ESTIMATING PRICING RIGIDITIES IN BILATERAL TRANSACTIONS MARKETS

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Many price indices are constructed using bilateral transaction prices. This paper shows how the time series behavior of cross-sectional price moments can reveal useful information about pricing behavior in bilateral transactions markets. Inference is formalized in a microlevel price determination model that allows for rigid pricing at the level of individual buyer/seller transactions as well as asymmetries in bargaining power. The model is used to estimate pricing rigidities in Norwegian salmon export transactions. Results suggest a high rate of price revisions and an informative salmon price index. The moments suggest price revisions are conducted at fixed time intervals consistent with optimal price revisions under costly information and that price revisions are more likely when transaction prices are below the reference price in the market.

Key words: Commodity prices, efficiency, indices, price adjustment, pricing rigidity.

JEL codes: C55, D40, Q13, Q14, Q17.

For many food commodities, transactions occur bilaterally, and there can be costs associated with price adjustments that create rigid prices. However, trade partners can often obtain information about the general price level by observing price indices constructed from sampled transaction prices. Examples include indices such as the FAO food price indices,[1] World Bank commodity price indices,[2] transportation cost indices such as the Baltic Dry Index, as well as various unit value measures computed from export or import data. The prices these indices are based on will necessarily not fully reflect market conditions at the time of reporting. If prices are from contracts in which pricing terms are infrequently updated, the price index will not reflect fully up to date market information. Because detailed contract terms in bilateral transactions are private information not available to price reporting agencies, this adds to uncertainty about the informational content of reported price indices.

This paper shows how the relationship between cross-sectional price moments—the mean, standard deviation, skewness, and kurtosis of transactions prices—can reveal useful information about pricing rigidity in the market. This includes information about the dominant type of price revision in the market (e.g. fixed intervals, deviations from a reference price), whether there are asymmetries in revisions, suggesting asymmetric bargaining power, and the rate at which prices are revised. The inference is formalized in a microlevel statistical price determination model that incorporates rigid pricing at the level of individual buyer/seller relationships.

It is well known that costs associated with revision of prices can lead to rigid pricing (Alvarez, Lippi, and Paciello 2011). Figure 2

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[1]http://www.fao.org/worldfoodsituation/foodpricesindex/en/
[2]http://www.worldbank.org/en/research/commodity-markets

below illustrates how the price distribution shifts under different levels of pricing rigidity. The more often the trade partners revise their prices, the more consistently the entire price distribution shifts with the arrival of new information. In the limit of full efficiency, the entire distribution shifts, and the dispersion and skewness of the distribution will be unrelated to the first moment, mean, of the distribution. As the market moves away from full efficiency, some mass of the distribution will be sticky and unresponsive to new information. With the arrival of new information, the distribution will then stretch and dispersion increase. Furthermore, if the skewness is negatively related to the first moment, this tells us that much of the distribution shifts with the new information, implying high but not fully efficient pricing. If skewness is positively related to the first moment, much of the price distribution is unresponsive to the flow of new information, and pricing efficiency can be classified as low. Furthermore, if price dispersion is correlated with the first moment, price revision rates differ conditional on price levels, implying asymmetry in revisions and potential bargaining power.

Information on pricing rigidity is relevant for assessing the representativeness of price indices constructed from transaction prices. Rigidness creates a conditional mean bias in the index because the data used to construct the index contain prices that have not been revised according to the newest market information. This index will underestimate positive news (price increasing news) and overestimate negative news (price decreasing news). Moreover, because price dispersion increases with the magnitude of common shocks, the representativeness of the index will decline exactly when the market experiences a significant flow of new information. Fewer firms will then find the index representative of their transactions. The moments can also reveal asymmetry in bargaining power in the market, which implies an unconditional mean bias in the price index. For instance, sellers will in general want to revise prices when their transactions are traded at prices lower than the reference price. If sellers systematically have greater bargaining power in price revisions, there is higher pricing rigidity with price decreasing news. We will observe higher price dispersion at lower price levels, and so a negative correlation between the first and second moment of the price distribution.

To illustrate the use of the model, we estimate it using the moments of the population of export transaction priced for Norwegian farmed salmon. The institutions of trade for salmon are well developed, with publicly available aggregate price and market data, a futures exchange, and a relatively stable and predictable regulatory regime (Asche, Oglend, and Zhang 2015; Asche, Misund, and Oglend 2019). Still, despite being a highly traded product (Oglend and Straume 2019), trade in salmon primarily takes place through private bilateral transactions because of heterogeneity in product quality and a high degree of perishability. This makes salmon a good case for our model, as it makes the specific trade relationships important and limits the usefulness of formal exchanges. This form of transaction is not unique to salmon and remains common in international trade for goods that are not homogenous storable commodities, and includes most meats, seafood, fruits, and vegetables. We evaluate two mechanisms for price revisions in the market: (*a*) updating the price according to price deviations from an observable reference price, and (*b*) updating at fixed time intervals (fixed probability of updating at individual levels), and we discuss results and implications of the estimated models. We also investigate asymmetric versions of these signals to reveal potential asymmetric bargaining power.

The study of commodity pricing efficiency, understood here as how prices update to reflect the flow of new information, has a long history. The seminal Enke-Samuelson-Judge-Takayama (ESTJ) spatial competitive equilibrium model (Enke 1951; Samuelson 1952; Takayama and Judge 1964) provided an early formalization of spatial price equalization. With the development of cointegration analysis and more robust statistical time series methods, a substantial empirical literature has investigated market integration and the Law of One price using aggregate price data (i.e. country level prices, aggregate product prices). Some examples include Ardeni (1989), Asche, Bremnes, and Wessells (1999), Baffes (1991), Fackler and Tastan (2008), Gobillon and Wolff 2015, Gonzalez-Rivera and Helfand (2001), McChesney, Shughart, and Haddock (2004), Bachmeier and Griffin (2006) and Li, Joyeux, and Ripple (2014). Many of these price analyses rely on price aggregates, that is, the first moment of the price distribution.

In this paper, we contribute to the literature on pricing rigidities by using the cross-

sectional moments of transaction prices to infer the type and rate of pricing rigidity in the market. Parity bounds models (Baulch 1997; Barrett and Li 2002; Negassa and Myers 2007) use transfer prices to differentiate equilibrium parity pricing (within cost bounds) from constrained pricing. Party bounds models have been applied to investigate pricing efficiencies in among other urea markets (Hu and Brorsen 2017) and the impact of tariffs on trade (Hillen 2019). Fackler and Tastan (2008) also develop a price determination model based on different regimes of pricing efficiency. Our paper contributes to this literature by investigating pricing efficiency at the level of individual trade relationships.

The use of firm level transactions prices connects our paper to the literature on buyer/seller transaction prices under imperfect information. Heise (2016) uses transaction-level U.S. import data to study the responsiveness of trade prices to changes in exchange rates. He finds a relative low exchange rate pass through, suggesting a relative high degree of individual level pricing rigidity. Allen (2014) uses transactions level prices to show that for trade in grains in the Philippines, roughly half of the observed regional price dispersion is due to frictions related to limited information. Several studies have also shown how access to better market information reduces pricing inefficiencies (Portes and Rey 2005; Jensen 2007; Aker 2010; Guillotreau and Jiménez-Toribio 2011). Dickstein and Morales (2018) highlight the important role of informational frictions in international trade, finding that individual traders have different degree of information about foreign markets and trade profitability. Imperfect information leads to pricing rigidities when acquiring information is costly. We show how this behavior can be modeled by the price revision signal and how it affects the time series behavior of the price moments.

The decision to revise prices depends on fixed costs (menu costs) and costly information (search costs). Although our model is a reduced form statistical model, we show how the implications of this can modeled through the specified price revision signal. Alvarez, Lippi, and Paciello (2011) show that with costly information it is optimal to revise prices at fixed time intervals, whereas with menu costs it is optimal to revise prices if they deviate from a given price bound. With fixed costs of revision there is a real option consideration

of revising prices that becomes more important as the volatility of fundamentals increases (Richards, Gómez, and Printezis 2016). Fixed prices have also been shown to be consistent with strategic behavior to facilitate tacit collusion at retail levels (Richards and Patterson 2005). Nakamura and Steinsson (2008) document a 10% median frequency of price changes per month for finished goods producers in the U.S. Our model can evaluate statistically whether revising prices with a fixed probability, consistent with optimal pricing under informational costs, or updating conditional on price deviations, consistent with menu costs, best fits the behavior of price moments.

Because our model only uses transaction price data, deeper inference on causes of pricing rigidities beyond what is revealed by the price moments is not delivered by our model. We investigate prices in a setting with many trade relationships, focusing on the distribution of prices. We do not explicitly consider the role of strategic behavior among either buyers or sellers as is done for instance in the retail pricing literature (i.e. Richards and Patterson 2005). However, we do show how asymmetric bargaining power enters the model through the price revision signal and how moments can be informative on asymmetric bargaining power in the market.

In the next section, we present the price determination model and its interpretation. We look at individual price properties, how the individual prices aggregate to determine properties of the cross-sectional price distribution, and how the moments are informative on pricing behavior. The subsequent section discusses the estimation of the model using a simulated moments approach. The model is then estimated on Norwegian salmon exports data, and estimation results and implications are discussed before we offer some concluding remarks.

Model

Our starting point is a set of N bilateral trade relationships for the exchange of a product. Denote by p_{it} the (log) transaction price in relationship i at time t. Associated with each trade relationship is a price revision signal $x_{it} \geq 0$. The transaction price for relationship i at time t is revised if $x_{it} > \tau_i$, were τ_i is a relationship specific transaction cost. The signal x_{it}

models the price revision mechanism. For instance, the signal $x_{it} = \max_j |p_{jt} - p_{it}|$ aligns price revisions to conventional full information no-arbitrage pricing. This signal is then a (gross) full information arbitrage signal, and the transaction cost τ_i reflects arbitrage costs. Competitive pressure will bound all prices, leading to the ESTJ bound, $x_{it} \leq \tau_i$ for all i.

In a large N market the full information signal is infeasible as it requires knowledge of all transaction prices. A more feasible limited information signal is $x_{it} = |c_t - p_{it}|$, where c_t is some observed reference price. Here, prices are revised if the current transaction price deviates sufficiently from the reference price. Updating based on deviations from a price bound is consistent with pricing under menu costs (Alvarez, Lippi, and Paciello 2011) and real option considerations (Richards, Gómez, and Printezis 2016). On the other hand, in markets with costly information prices are optimally revised at fixed time intervals. To model this, the updating signal is expressed as a latent Gaussian signal $x_{it} = |z_{it}|\sigma_x$, where $z_{it} \sim N(0, 1)$. In the empirical section below, we evaluate both theses limited information signals.

The (log) reference price c_t in the market might be an index price or some approximation of an efficient full information price in the sense of Fama (1991) and Malkiel and Fama (1970). The role of the reference price is to guide price revisions and is necessary to specify a complete statistical model. Let $t = 0$ denote the first trade period, and T the last trade period of a trade relationship i. We model the transaction price at time $T \geq t > 0$ as

$$(1a) \quad p_{it} = c_t + \epsilon_{it}^c \text{ if } x_{it-1} > \tau_i, \epsilon_{it}^c \sim N\left(0, \sigma_{ic}^2\right)$$
(revise price)

$$(1b) \quad p_{it} = p_{it-1} + \epsilon_{it}^p \text{ if } x_{it-1} \leq \tau_i, \epsilon_{it}^p \sim N\left(0, \sigma_{ip}^2\right).$$
(maintain price)

Revised prices are assumed centered around the refence price c_t, whereas maintained prices are centered around the last period price. Deviations from the reference price, ϵ_{it}^c, and previous period price, ϵ_{it}^p, are treated as uncorrelated Gaussian pricing errors.

The model accommodates several empirically relevant pricing policies. For instance, if $x_{it} > \tau_i$ and $\sigma_{ic}^2 = 0$ for all t, pricing is fully efficient and equals the reference price c_t at all

times. When $\sigma_{ic}^2 > 0$ the price can deviate from the reference price, for instance due to commodity heterogeneity. If $x_{it} \leq \tau_i$ for all t, pricing is uncorrelated with the reference price. If $\sigma_{ip}^2 = 0$, the price is fixed between revision periods.

The model makes the simplifying assumption that transactions take place every period. Implicitly a trade relationship is then understood as a sequence of consecutive trades such that a price is available each period. Relationships with infrequent trade are treated as separate trade relationships. Ultimately if $T = 1$ (one trade period), the relationship is a spot trade relationship. The transaction cost, which together with the price revision signal determines the rate of price revisions, might map to economically relevant characteristics of each trade relationship that influences the rate of price revisions. This might include common language, culture, distance to market, or history of trade. For instance, a trade relationship that has a history of frequent transactions might allow for lower pricing rigidities, as suggested by Heise (2016). In our statistical model such characteristics are treated as unobserved heterogeneity absorbed by the private revision signal and transaction cost.

It can be convenient to write the model in error-correction form. For $(T - 1) \geq t > 0$, the price dynamics can be stated as,

$$(2a) \quad \Delta p_{it+1} = \omega_{it}\Delta c_{t+1} + \omega_{it}(c_t - p_{it}) + u_{it+1},$$

$$(2b) \quad u_{it+1} = (1 - \omega_{it})\epsilon_{it+1}^p + \omega_{it}\epsilon_{it+1}^c,$$

where $\omega_{it} = 1$ if $x_{it} > \tau_i$, and zero otherwise. In this formulation, rigid pricing occurs as ω_{it} switches between zero (maintain price) and one (revise price). With fully efficient pricing, $\omega_{it} = 1$ for all t, the individual price is normally distributed around the reference price. This will occur at zero transaction cost given that the revision signal is not degenerate. Statistically, the model is a regime-switching error-correction model with error-correction present in the revision state.

Individual Price Properties

The spread between the individual price p_{it} and the reference price in an open ended contract (T infinite) is globally stationary as long as (a) the updating signal x_{it} has a stationary density, and (b) there is a non-zero probability of a price revision ($E(\omega_{it}) > 0$), where

expectations are taken over the stationary density of the updating signal. Formal details can be found in the online supplementary appendix.

Global stationarity is not enough for the individual price to be an unbiased measure of the reference price. In the online supplementary appendix, we show that sufficiency requires that the signal x_{it} is uncorrelated with the reference price and pricing errors. In words, the decision to revise prices cannot be correlated with the history of the reference price and/or pricing errors (which then includes the history of the transaction price).

If price revisions are more likely to occur when the reference price is high, for instance due to greater seller bargaining power, this will raise the average transaction price. The unconditional mean transaction price will then exceed the unconditional mean reference price. There will be an asymmetric rate of price revision giving the effect that the price will go up more easily than down, as investigated in the price asymmetry literature.[3] As shown in Richards, Gómez, and Lee (2014), asymmetry in price adjustments might also occur if any one side of the transaction more intensively searches out new pricing relevant information in response to rising or declining reference prices. Asymmetry can be evaluated empirically by formulating price revision signals that depend on price levels. We will explore this in the next section.

When the updating signal has a stationary density, the unconditional variance of the transaction price can be written as,

$$var(p_{it}) = \left(\sigma_c^2 + E(c_t)^2 + \sigma_{ic}^2\right) + \left(E(\omega_{it})^{-1} - 1\right)\sigma_{ip}^2 - \frac{E(\omega_{it})E(c_t)^2}{2 - E(\omega_{it})},$$

where $E(c_t)$ and σ_c^2 is the unconditional mean and variance of the reference price. See the online supplementary appendix for more details on this expression. Fully efficient pricing, $E(\omega_{it}) = 1$, equates the transaction price variance to the reference price variance plus pricing error, that is, $\sigma_c^2 + \sigma_{ic}^2$. In the open-ended contract, price variance will increase as rigidness, a lower $E(\omega_{it})$, increases.

Aggregate Price Moments

We proceed to investigate the implications of the model for the shape of the cross-sectional price distribution. For ease of presentation we drop time subscripts and assume the reference price is given; that is, we focus on the distribution of prices around the reference price. We address the following question: *given a cross-section of prices $\{p_i\}$ and revisions $\{\omega_i\}$, what are the next period moments of the cross-sectional price distribution?* We focus on the first four conditional moments,

$$(3) \quad m_1 = \sum_{i=1}^{N} E(p_i'),$$

$$m_n = \sum_{i=1}^{N} E(p_i' - m_1)^n, \text{ for } 4 \geq n > 1,$$

where p_i' denotes next period price. Let μ_c^n be the *nth*-moment of revised prices, μ_p^n the *nth*-moment of maintained prices, and $\bar{\omega}$ be the share of prices that are revised. To simplify the notation, we assume homogenous individual pricing error variances, $\sigma_{ip}^2 = \sigma_{\varepsilon^p}^2$ and $\sigma_{ic}^2 = \sigma_{\varepsilon^c}^2$, for all i. With this, the first four conditional forward moments are,

$$(4a) \quad m_1 = (1 - \bar{\omega})\mu_p^1 + \bar{\omega}\mu_c^1,$$

$$(4b) \quad m_2 = (1 - \bar{\omega})\left(\sigma_{\varepsilon^p}^2 + \mu_p^2\right) + \bar{\omega}\left(\sigma_{\varepsilon^c}^2 + \mu_c^2\right),$$

$$(4c) \quad m_3 = (1 - \bar{\omega})\left(3\sigma_{\varepsilon^p}^2\left(\mu_p^1 - m_1\right) + \mu_p^3\right) + \bar{\omega}\left(3\sigma_{\varepsilon^c}^2\left(\mu_c^1 - m_1\right) + \mu_c^3\right),$$

$$(4d) \quad m_4 = (1 - \bar{\omega})\left(\mu_p^4 + 6\sigma_{\varepsilon^p}^2\mu_p^2 + 3\sigma_{\varepsilon^p}^4\right) + \bar{\omega}\left(\mu_c^4 + 6\sigma_{\varepsilon^c}^2\mu_c^2 + 3\sigma_{\varepsilon^c}^4\right),$$

From (4a) we see that the conditional mean will have a bias equal to, $m_1 - \mu_c^1 = (1 - \bar{\omega})\left(\mu_p^1 - \mu_c^1\right)$. Because $1 - \bar{\omega} \geq 0$, the conditional mean will underestimate the reference price when the reference price increases, $\mu_p^1 - \mu_c^1 < 0$. Specifically, a 1% increase in the reference price is associated with a $\bar{\omega}$ percent increase in the cross-sectional mean price. The conditional mean price will contain a mixture of new and old market information. Equation (4a) reflects this weighted average. The top left panel of figure 1 shows an example of the relationship between mean bias and the reference price. The blue line is

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[3]Meyer and von Cramon-Taubadel (2004) provides a review of this literature.
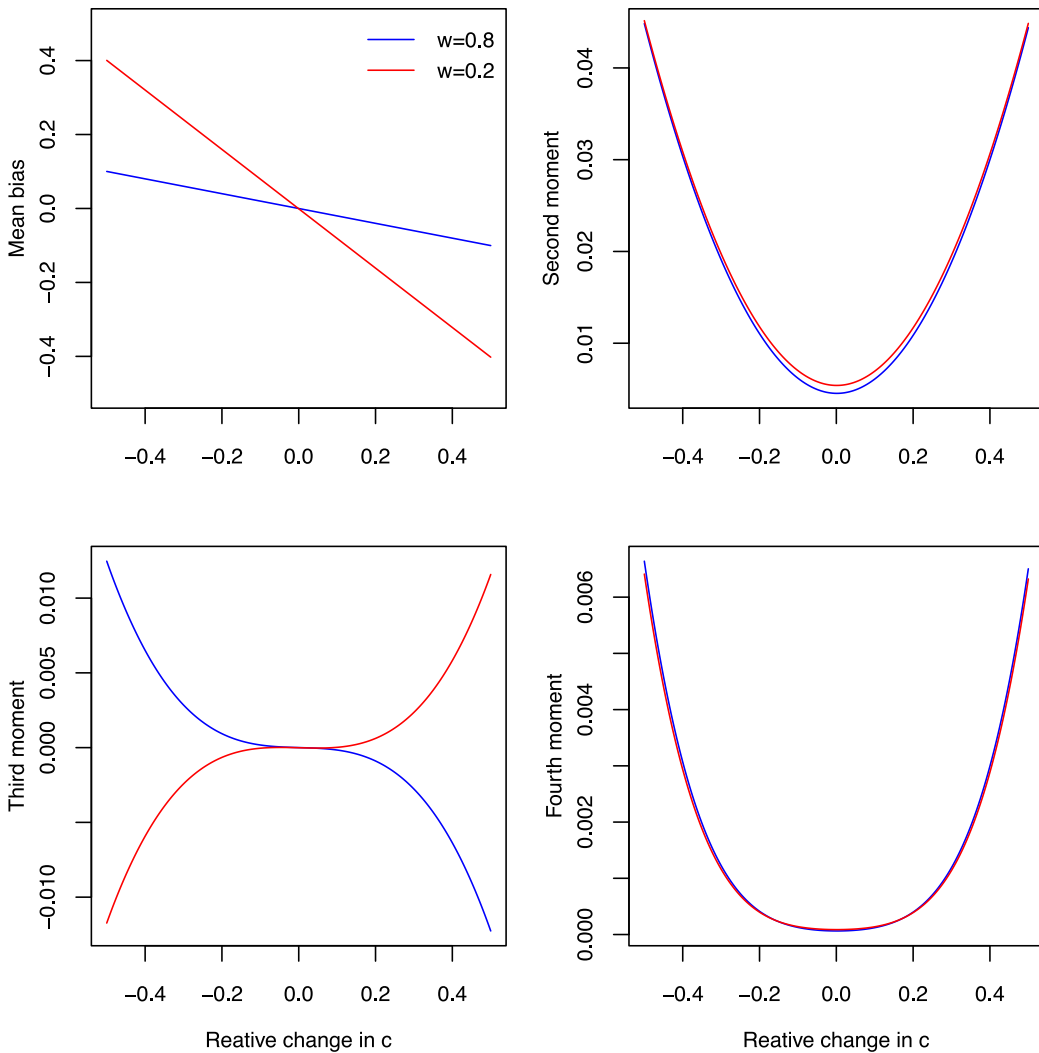
Figure 1. Moments of cross-sectional trade price distribution as a function of relative change in the full information price

Notes: For red lines $\bar{\omega} = 0.2$, for blue lines $\bar{\omega} = 0.8$. All models have $\sigma_{\varepsilon^p} = 0.075, \sigma_{\varepsilon^c} = 0.065$. Gaussian updating signal used such that a fixed percentage of prices update each period.

an example market with a high rate of price revision (80% of prices are revised every period), whereas the red line is a market with a low rate of revisions (20% of prices are revised every period). An increase (decrease) in the reference price is associated with a negative (positive) mean bias. The bias shrinks as pricing becomes less rigid, more efficient.

Price dispersion in (4b) is a convex function of the mean bias. Formally, $\frac{dm_2}{d\mu_c} = -2\bar{\omega}(m_1 - \mu_c^1)$ such that $\frac{d^2 m_2}{d^2 \mu_c} > 0$. An example is shown in the top right panel of figure 2. Dispersion is minimized when the mean bias is zero. A large

common shock (large change to the reference price) increases the mean bias and price dispersion, whereas more quiet market conditions will generally reduce the mean bias and dispersion as the more rigid contracts catch up to the reference price. Consequently, the representativeness of a price index measure will decline when the market is subject to large common shocks.

Although dispersion is positively related to the magnitude of the mean bias, the sign of the relationship between the third moment (skewness) and mean bias will depend on the rate of price revision in the market, $\bar{\omega}$. As
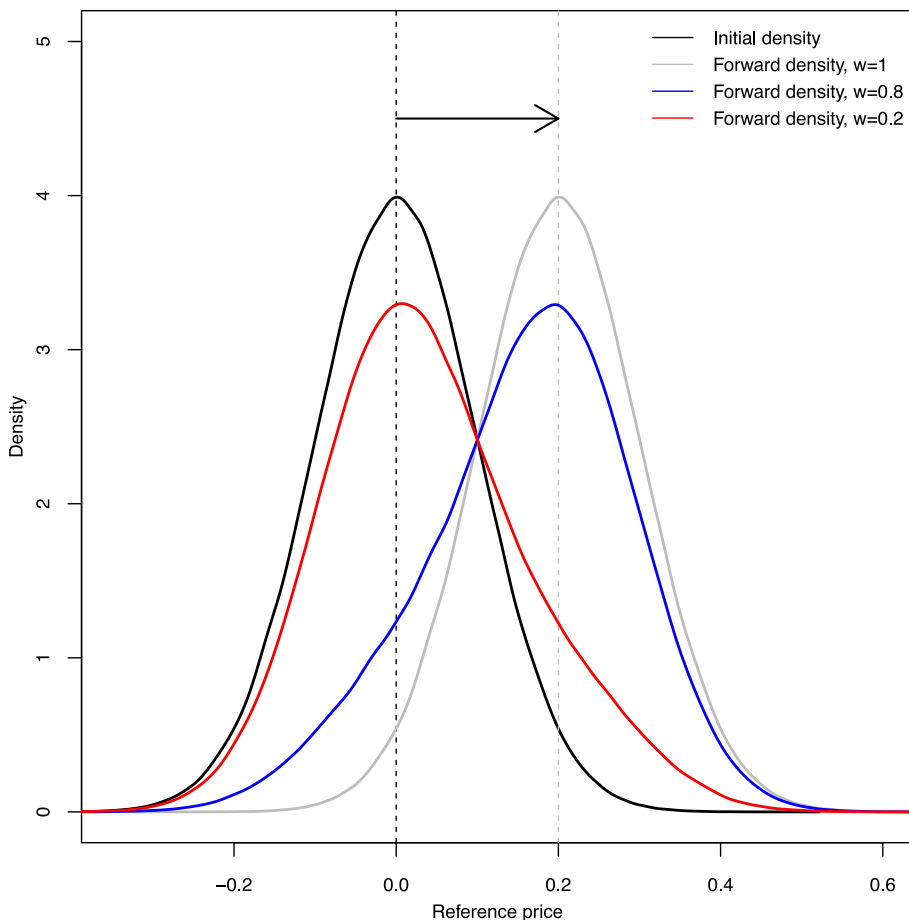
Figure 2. Effects of change in full information price on cross-sectional trade price distribution

Notes: Example has $\sigma_{e^p} = 0.1, \sigma_{e^c} = 0.1$. Gaussian updating signal used such that a fixed percentage of prices update each period.

the rate of revision increases, more of the density of the distribution will move in the same direction as the reference price. However, because not all prices revise, the movement of the distribution is not uniform. With $\bar{\omega}$ sufficiently high the distribution will become negatively (positively) skewed following an increase (decrease) in the reference price. On the other hand, when rigidness increases, the opposite occurs and a change in the reference price will shift a smaller density mass of the distribution. When $\bar{\omega}$ becomes sufficiently small, skewness and the reference price will move in the same direction. The exact thresholds by which this qualitative shift occurs will depend on model parameters (see 4c). This relationship is highlighted in the bottom left panel of figure 1. Skewness is informative on the overall *rate* of rigid pricing in the market.

The fourth moment behaves similarly to the second moment and contains no significant

new information. This is shown in the bottom right panel of figure 1.

Figure 2 exemplifies different shifts in the price distributions following a 20% increase in the market reference price. The initial distribution is Gaussian (black line). The gray line shows a uniform shift in the entire distribution when all prices are revised, full efficiency. This preserves the shape of the distribution. The blue line shows the shift when 80% of prices are revised. The prices that do not update cluster around the initial price levels, which becomes the left tail of the new distribution, creating negative skewness. With only 20% revisions (red line), the maintained prices dominate and define the mode of the distribution. The reference price change now leads to an increase in the right tail of the distribution only, creating positive skewness.

Figure 2 suggests an additional feature of the distribution relevant to the rate of rigid

pricing in the market. With a sufficiently high rate of revision, the efficient trade relationships will sort around the mode of the price distribution, whereas rigid relationships sort to the tails. The opposite will occur in a market with a low rate of revision. This sorting to the tails behavior will be explored empirically below where we use regression models to estimate reduced form conditional revision rates conditional on which percentile of the price distribution the individual trade relationship price is located.

The online supplementary appendix shows a case of how pricing rigidities affect price analysis using indices of rigid transaction prices. OLS estimates of price convergence between two separate index prices in the same market will in general be biased due to the differences in variance of transaction prices when price revisions are heterogenous across trade relationships. Specifically, when more rigid prices are more volatile, price convergence will be underestimated as the OLS estimator over weights inefficient price relationships.

Finally, it is worth noting the effects of unequal bargaining power on the aggregate moments. Asymmetric bargaining power is defined as a non-zero correlation between the price revision signal and price levels. As such, with asymmetric bargaining power the revision rate will vary conditional on the price level. For instance, if the seller has higher relative bargaining power, a reference price increase (leading to a low relative transaction price) will have a higher probability of revision than a reference price decline (leading to a high relative transaction price). When the revision signal is symmetric, the standard deviation of the price distribution is symmetric in the mean bias (or first moment), as is the case for the example in figure 1 (top right panel). However, with asymmetric bargaining power, price dispersion might be positively related to the mean bias (prices revise more aggressively when transaction prices are low relative to the reference price) or negatively related to the mean bias (prices revise more aggressively when transaction price are high relative to the reference price).

Estimation

To estimate the model, we utilize the mapping between individual pricing rigidness and aggregate price moments. For a choice of updating signal, transaction cost distribution,

reference price, and size of the market, N, we simulate aggregate moments from the model. These are matched to observed moments. As we are moving to aggregate moment matching, we will assume homogenous individual pricing error variances, that is, σ_{ic}^2 and σ_{ip}^2 fixed across i in the estimation of the model.

The transaction cost distribution should be continuous and non-negative. To satisfy this we choose the parsimonious one-parameter Rayleigh distribution. The single scale parameter φ determines the mean and variance of transaction costs. As the scale parameter φ tends to zero, the mean and dispersion of the transaction cost tend to zero. Hence, the size of φ measures the heterogeneity and scale of rigid pricing. Other distributions could of course be chosen. The online supplementary appendix shows results for a log-normal cost distribution, which allows dispersion and mean to be disentangled.

The choice of updating signal is important and is informative on the dominant type of price revision type in the market. We consider two different signal types. The first is the mean price distance measure, $x_{it} = |p_{it} - c_t|$, where c_t is the reference price used in the estimation. This signal is consistent with menu costs. This signal predicts that the likelihood of a price revision increases in the number of periods since the previous revision, that is, as current price become increasingly outdated. Mean aggregate adjustment rates will increase in the cross-sectional dispersion of the price distribution and in the conditional mean pricing error. Price moments will be mean reverting.

The second signal type we consider is the latent Gaussian signal, $x_{it} = |z_{it}|\sigma_x$, where $z_{it} \sim N(0, 1)$ and σ_x is fixed such that the variance of the latent signal matches the variance of the price distance signal. The variance must be fixed to identify the transaction cost distribution. This signal is consistent with costly information. Relationship prices are revised with a fixed probability each period. *A priori* this signal is consistent with updating prices at fixed time intervals for instance as specified in a contract. The rate of updating is independent of the moments of the cross-sectional distribution.

We also investigate asymmetric versions of these signals. With asymmetry the probability of a price revision can vary conditional on the relationship price being above or below the reference price. For the price distance model, the price updates if $p_{it} - c_t > \tau_+$ or $p_{it} - c_t \leq -\tau_-$. For the latent Gaussian model, the

probability of updating is $Prob(x_{it} > \tau_+)$ if $p_{it} > c_t$ and $Prob(x_{it} > \tau_-)$ if $p_{it} \leq c_t$. For both signals, τ_+ and τ_- are generated from independent Rayleigh distributions with scale parameters φ_+ and φ_-. The symmetric models are nested in their respective asymmetric specifications allowing for statistical inference on the presence of asymmetry.

Because the model does not endogenously determine the equilibrium market price, an exogenous measure of the reference price, c_t, is necessary for estimation. The price is assumed representative of revised prices in the market, and simulated moments are conditional on the reference price data. A non-stationary reference price will not affect the analysis. Results should be interpreted conditional on the reference price used as a measure of updated transaction prices. In the robustness section we discuss potential biases due to the chosen reference price.

The estimation method starts by drawing N transaction costs from the Rayleigh distribution. These are fixed in time. Given the initial reference price c_1, we generate an initial - cross-sectional price distribution by drawing N prices p_{i1} from a Gaussian distribution $N(c_1, \sigma_{start}^2)$, where the variance, σ_{start}^2, is estimated together with the other parameters. The model is then used to determine next period prices. This process is continued over the full sample period.

Four parameters are estimated for each symmetric updating signal, $\boldsymbol{\theta} = [\varphi, \sigma_{start}, \sigma_p, \sigma_c]$. Five parameters are estimated with asymmetry. The estimation seeks to fit the time series of simulated and actual cross-sectional standard deviation and skewness. The first and fourth moment are reserved for out-of-sample model validation. We explore implications of estimating the model using different permutations of the set of moments below. Let $G_t = [\widetilde{m}_{2t} - m_{2t}, \widetilde{m}_{3t} - m_{3t}]$ be the difference between the model predicted and actual moments at time t. Let Σ be the covariance matrix of the actual moments, and $\Sigma = LL^*$ the Cholesky decomposition of the covariance matrix. We then have the standardized and orthogonalized moment conditions $J = (\boldsymbol{L}^{-1} \otimes \boldsymbol{I}_T)vec(\boldsymbol{G})$, where $\otimes$ is the Kronecker product and vec vectorizes the $[T \times 2]$ matrix of unscaled moment conditions. The estimator searches over $\boldsymbol{\theta}$ to minimize the inner product, $J^T J$.

Because the time series of the moments are potentially heteroskedastic and persistent, we implement block bootstrapping to derive finite sample standard errors of estimated parameters and other statistics. We generate new samples of the moments and reference price by sampling blocks of length twenty months with replacement from the original data. We generate 500 new time series of individual length equal to the original sample, 108 periods. The model is then estimated on each bootstrapped sample using the actual data estimated parameters as starting values.

Individual relationship adjustment rates could potentially be inferred by estimating relationship specific error-correction models (2a-b) treating ω_{it} as a constant parameter to be estimated. However, because ω_{it} (the price revision state variable) is stochastic and potentially endogenous, estimates are potentially biased (as discussed for the price index analysis above). Furthermore, inference might be subject to small sample problems for short-lived trade relationships. Treating ω_{it} as a constant parameter to be estimated also prevents inference on the revision signal type in the market.

Empirical Analysis

We estimate the model on firm-level data of Norwegian fresh farmed salmon exports. The data contain the population of all exporter/importer transactions of fresh salmon from 2006 to 2014, collected from custom declarations. It provides anonymous ID's for the exporting and importing firm, the date for the transaction, the FOB value (in NOK), the weight of the shipment (in kg), and the destination country.

Norway is the world's second largest seafood exporter, and farmed salmon accounts for two-thirds of the value of Norwegian seafood exports (Bergesen and Tveterås 2019). It is the largest producer of Atlantic salmon (Asche and Bjørndal 2011), and most salmon produced in Norway is exported ($\sim$95%). The salmon price is characterized by periods of varying price volatility (Asche, Misund, and Oglend 2019; Dahl and Yahya 2019) and price spikes (Asche, Oglend, and Kleppe 2017; Oglend and Straume 2020), making it a good candidate to explore deviations from a reference price as a signal.

The institutions of trade for salmon are well developed, with publicly available aggregate price and market data, a futures exchange,

Table 1. Descriptive Statistics of Data

	Mean	Std.	Q05	Q50	Q95	Skewness	Kurtosis
p_{it}	3.53	0.23	3.19	3.51	3.90	0.13	2.17
$\triangle p_{it}$	0.006	0.115	−0.184	0.007	0.190	−0.17	4.98
$\triangle \hat{c}_t$	0.005	0.094	−0.160	0.010	0.139	−0.34	3.38
$p_{it} - c_t$	0.06	0.12	−0.11	0.05	0.26	0.70	7.41
N_t	885	143	665	864	1130	0.31	2.27

Note: All prices in logs. N_t is monthly number of trade relationships. Q05, Q50, and Q95 refer to the 5th, 50th, and, 95th percentile of the full sample empirical distributions.

and a relatively stable and predictable regulatory regime (Asche, Oglend, and Zhang 2015; Asche, Misund, and Oglend 2019). Together with the relatively homogenous nature of salmon, this suggests we should observe a high rate of price revision to new market information. Still, trade in salmon is done through bilateral transactions with private information, which is expected to add price rigidity.[4]

We use the salmon futures contract settlement price as a reference price. A futures exchange for salmon (Fish Pool) was established in 2006 (Asche, Oglend, and Zhang 2015). Futures contracts on salmon are settled against a salmon price index (the Fish Pool Index, FPI) in the maturity month. The stated objective of this price index is to give a correct reflection of the salmon market price, be possible to re-examine/verify, and remain transparent and neutral to all parties. The FPI is constructed as a weighted average across different salmon price measures.[5] Using the futures market settlement price as a measure of the reference price has the added benefit of providing potentially useful information on how individual trade prices relate to the settlement price.

A transaction between an exporter and importer defines a trade relationship. We define the price (unit value) p_{it} for relationship i in month t as the average across all transaction prices in an exporter/importer pair in a month. There are 108 monthly observations of the cross-section from January 2006 to December 2014. We exclude exporters and importers with less than 100 transactions over the sample period to focus on active trade relationships. We also exclude relationships that only traded one month as these relationships contain no information on price dynamics. The data consist of eighty-six exporters and 1,152 importers forming 6.510 unique trade relationships.

Table 1 shows some descriptive statistics on the full sample distribution of log prices. The first row shows that the unconditional distribution is close to symmetric, with approximately 90% of prices being within 35% of the cross-sectional mean. The unconditional cross-sectional standard deviation is 23%. If we look at the cross-section by month (not shown), we find that the average monthly cross-sectional variance is 11.3%. Because this variation excludes shifts in the distribution over time, we can deduce that around three-fourths of the variance is due to shifts in the mean over time, which approximates common pricing in the market. Deducting the full information price from individual trade prices reduces overall variance by 77%, confirming that the reference price approximates well common pricing for the trade relationships.

The final row of the table refers to the number of monthly trade relationships. On average, each month has 885 active trade relationships. This statistic hides an increasing trend over time due to growth in production and trade. However, given the large number of relationships, variation in N is not expected to play a major role in the analysis.

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[4]Larsen and Asche (2011) show that about a third of the export transaction for Norwegian salmon to France had contracts that updated prices at different intervals.

[5]Specifically, prices that have been used as: Selling Price Farmers, Farmers Index (FI), NASDAQ Index of Salmon Exporters Price (NASDAQ) price, FHL price, Export price (FHL), Statistics Norway Customs Statistics (SSB), NOS clearing price, Exporters purchase price (NOS), Mercabarna market price (MMP) Barcelona, Fish Pool European Buyers Index (FPEBI), Rungis Index Paris Price (Rungis).

Estimation Results

Table 2 shows model parameter estimates together with bootstrapped 90% confidence intervals for all four models. Confidence intervals suggest the moments contain varying degree of information on the different model parameters. The standard error of pricing

Table 2. Model Parameter Estimates

	Symmetric		Asymmetric	
	Price distance	Latent Gaussian	Price distance	Latent Gaussian
σ_p	0.113 (0.043,0.157)	0.1126 (0.00,5.409)	0.122 (0.023,0.166)	0.0836 (0.000,3.17)
σ_c	0.109 (0.103,0.116)	0.0750 (0.059,0.095)	0.093 (0.052,0.113)	0.0648 (0.043,0.087)
φ	0.017 (0.011,0.028)	0.0084 (0.004,0.0142)	—	—
φ_+	—	—	0.0851 (0.031,0.213)	0.0129 (0.007,0.018)
φ_-	—	—	0.0058 (0.003,0.009)	0.0081 (0.004,0.013)
σ_{start}	0.0623 (0.032,0.105)	0.0777 (0.045,0.116)	0.0523 (0.019,0.909)	0.0813 (0.051,0.123)

Note: Numbers show estimates and the 90% confidence intervals below in parenthesis. Confidence intervals are derived by estimating the model on 500 block bootstrapped resamples of the time series of moments and reference price. Block length of twenty months used for draws.

under maintained prices, σ_p, appears difficult to estimate precisely. The moments are more informative on the pricing error of revised prices, σ_c, and especially the scale of the cost distribution, φ, which directly maps to the rate of price revisions in the market.

No rigid pricing occurs when the scale estimate of the transaction cost is zero, this is clearly rejected by the estimation results. The online supplementary appendix shows that this is also rejected when considering an alternative two-parameter log-normal transaction cost distribution.

Table 3 reports some model fit statistics. The objective function value is the minimized sum of squared residuals. F-tests for the null of symmetry, $\varphi_+ = \varphi_-$, gives F(1,212) = 3.17 (p-value 0.08) for the price distance model, and F(1,212) = 7.93 (p-value 0.005) for the latent Gaussian model. Using the bootstrapped

sample of minimized objective function values to test for significant differences in mean function values produces a t-statistic of 2.1 for the threshold model and 9.18 for the latent Gaussian model. We reject symmetry in favor of asymmetric adjustments.

Unlike asymmetry, signal types are not nested. We can evaluate signals by how well they explain the data. Compared to the price distance model, the latent Gaussian models provide better fits in terms of objective function values and correlations between model predicted and data moments. Looking at the standard deviation of the residuals we observe that it is the improved modeling of skewness that separates the latent Gaussian model from the price distance model. Recall that the estimation only seeks to fit the standard deviation and skewness. It is reassuring that the model can produce positive correlations also toward

Table 3. Model Fit to Data

	Symmetric		Asymmetric	
	Price distance	Latent Gaussian	Price distance	Latent Gaussian
Obj. func. value	230.9	197.9	217.8	172.0
	Correlations between actual and model predicted moments			
Bias	0.405	0.588	0.414	0.607
Std	0.211	0.264	0.328	0.448
Skewness	0.255	0.792	0.344	0.853
Kurtosis	−0.203	0.077	0.145	0.267
	Model residuals standard deviations			
Bias	0.0228	0.0292	0.0311	0.0355
Std	0.0229	0.0244	0.0234	0.0254
Skewness	0.9433	0.6567	0.9099	0.5067
Kurtosis	1.8440	2.0929	1.8106	2.7997

Note: Obj. func. value is the objective function value the estimation procedure seeks to minimize, the inner product, $J^T J$. Model residuals standard deviations is the standard deviation of the difference between the actual moment and mode predicted moment. Note that it is only the Std. and Skewness that are fitted in the estimation.

the out-of-sample moments: mean bias and kurtosis.

In table 4 we look at data and model predicted cross-correlations in moments. Values in parentheses are 90% bootstrapped confidence intervals. In a fully efficient market these correlations would be zero. This is clearly rejected by the data. However, the table does suggest an overall high pricing efficiency as revealed by the positive correlation between skewness and mean bias.

The symmetric latent Gaussian model produces correlations between skewness and mean price (and bias) in line with the data. However, the symmetric models are unable to reproduce the observed positive correlation between the mean bias and dispersion of the price distribution. This is remedied when allowing for asymmetric signals.

Figure 3 plots the actual mean bias, standard deviation, skewness, and kurtosis together with the predicted moments from the asymmetric latent Gaussian model. The plots also show $\pm$ two standard deviation confidence bounds for model moments as derived from the bootstrapped data. The online supplementary appendix also shows plots for the asymmetric price distance model. We observe a close fit to the fitted moments, especially skewness. The variation in the model predicted mean bias tracks the variation in the actual mean bias, albeit with somewhat greater standard deviation.

Figure 4 plots the estimated distribution of price adjustment rates, ω_{it}, conditional on low prices (top) and high prices (bottom). The blue line is the distribution for the price distance model, the red line the latent Gaussian model. The median monthly rate of upward price revisions (adjustments to low transactions prices) is 0.33 for the latent Gaussian model and 0.42 for the price distance model. For downward price revisions, it is respectively 0.28 and 0.23. Both models predict higher probability of price revision when prices are below reference prices. The total monthly rate of adjustment is the sum of the adjustment rate to low and high prices.

To summarize, we have used the model to show how the observed price moments for exported salmon suggest a bilateral market with high, but not perfect, pricing efficiency. Moments favor prices being revised at a fixed rate (fixed intervals) rather than as a response to deviations from the market reference price. This is consistent with optimal price revisions under costly information. Finally, the

Table 4. Cross-Correlations of Moments, Actual, and Model Predictions

| | Actual | Models | | | |
| | | Symmetric | | Asymmetric | |
		Price distance	Latent Gaussian	Price distance	Latent Gaussian
Corr(price, skewness)	−0.75 (−0.72,−0.85)	−0.15 (−0,40,0.25)	−0.56 (−0.76,−0.33)	−0.12 (−0.35,0.18)	−0.72 (−0.50,−0.88)
Corr(bias,skewness)	0.58 (0.42,0.69)	0.92 (0.15,0.96)	0.77 (0.64,0.95)	0.96 (0.56,0.98)	0.59 (0.44,0.74)
Corr(bias,std)	0.45 (0.24,0.64)	0.13 (0.08,0.16)	0.13 (0.08,0.14)	0.64 (0.5,0.95)	0.57 (0.45,0.93)
Corr(bias,kurtosis)	0.04 (−0.16,0.19)	0.19 (0.10,0.37)	0.01 (−0.08,0.16)	−0.27 (−0.39,0.05)	−0.05 (−0.15,0.41)

Note: Numbers show estimates and the 90% confidence intervals below in parentheses. Confidence intervals are derived from the finite sample of correlations simulated from models estimated on block bootstrapped resamples of the time series of moments and reference price. 500 bootstrap samples are used with block length of twenty months used for draws to generate samples.
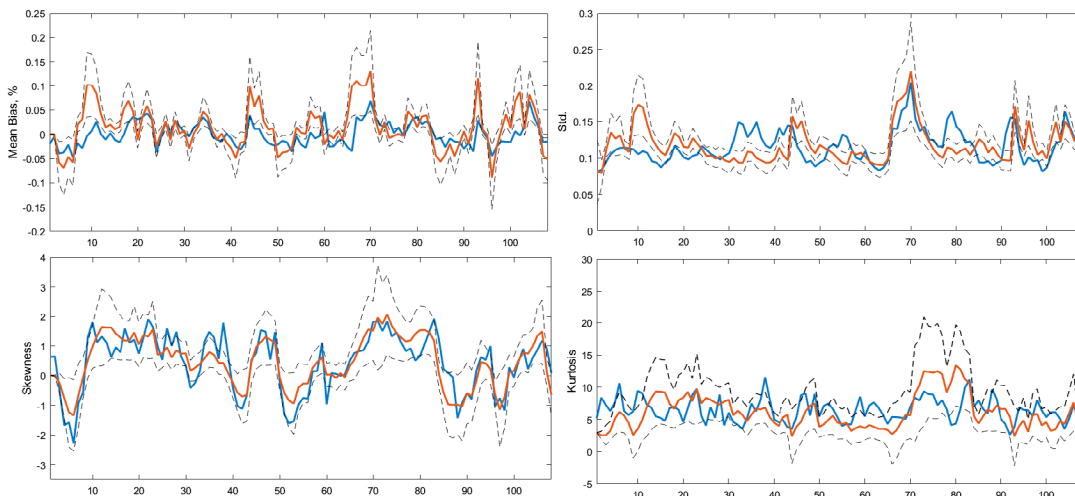
Figure 3. Actual and model predicted moments of the cross-sectional price distribution over time for the latent Gaussian asymmetric signal model (table 2)

Notes: *Std. and skewness are fitted by the model.* Solid blue line is the data moment, wheras solid red line is mean model predicted moment. Dotted lines are ± two standard deviations from the mean, where standard deviations are derived from models estimated on the 500 block bootstrapped samples.
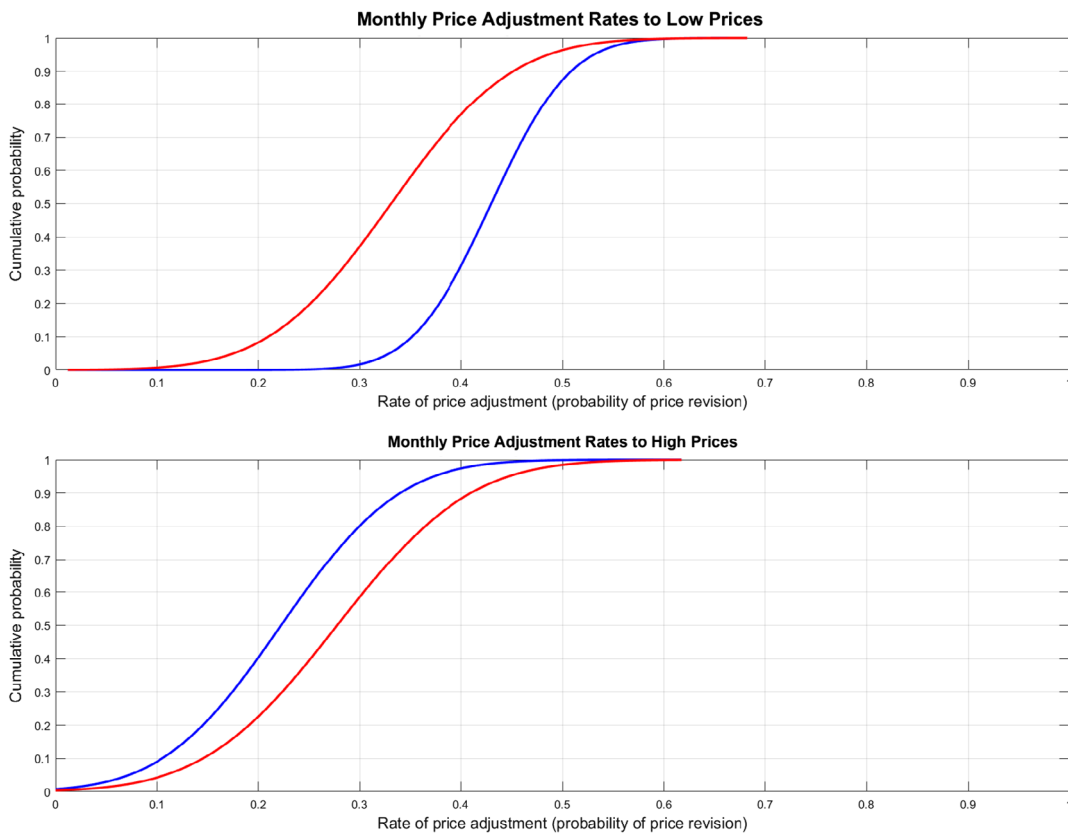

Figure 4. Heterogeneity in adjustment rates.

Notes: Blue (price distance model), red (latent Gaussian model). Top panel shows the mean monthly rate of price adjustment when relationship prices are low as defined by the asymmetric models. Bottom panel shows equivalently for high relationship prices. Total monthly rate is the sum of the two high and low price rates.

moments point to asymmetric price revisions. The asymmetry is such that price revisions are more likely when relationship prices are low relative to the reference price $(\varphi_- < \varphi_+)$. This supports exporter relative bargaining power when revising prices. This is consistent with importers outnumbering exporters in the salmon export market, there are approximately thirteen importers per exporter. Furthermore, the Herfindahl index for exporters in terms of trade values is 0.13, whereas it is 0.0045 for importers.

Robustness

Recall that a reference price was needed as data for the estimation. Using a reference price that is itself some weighted average of the underlying transaction prices risks introducing bias in the measure of revised prices. For the arguably most extreme case where the reference price is a simple average of transaction prices, the reference price will equal the first moment of the price distribution. There can then be no mean bias, and estimation using the first moment would conclude that pricing is perfectly efficient. In general, with a biased reference price the mean bias will be small compared to skewness and dispersion. To evaluate this, it is useful to not use the mean bias when fitting the model. One can then compare the size of the model predicted mean bias with the actual mean bias to infer possible bias in the reference price. If the model predicts greater mean bias than the actual data, this suggests endogenous bias. We observe in figure 3 that the predicted mean bias had greater variation than the data mean bias, which does suggest some bias in the reference price.

To evaluate the robustness of model estimates to the reference price, we consider two alternative reference prices. The first uses the exchange traded futures price in the settlement month. For the second, we allow for a proportional adjustment to the original reference price. Given the biased reference price is a monotone function of the true reference price, a monotone adjustment can be done to partly correct the bias. We use a scaled reference price θc_t as a measure of the reference price, where θ is estimated together with the other parameters.

Table A3 in the online supplementary appendix shows parameter estimates and correlations between actual and model predicted moments using the two alternative reference prices. We note that using the scaled reference price gives variation in predicted mean bias more in line with the actual mean bias, suggesting a reduction in bias. Although the unscaled reference price produced a mean bias with 42% higher standard deviation than the actual mean bias, the scaled reference estimate is only 13% higher. Overall, the estimates and above findings are robust to these alternative reference price measures.

Another modeling choice is which moments to fit. We fitted the standard deviation and skewness, using the mean bias and kurtosis as additional out-of-sample checks on the model. A relevant question is how altering the set of fitted moments affects the estimation. Answering this can provide useful information on which moments are informative on which parameters. Table 5 reports estimation results for all combinations of the three first moments, as well as using all four moments. Asymptotic standard errors are provided as measures of the informativeness of the data moments. When fitting only one moment, skewness is the most informative moment. Combining skewness with the second moment improves efficiency, leading to a substantial reduction in asymptotic standard errors and providing estimates similar to the results using all three or all four moments.

Finally, results using a log-normal cost distribution suggests that the one parameter cost distribution is not a serious restriction on the cost distribution. See tables A1 and A2 in the online supplementary appendix for some results using a log-normal cost distribution.

Sorting to the Tails of Rigid Prices

Our analysis suggests a high rate of price revision as defined by a negative relationship between the first moment and the skewness of the price distribution. In these markets, the most efficient trade relationships will tend sort around the mode of the price distribution, whereas rigid prices sort to the tails. In other words, the tails are stickier than the mode. We evaluate this prediction using individual trade relationship price regressions.

To start, the two top panels of figure 5 show model estimated transaction costs (left) and price revision rates (right), conditional on price quantiles. We use the asymmetric models estimates in table 2. The panels

Table 5. Estimation Results Using Different Combinations of Moments to Fit

| | Model: Asymmetric latent Gaussian signal | | | | | | | |
| | Moments used in estimation: | | | | | | | |
	m_1	m_2	m_3	m_1, m_2	m_2, m_3	m_1, m_3	m_1, m_2, m_3	m_1, m_2, m_3, m_4
σ_p	0.0046 (2.3558)	0.9562 (0.1684)	0.0847 (0.0115)	1.9074 (0.4122)	0.0836 (0.0114)	0.9156 (0.2027)	0.0991 (0.0088)	0.2491 (0.0072)
σ_c	0.0001 (0.0973)	0.0855 (0.0082)	0.0741 (0.0050)	0.0799 (0.0147)	0.0648 (0.0020)	0.1031 (0.0149)	0.0611 (0.0027)	0.0773 (0.0020)
φ_-	0.0036 (0.0005)	0.0048 (0.0001)	0.0139 (0.0001)	0.0034 (0.0001)	0.0129 (0.0001)	0.0046 (0.0001)	0.0136 (0.002)	0.0083 (0.0001)
φ_+	0.0030 (0.0004)	0.0010 (0.0004)	0.0087 (0.0002)	0.0015 (0.0001)	0.0081 (0.0001)	0.0033 (0.0001)	0.0088 (0.002)	0.0061 (0.0001)
σ_{start}	0.0212 (1.7959)	0.0828 (0.0210)	0.4016 (0.1896)	0.0919 (0.0192)	0.0813 (0.0195)	0.6345 (1.1552)	0.0998 (0.0239)	0.1275 (0.0192)
Correlations between actual and model predicted moments								
Bias	0.457	0.465	0.624	0.450	0.607	0.469	0.62	0.536
Std	0.219	0.424	0.135	0.402	0.448	−0.128	0.46	0.349
Skewness	0.426	0.479	0.866	0.425	0.853	0.515	0.86	0.735
Kurtosis	−0.010	−0.106	0.310	−0.012	0.270	0.079	0.23	0.290
Model residuals standard deviations								
Bias	0.0219	0.0218	0.038	0.022	0.036	0.022	0.038	0.026
Std	0.0265	0.0209	0.041	0.021	0.025	0.057	0.026	0.023
Skewness	3.7081	0.8798	0.4840	1.031	0.506	0.833	0.530	0.662
Kurtosis	68.88	3.821	2.7413	4.704	2.800	2.734	3.851	2.361

Note: Asymptotic standard errors used. Moments refers to the moments used to fit the model: m_1 is mean bias, m_2 is standard deviation, m_3 is skewness, and m_4 is kurtosis. Model residuals standard deviations takes the standard deviation of the difference between the model predicted and actual moments.
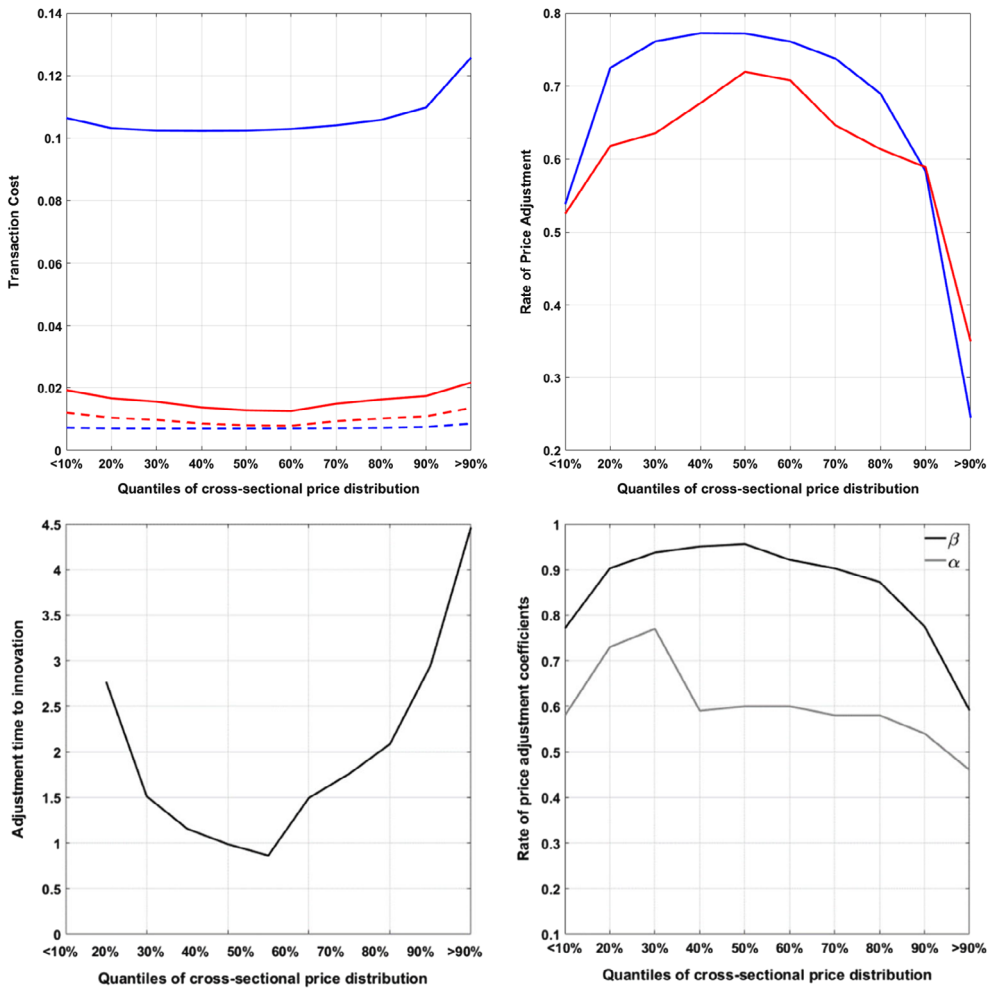
Figure 5. Sorting to the tails of inefficient prices

Notes: Top left panel: Model estimated transaction costs conditional on quantile position of trade relationship in aggregate price distribution (blue: Asymmetric Price distance model, red: Asymmetric latent Gaussian model, solid line for adjustments to high prices, τ_+, dotted line for adjustments to low prices, τ_-). Top right panel: Model estimated rate of price adjustment. Bottom left panel: Estimated adjustment time in individual trade relationship price regressions, see equation (6). Bottom right panel: Estimated individual price revision (see equation (5)).

highlight the model predicted sorting effect. We note the higher cost and lower adjustment rate at the upper quantile, high prices.

We compare these predictions with reduced form estimates of adjustment parameters. To derive comparable reduced form estimates, let $I(p_{it} \in \boldsymbol{A}_q)$ be the indicator function taking a unit value if $p_{it} \in \boldsymbol{A}_q$, where $\boldsymbol{A}_q$ for $q = \{1, 2, \ldots, 10\}$ are real valued disjoint sets that partition the cross-sectional price distribution into ten equally spaced percentiles. Individual relationship price dynamics are estimated using the following conditional panel error correction model,

$$(5) \quad \begin{aligned} \Delta p_{it} = \mu_i + \sum_{q=1}^{n} \left(\beta_q \Delta c_t + \alpha_q (c_{t-1} - p_{it-1}) \right) \\ I(p_{it-1} \in \boldsymbol{A}_q) + u_{it}, \end{aligned}$$

where μ_i is a fixed effect accounting for unobserved time invariant heterogeneity in individual trade relationships, and u_{it} is the individual, possibly heteroskedastic, and weakly dependent error process. The reduced form model approximates the statistical pricing model.

The parameters of interest are β_q and α_q, the instantaneous elasticity and the reduced form

adjustment rate, respectively. The bottom left panel of figure 5 shows estimated conditional adjustment times,

$$(6) \quad h(0.1) = \left[\frac{log(0.1) - log(1-\beta)}{log(1-\alpha)} + 1 \right],$$

which gives the periods in months needed to correct 90% of a given pricing error $(c_t - p_{it})$. Because higher transaction costs reduce the rate of adjustment, the adjustment time will be a monotonic measure of transaction costs. The bottom right panel shows estimates of β_q and α_q.

The reduced form regression results confirm the prediction of the model. The tails of the cross-sectional price distribution tend to be populated by trade relationships with more rigid pricing. We also note that the individual relationship regression estimates provide corroborating support for asymmetry—the upper quantile trade relationships trading at high prices relative to the reference price have longer adjustment times and lower adjustment rates.

The tails define the "border" of the market, just as in spatial arbitrage models where more distant markets have higher arbitraging costs. Practically, these results suggest that the representativeness of the price index can be improved by trimming away prices that populate the tails of the cross-sectional price distribution.

Conclusions

Rigid pricing typically occurs in economic environments where it is costly to revise prices (i.e. menu costs) and/or information is limited and costly. This is especially relevant for bilateral transactions markets where prices and contract terms are private information, as one typically observes in much trade with agricultural products. Rigid pricing as a source of pricing inefficiency affects the representativeness of price indices. This is relevant to both research and policy that relies on aggregate price measures created from transactions data.

This paper has shown how information in the moments of the price distribution can be used to infer underlying pricing rigidity in the market. This was formalized through a model of rigid pricing at the level of individual trade relationships. We show how

rigid pricing maps to the moments of the price distribution in the market. With rigid pricing common price index measures will reflect a mixture of updated and old market information, and the average rate of price revision will determine the relative weighting of new and old information. Hence, with high rigidity price indices will underestimate the price impact of new market information. Furthermore, the cross-sectional price dispersion will increase with the flow of new price relevant market information. This means the representativeness of indices will decline in periods of large common market shocks. Rigid pricing generates conditional skewness in the price distribution, and the relationship between skewness and the first moment of the distribution is informative on the overall level of pricing efficiency. Specifically, a high, but not perfect, price efficiency market can be defined as showing a negative relationship between skewness and the mean price in the market. Finally, a positive or negative correlation between price dispersion and the mean implies asymmetric price revisions in the market, a sign of potential asymmetry in bargaining power between buyers and sellers.

We show how to estimate the model using simulated non-linear least squares methods. The model was estimated on export transactions of farmed Norwegian salmon. We evaluate two price revision strategies, one based on price bound consistent with menu costs and one based on price revisions at fixed time intervals, consistent with costly information. We also evaluate asymmetric versions of these signals.

The moments support asymmetric revision with a latent Gaussian signal. This means prices are primarily revised at fixed time intervals, a fixed rate, rather than revising based on deviation from the reference price. The asymmetry suggest a larger probability of upward price revisions, consistent with exporter relative bargaining power. We reject full pricing efficiency in favor of a high, but not perfect, efficiency. This means that despite the private nature of transaction terms, salmon transaction prices are well represented by a price index. Most of the pricing of exports at the individual level is common across all transactions. This highlights that bilateral transactions markets, despite the private nature of price, can display a large degree of common pricing, and informative price indices.

Supplementary Material

Supplementary material are available at American Journal of Agricultural Economics *online.*

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