 + \tau_w - \frac{1}{\phi_w}\frac{\partial P_w}{\partial Q}Q, \tag{11}$$

and equation (8) becomes

$$P_r = P_w + \tau_r - \frac{1}{\phi_r} \frac{\partial P_r}{\partial Q} Q, \tag{12}$$

P_r, P_w and Q are equilibrium objects which are defined from these equations and the demand equation $P_r = P_r(Q)$. $\frac{\partial P_w}{\partial Q}$ can also be expressed from primitives using equation (8)

$$\frac{\partial P_w}{\partial Q} = \frac{\partial P_r}{\partial Q} + \frac{1}{\phi_r} \frac{\partial^2 P_r}{\partial Q^2} Q + \frac{1}{\phi_r} \frac{\partial P_r}{\partial Q} = \frac{\partial P_r}{\partial Q} \left(1 + \frac{1 + E_r(Q)}{\phi_r} \right), \tag{13}$$

where $E_r(Q) \equiv \left(\frac{\partial^2 P_r}{\partial Q^2} / \frac{\partial P_r}{\partial Q} \right) Q$ is the slope elasticity of the demand curve. Substituting $\frac{\partial P_w}{\partial Q}$ from (13) into (11) we get

$$P_w = P_0 + \tau_w - \frac{1}{\phi_w} \left(1 + \frac{1 + E_r(Q)}{\phi_r} \right) \frac{\partial P_r}{\partial Q} Q \tag{14}$$

We can also substitute P_w in (12) with the expression in (14) and get

$$P_r = P_0 + \tau_w + \tau_r - \frac{1}{\phi_w} \left(1 + \frac{1 + E_r(Q)}{\phi_r} + \frac{\phi_w}{\phi_r} \right) \frac{\partial P_r}{\partial Q} Q \tag{15}$$

Equation (15) has a very interesting economics interpretation: the final price P_r is the original price P_0 plus all marginal costs necessary to reach the final consumer $\tau_w + \tau_r$ and plus the combined markup for both oligopolistic markets.

Finally, equations (15), (14) and exogenous demand equation $P_r = P \equiv P(Q)$ define the solution to the endogenous objects P_r, P_w and Q as functions of the parameters employed by the model. With the equilibrium of the model in hand, we can now discuss the additional assumption required to identify trade costs from price data.

2.3 The case of constant slope elasticity

As was shown in the example section 2.1, the condition that allows us to connect the model and the data is a certain assumption on the demand function. The slope elasticity of the demand curve, $E_r(Q)$, should be constant. As discussed in (Atkin & Donaldson, 2015) and

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(Bulow & Pfleiderer, 1983) the demand function needs to take the following form (also called Bullow-Pfleidered demand function).

$$P(Q) = A - b(Q)^\delta \tag{16}$$

where $\delta > 0$, $A > 0$ and $b > 0$.[4]

It is easy to see that in this case we have $E_r(Q) = 1 - \delta$ and that equations (14) and (15) can be re-written as follows

$$P_w = \frac{\phi_w}{\delta + \phi_w}(P_0 + \tau_w) + \frac{\delta}{\delta + \phi_w}(A - \tau_r) \tag{17}$$

$$P_r = \frac{\phi_r}{\delta + \phi_r} \cdot \frac{\phi_w}{\delta + \phi_w} \cdot (P_0 + \tau_w + \tau_r) + \frac{\delta \cdot (\delta + \phi_r + \phi_w)}{(\delta + \phi_r)(\delta + \phi_w)} \cdot A \tag{18}$$

These equations will take an important part in the estimation of the model parameters. They, however, contain a variable that is impossible to pick from the data from only price data: the demand function parameter A. Nevertheless, we can combine the equations and get another euqation, which, will already be cleaned of A. We multiply the first equation by $\frac{\delta}{\delta + \phi_r}$ and substruct from it second equation to get the following simple expression

$$P_w - P_r - \alpha \cdot (P_r - P_w) = \tau_w - \alpha \cdot \tau_r \tag{19}$$

where $\alpha = \frac{\delta + \phi_r}{\phi_w}$.

To understand better intuition behind α we introduce the pass-through rates, i.e., the coefficients that shoow how much is passed to the wholesale and retail markets as a reaction to a price decrease at the origin.

Define $\rho_w \equiv \frac{\phi_w}{\delta + \phi_w}$ and $\rho_r \equiv \frac{\phi_r}{\delta + \phi_r} \cdot \frac{\phi_w}{\delta + \phi_w}$. Next, we conduct the following "thought

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[4]In a more general case Bullow-Pfleiderer demand has three different functional forms for $\delta > 0$, for $\delta = 0$ and for $\delta < 0$. For us, however, to be able to identify the trade costs completely, it is important that $\delta > 0$.

experiment": assume that proce at the origin, P_o, drops by 1. As a result, P_w drops by ρ_w and P_r drops by ρ_r, which is obvious from equations (17) and (18). α, expressed via pass-through rates, can be written as

$$\alpha = \frac{1 - \rho_w}{\rho_w - \rho_r} \tag{20}$$

Therefore, α is the ratio of the markup that the wholesale traders receive and the markup that the retail traders receive. The fact that we can estimate α from the price data allows us to pin down the transportation costs.

The equarions (17), (18) and (19) together with the definition of α, equation (20), are the main equations that will be used in the estimation in the sections that follow.

3   Taking the model to the data

So far, to simplify the exposition of the model, we abstracted from multiple periods (t) and crops (k). To discuss the estimation of the model, we now have to bring the subscripts associated with each of these dimensions. We also introduce some assumptions.

Assumption 1: We have at least two commodities with the same origin and destination

While the estimation of the vast majority of the parameters do not require it, we can identify and estimate transportation costs only if we have more than one commodities transported along the same route.

Assumption 2: Parameters: τ_w, τ_r, ϕ_w^k, ϕ_r^k, δ^k and A^k are fixed over time.

We can imagine that transportation costs may be changing over long periods, however, for estimation we can always pick time periods where these parameters are constant.

Assumption 3: τ_w, τ_r are the same across different commodities.

The application of this model requires us to pick commodities with similar transportation costs. Alternatively, we are only able to estimate some linear combination of τ_w and τ_r.

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Assumption 4: Demand fluctuations at the destination are independent of prices at the origin, P_0 and transportation costs τ_w and τ_r.

This is the most important assumption that allows us to consistently estimate key model parameters. Atkin and Donaldson (2015) provide some arguments why this assumption is reasonable in a similar set-up.

We esttimate the parameters in two steps.

In **step 1** we take to data equations (17) and (18). This is simple enough: for each origin and destination we take three price series: $P_{0,t}^k$, $P_{w,t}^k$ and $P_{r,t}^k$. We regress $P_{w,t}^k$ to $P_{0,t}^k$ and $P_{r,t}^k$ to $P_{0,t}^k$ for each commodity separately. We use the estimates for the next step.

In **step 2** we write equation (19) for the two commodities that we chose. Instead of $P_{0,t}^k$, $P_{w,t}^k$ and $P_{r,t}^k$ we can use average price. The estimates of α can be obtained by manipulating the estimates from step 1. The details are as follows

3.1 Step 1

In this step we conduct four regressions

Regressions (21) and (22) are for commodity 1:

$$P_{w,t}^1 = c_{11} + \rho_w^1 \cdot P_{o,t}^1 + \varepsilon_t^{11} \tag{21}$$

$$P_{r,t}^1 = c_{12} + \rho_r^1 \cdot P_{o,t}^1 + \varepsilon_t^{12} \tag{22}$$

Regressions (23) and (24) are for commodity 2:

$$P_{w,t}^2 = c_{21} + \rho_w^2 \cdot P_{o,t}^2 + \varepsilon_t^{21} \tag{23}$$

$$P_{r,t}^2 = c_{22} + \rho_r^2 \cdot P_{o,t}^2 + \varepsilon_t^{22} \tag{24}$$

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We estimate coefficients ρ_w^1, ρ_r^1, ρ_w^2 and ρ_r^2 from these regressions and then take the estimates to derive estimations of α^1 and α^2.

The estimate for α^1 is

$$\hat{\alpha}_1 = \frac{1 - \hat{\rho_w^1}}{\hat{\rho_w^1} - \hat{\rho_r^1}} \tag{25}$$

The estimate for α^2 is

$$\hat{\alpha}_2 = \frac{1 - \hat{\rho_w^2}}{\hat{\rho_w^2} - \hat{\rho_r^2}} \tag{26}$$

3.2 Step 2

In the step 2 we take equation (19) for two commodities, we use stimates for α_1 and α_2 that we derived earlier, we take average prices for origin, wholesale, and retail, and we compute transportation costs τ_w and τ_r as a solution to a system of equations

$$\bar{P}_w^1 - \bar{P}_r^1 - \hat{\alpha}_1 \cdot (\bar{P}_r^1 - \bar{P}_w^1) = \tau_w - \hat{\alpha}_1 \cdot \tau_r \tag{27}$$

$$\bar{P}_w^2 - \bar{P}_r^2 - \hat{\alpha}_2 \cdot (\bar{P}_r^2 - \bar{P}_w^2) = \tau_w - \hat{\alpha}_2 \cdot \tau_r \tag{28}$$

The solutions to these equations will be our estimates for τ_w and τ_r.

4 Simulations

To study the properties of our estimators we conducted Monte-Carlo simulations. We simulate price data for two commodities. We use arbitrary values for model parameters and we use our model to smulate price data series. Then we add a little noise and use our method in an attempt to recover the parameter values of our interest, i.e., transportation costs.

α_1	α_2	T	τ_W	$\overline{\tau_W}$	$SDEV(\tau_W)$	τ_R	$\overline{\tau_R}$	$SDEV(\tau_R)$
1.4	1.5	600	60	**73.5**	**27.4**	20	**29.0**	**18.5**
0.9	1.3	600	60	**59.0**	**5.0**	20	**19.1**	**4.6**
1.1	1.7	600	60	**59.6**	**3.5**	20	**19.7**	**2.5**
0.7	1.3	600	60	**59.8**	**2.2**	20	**19.8**	**2.2**
1.2	1.1	600	60	**73.3**	**30.8**	20	**31.9**	**26.9**
3.6	3.9	600	60	**74.2**	**21.9**	20	**23.6**	**5.8**
4.1	3.5	600	60	**71.5**	**28.0**	20	**23.3**	**7.7**
3.3	4.0	600	60	**68.6**	**25.1**	20	**22.1**	**6.5**
3.8	3.6	600	60	**76.8**	**20.4**	20	**24.6**	**5.6**
3.8	3.8	600	60	**78.4**	**23.4**	20	**24.8**	**6.1**

We conduct a number of simulations for different parameter values. In each simulation we use the following algorithm.

- We work with $K = 2$ commodities

- We define the length of the series. We use $T = 600$ time periods.

- For each commodity we randomly generate values for exogenous parameters $P_{0,t}$, ϕ_w, ϕ_r, δ, A, and also τ_w and τ_r.

- Using equilibrium equations we solve for price serieses $P_{w,t}$ and $P_{r,t}$.

- We repeat the following 10,000 times

  - We add a small noise to the prices

  - Using our method we recover ϕ_w and ϕ_r.

- We compute mean and variance of the estimates and report them

We conduct ten series of simulations each with the following parameter values. For the sake of clarity we report only the most important variables.

Given these results we can conjecture the following properties of the estimators.

- As we increase the length of the series the variance of the estimator decreases[5]

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[5]We also condicted simulations for $T = 200$

- Our estimator behaves the best when both retail and wholesale markets admit a significant degree of monopolization. In other words, if one market is close to perfect competition the variance of our estimator is very high

- If α_1 is close to α_2 the variance of the estimator is very high

We also attempted to do the simulations with more than two commodities. However, so far it is unclear how to combine the data in an efficient way.

5 Ghanaian data example

We use price data from Ghana as an example application for our theory. Our data source for agricultural prices comes from the Ministry of Food and Agriculture (MOFA). For this example we chose price data from two "polar" markets in Ghana: Bolgatanga (on the north of the country) and Accra (on the south of the country). We pick two commodities: Cowpea and Millet since it is reasonable to argue that the tranportation costs are similar. We pick data from Jan 2013 to Dec 2015.

The figure 3 shows the data for wholesale prices at the origin market (Bolgatanga) and both retail and wholesale prices at the destination market (Accra).
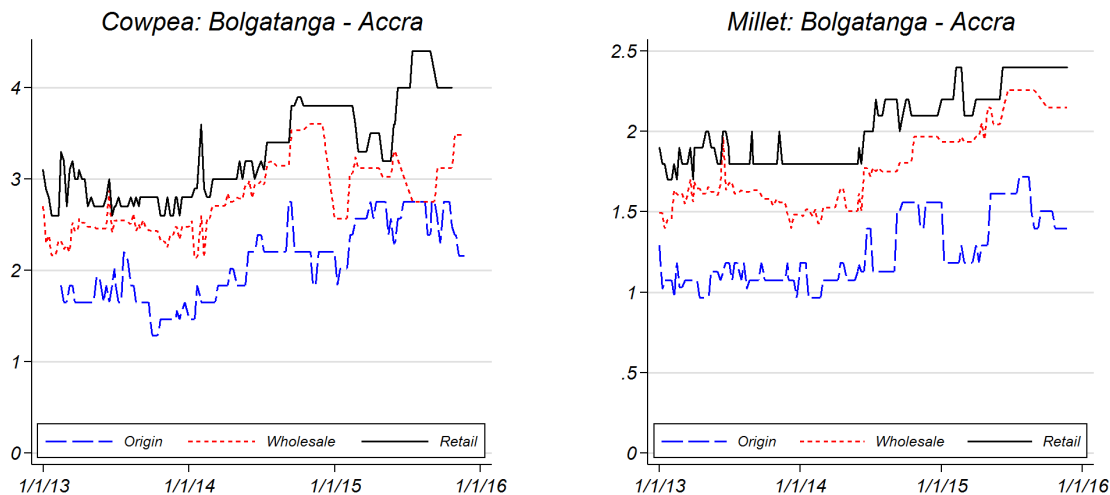
Figure 3: Price series for cowpea and millet

6 Conclusion

Historically, researchers have been estimating trade costs just by looking at price differences at different locations. These estimations assume perfect competition and are biased in the environment where traders have monopolistic power (Atkin and Donaldson (2015)). We also analyze the environment with monopolistically competitive traders and we introduce a supply chain of traders delivering goods to the final location via one or more intermediary points. We show that if the demand on the intermediate market is shaped by the demand on the final market all components of price gaps can be estimated using variations in prices.

We attempted to apply the setting to agricultural markets in Ghana where good price data is available for both wholesale and retail markets and the wholesale market represents the intermediate market where the demand is shaped by the same final demand as in the retail market.

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