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ABSTRACT

When are Supply and Demand Determined Recursively Rather than Simultaneously? Another look at the Fulton Fish Market Data*

When a supply and demand model is recursive, with errors uncorrelated across the two equations, ordinary least squares (OLS) is the recommended estimation procedure. Supply to a daily fish market is determined by the previous night's catch, so this would appear to be a good example of a recursive market. Despite this, data from the Fulton fish market are treated in the literature, without explanation, as coming from a simultaneous-equations market. We provide the missing explanation: inventory changes, influenced by current price, affect daily supply. Instrumental variable estimates using the full data set differ very little from OLS estimates using only observations with little inventory change, providing strong support for our explanation. Finally, we note that because of inventory changes, estimates of supply price elasticities in high-frequency markets must be interpreted with care.

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Introduction

It is well-known that a recursive equation system can be estimated unbiasedly using ordinary least squares (OLS), so long as errors are uncorrelated across equations. Greene (2003, p.411) has a good exposition. In light of this, researchers should be eager to take advantage of any situation in which a simultaneous equation model can be formulated as a recursive system. Doing so would rationalize the use of OLS, avoiding the small-sample bias and loss of precision inherent in alternative instrumental variable (IV) procedures. In this paper we look at the simplest simultaneous equation system, a supply and demand model, and ask under what circumstances it would be legitimate to model it as a recursive system.

We were motivated by data from the Fulton fish market. In this daily market, supply is determined by the catch the night before, so that it looks to be a prime candidate for modeling supply and demand as a recursive market. Yet, papers in the literature using these data, including Graddy (1995), Angrist, Graddy, and Imbens (2000), Chernozhukov and Hansen (2001), Lee (2004) and Graddy (2006), estimate using instrumental variables, with little explanation for why a recursive model is not appropriate, beyond cursory statements such as “Because quantity sold and price are endogenous…” (Graddy, 1995, p.86). Further, econometrics textbooks have been using these data for illustrations and in assignments, also without explaining why they can be viewed as representing simultaneous determination of price and quantity. One textbook, Murray (2006, p.604), even goes so far as to state that these studies “typify simultaneous supply and demand studies.”

In this paper we offer an explanation of why a recursive model is not appropriate for the Fulton fish market data, and indeed is not appropriate for any high-frequency market in which buffer stocks play an active role. The essence of our explanation is as follows. If the quantity supplied can be affected by inventory depletions or additions, even if inventory can only be held for a short amount of time, as in the case of fish, current price can affect vendors' decisions about how much supply to make available on the market. The data provide strong support for this explanation. Instrumental variable estimates using the full data set differ very little from OLS estimates using only observations with little inventory change. A second contribution of this paper is to note that if vendors do behave in this fashion, estimates of supply price elasticities require careful interpretation.

Literature review

The literature on this issue begins with Wold (1954) who argues that multi-agent models are necessarily recursive rather than simultaneous because it takes time for agents to respond to their environments. The modern simultaneous equations literature pays only lip service to Wold, however. Hausman (1983, p.402), for example, simply states that the recursive model, in conjunction with uncorrelated errors, "seems unacceptable in most model specifications," but offers neither an explanation of this view nor an example of a market that would satisfy the assumptions of the recursive model.

Rothenberg (1990, p.231-2), is an exception, offering an explanation for why the Wold view is ignored: “When time is explicitly introduced into the model, simultaneity disappears and the equations have simple causal interpretations. But, if response time is short and the available data are averages over a long period, excess demand may be close to zero for the available data. The static model with its simultaneity may be viewed as a limiting case, approximating a considerably more complex dynamic world. This interpretation of simultaneity as a limiting approximation is implicit in much of the applied literature and is developed formally in Strotz (1960).”

From this it seems that a crucial characteristic of data that renders them eligible for recursive modeling is the frequency of observations. Darnell (1994, p.346), for example, writes “Institutional realities may deny feedback and allow only one-way causal chains if the frequency of the data is high. If, for example, daily data are available on some variables it may be quite reasonable to impose a hierarchical causal chain, but if the data are monthly the strict hierarchy may be subsumed within the data and will appear, then, as simultaneous determination of the variables via feedback with all the commensurate identification and estimation issues that affect simultaneous models.”

Here is how the Strotz/Rothenberg/Darnell argument would apply to the Fulton fish market data. Suppose that on a daily basis the fish market is recursive because fish caught last night determine today’s supply and so supply is unaffected by current price. But suppose that today’s price serves as tomorrow’s expected price. If the fish market data were monthly, the monthly price in the data would be an average. In a month with a high average price we would expect fishermen, as they experience higher prices during the course of the month, to react by fishing more intensively and so catch more fish. There would be simultaneity in the monthly data despite no simultaneity in the daily data.

In summary, this literature explains why weekly or monthly data are characterized by simultaneity, but leaves open the question of how to model with high-frequency data such as daily data. A reader is left with the impression that for the case of high-frequency data a recursive model is appropriate unless explicitly argued to the contrary. But no hint is provided for how a high-frequency market could exhibit simultaneity. One purpose of this paper is to supplement this literature by presenting an argument for why any high-frequency data from a market with inventories must be modeled as simultaneous, not recursive.

A natural place to look for information on this issue is the textbook literature. Simultaneity is one of the original reasons for why econometrics was developed as a separate branch of statistics, a consequence of which is that most textbooks contain a chapter on simultaneous equations. Only about a quarter of the forty textbooks we looked at discuss recursive systems, however, and of those that do, no explicit examples of recursive supply and demand markets are offered. One or two texts mention that agricultural markets might be recursive. Pindyck and Rubinfeld (1998, p.348), for example, state "In the supply equation the quantity supplied depends only on the price level in the previous year (as one might expect with farm products)." That this is not a good example is illustrated very clearly by Suits (1955), the first study to apply simultaneous equations estimation procedures to supply and demand. Suits recognizes that potential supply is determined in the watermelon market by plantings made long before the watermelons are brought to market, and so cannot be affected by current watermelon price. But he notes that current price will determine how many of the watermelons in the field will actually be brought to market, and so there is simultaneity after all. Murray (2006, p.613) has a nice textbook exposition. This example illustrates that reasons for simultaneity may be more subtle than the textbook literature would have us believe.

Simultaneous Equations with Buffer Stocks

The essence of our explanation for why the Fulton fish market suffers from simultaneous equation bias is that supply in this market is influenced by inventory changes. The quantity “supplied” to this market is last night’s catch minus an inventory change. It seems reasonable to expect that if the market price on a particular day is abnormally low, an agent may choose not to sell all of last night’s catch on today’s market, bumping up his inventory in the hope that tomorrow’s price might be better. (Indeed, based on weather forecasts he may have good reason to believe that tomorrow’s price will be better, or worse.) If the market price on a given day is abnormally high, an agent may choose to augment last night’s catch with inventory he has left from the previous day. In this way current price affects the supply offered on the market and creates the simultaneity assumed by the literature using these data.

Here is a simple model to illustrate this phenomenon. Q_t, supply on day t, is given by the previous night catch less day t’s change in inventory.

We model the previous night catch as $\alpha + \eta W_{t-1} + u_{t-1}$ where W_{t-1} is the previous night weather and u_{t-1} is a traditional error term.

We model the change in inventory as $\theta(P_n - P_t) + v_t$ where P_n is the normal price (or, alternatively, the next day's anticipated price), P_t is price on day t, and v_t is an error. All this gives rise to the following supply function:

(1) $Q_t = \alpha + \eta W_{t-1} - \theta(P_n - P_t) + u_{t-1} - v_t$

The demand for fish on day t is given by the inverse demand function

(2) $P_t = \gamma + \delta Q_t + \varepsilon_t$

where ε_t is a traditional error term and we have incorporated the equilibrium condition that quantity demanded equals quantity supplied.

If θ is zero or if in every period P_n matched P_t, inventory change would be given by v_t, a scenario we describe as "inventory change close to zero" or "no inventory change." In this situation we would have the recursive system

(3) $Q_t = \alpha + \eta W_{t-1} + u_{t-1} - v_t$

(4) $P_t = \gamma + \delta Q_t + \varepsilon_t$

For OLS to be unbiased for estimation of this recursive system ε_t must be uncorrelated with u_{t-1} and v_t. It seems safe to assume that ε_t and u_{t-1} are uncorrelated; there is no good reason why the error associated with the previous night's catch should influence the error in today's demand.

Assuming that ε_t and v_t are uncorrelated is more problematic. A particularly strong demand (a high ε_t) might cause inventories to be fully depleted according to the $(P_n - P_t)$ specification, in which case v_t would need to be positive (because inventories cannot be negative), generating a positive correlation between ε_t and v_t. When inventory change is close to zero (i.e., when we have a recursive system) this correlation is unlikely because it is only triggered by large positive values of ε_t which fully deplete inventories.

The main consequence of all this is that the recursive system given by equations (3) and (4) does not suffer from simultaneous equations bias. Equation (3) can be estimated unbiasedly by regressing Q_t on W_{t-1} using OLS, and equation (4) can be estimated unbiasedly by regressing P_t on Q_t using OLS.

But if inventory change is affected by P_t, as modeled in equation (1), then simultaneity appears. An increase in ε_t increases directly P_t from equation (2), but this increase in P_t affects Q_t from equation (1), so the equation (2) error ε_t and regressor Q_t are correlated. This creates simultaneous equation bias using OLS. Equation (2) must be estimated using an IV procedure. This conclusion is strengthened by considering possible correlation between ε_t and v_t.

An implication of the above explanation is that whenever inventory change is "close to zero" there is little or no simultaneity in the data; in this case we know that P_t has had little or no impact on Q_t because any such impact is entirely through inventory change. Consequently, if we were to pick out those observations without substantive inventory change and estimate using OLS using just these observations, we should produce a demand elasticity estimate comparable to that produced by using IV with all the data. Doing this for the Fulton fish data should serve as an empirical check on the role of inventory change creating simultaneity in this market, through a model as described above. We report on this later.

This is a generic explanation for simultaneity; it applies to any high-frequency market in which sellers influence supply by adjusting inventories in response to price changes. One implication of this, as already noted, is that what appear to be recursive markets are not in fact recursive insofar as estimation is concerned. A second implication, to which we now turn, is that new meaning needs to be attached to estimates of the price elasticity of supply in such models.

Interpreting Supply Curve Estimates

The traditional interpretation of the supply curve is that it tells us how a producer changes output in response to a price change. If we now recognize that the quantity sold on a market is not necessarily what is produced during the period, but rather embodies inventory changes, the slope on the quantity variable reflects two types of quantity changes in response to price changes. This may or may not be the meaning we have in mind when we report elasticity estimates.

Consider a high-frequency market in which price bounces around for reasons sufficient to allow identification of the supply curve. The traditional definition of the supply curve could take the form

$S_{producer} = \kappa + \lambda P$

where λ measures the change in the amount produced by the producer in response to a price change. Now suppose that the seller in this market, who may or may not be the producer, exploits price changes by adjusting inventories according to

$\Delta_{inventory} = \theta(P_n – P)$

where P_n is the "normal" price, for example a long-run average. (It could alternatively be whatever price is expected to prevail tomorrow.) Now the actual supply in this market becomes

$S_{actual} = \kappa + \lambda P - \theta(P_n – P) = \kappa* + (\lambda+\theta)P.$

Estimation using traditional simultaneous equation estimation techniques produces an asymptotically unbiased estimate of $\lambda+\theta$, not an estimate of λ. In some contexts, in which short-run behavior is of interest, this may be what we want. But in other contexts, in which longer-run reactions to a permanent change in price are of interest, this is not estimating what we want to estimate. This problem does not characterize markets in which available data are averages over longer time periods because over these time periods inventory changes would be mostly averaged away. To the best of our knowledge, this phenomenon is not recognized in the literature.

In imperfectly competitive markets, the interpretation of the supply curve (which is now a pricing curve) will be different. In this case, fish vendors could be manipulating inventories in order to set prices, so that the causation goes from inventory change to price change rather than from price change to inventory change as argued earlier. Indeed, empirical regularities in the data suggest that inventories are playing a very active role in the supply side of this market. Increases (decreases) in inventories above (below) the norm cause vendors to increase (decrease) supply by drawing down (building up) inventories, but not by as much as the initial inventory change. And fishers as well as vendors are affected by inventory levels; when inventory is high (low) a smaller (larger) amount of fish tends to be delivered.[1] Nonetheless, the earlier logic regarding simultaneity holds. An increase in the demand error term will have an effect on the firm's pricing equation (and thus quantity supplied) through manipulation of inventories: the demand error term and quantity will be correlated. Furthermore, small inventory change would continue to correspond to a situation in which there is little simultaneity.

The Fulton fish market data

Graddy (2006) provides a very good description of the Fulton fish market data. These are 111 daily observations on price and quantity of whiting in 1991-2, along with weather information serving as instrumental variables. The instrumental variable "stormy" is a dummy variable constructed from moving averages of the previous three days' wind speed and wave height (before the trading day). Stormy indicates wave height greater than 4.5 feet and wind speed greater than 18 knots. A second instrumental variable, "mixed," is a dummy variable constructed in similar fashion, representing days with severe weather, but less severe than "stormy" days. Mixed indicates wave height greater than 3.8 feet and wind speed greater than 13 knots when Stormy equals zero.

The data were aggregated from information on quantity sold and price each day to each customer. There are two complications with the data. First, not all buyers pay the same price per pound of whiting. We ignore this complication and assume that all buyers pay the same price, measured as the average of individual transactions prices weighted by quantities sold. Secondly, the data refer to one of six agents selling whiting in this market. We assume that this dealer's market share was constant during the period, so that we can analyse his quantities as if they were market quantities. Making these kinds of assumptions using economic data is commonplace, reflecting Kennedy's (2002) eighth commandment of applied econometrics: Thou shalt be willing to compromise.

If whiting were extremely perishable, last night's catch would all have to be sold today, and this would be a recursive market. But, whiting stays sufficiently fresh to sell for at most four days after it is received, although it is usually sold the day it is received or the day after. On 54% of the days, total quantity sold exceeds total quantity received. Furthermore, the mean daily total quantity sold is less than the mean total quantity received by 92 pounds (the standard deviation is equal to 3,024 pounds), or by 1.4% of the quantity sold. This amount is likely to be unrecorded sales or shrinkage. During this period inventories never fell to zero, nor rose to a level that could not be accommodated, so there are no limit problems with these data. Average daily fish sales during this period were 6300 pounds, with an average absolute value of daily inventory change of 2500 pounds. Despite the perishable nature of this product, average inventory holdings were more than 2000 pounds higher than average daily sales.

These figures are all consistent with our story that inventories are playing an important role in this market. The main implication of this additional information is that the recorded quantity of whiting sold each day does not necessarily equal the quantity caught the night before. Furthermore, in equilibrium, one would expect the mean quantity received to be slightly more (by 92 pounds) than the mean recorded quantity sold in order to allow for unrecorded sales and shrinkage.

Figure 1 plots the daily difference between the total quantity received and the total quantity sold, adjusted by 92 pounds each day for unrecorded sales and shrinkage. As is evident, the daily difference is quite variable. The big upward spike took place on Friday, March 13, during Lent, when an unusually large quantity of fish was received. Sales on Friday were relatively smaller than on previous Fridays, which appeared to continue throughout Lent. On the following Monday, the day of the large negative spike, very little fish was received, and most fish was sold from inventory.[2]

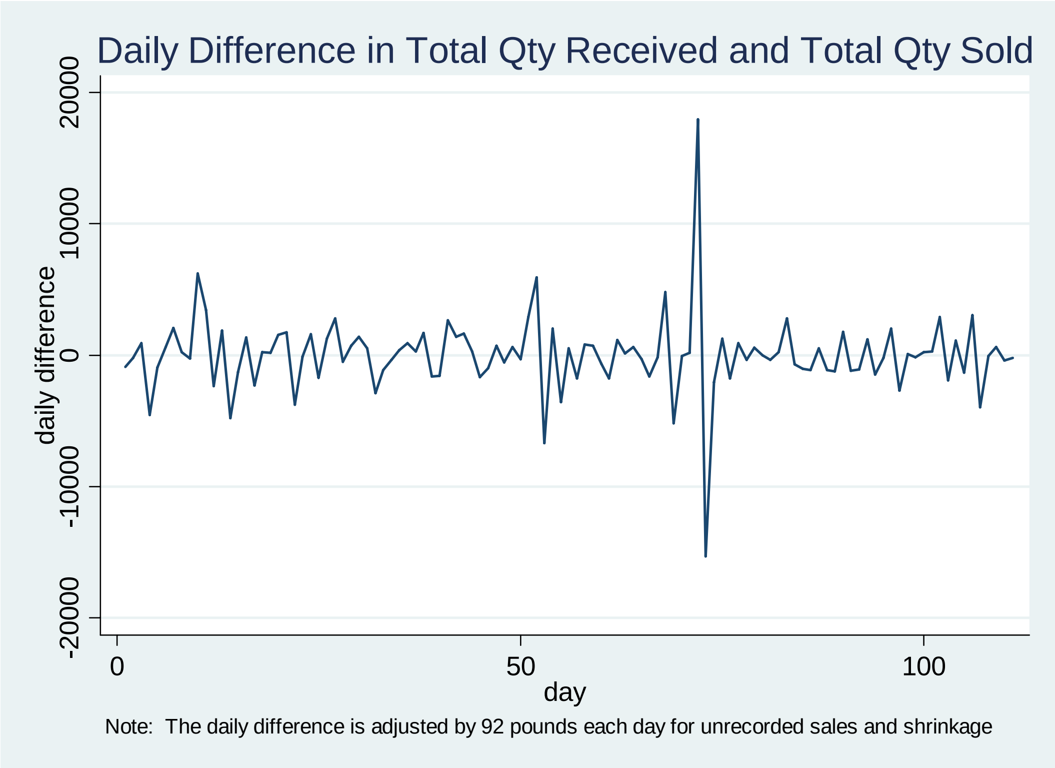
Daily Difference in Total Qty Received and Total Qty Sold
daily difference
20000
10000
0
-10000
-20000
0
50
100
day
Note: The daily difference is adjusted by 92 pounds each day for unrecorded sales and shrinkage

Figure 1

For the purposes of our estimation below, we define days in which inventory change is “close to zero” in the following somewhat arbitrary fashion. We estimated the standard error of daily inventory changes (3021 pounds) and used it to calculate the standard error (287 pounds) of the average of the daily inventory changes. Any day during which inventories changed by less than twice this latter standard error was considered to be a day of “close to zero inventory change” or “no inventory change.” This gave rise to 34 “no inventory change” days, and 77 days with substantive inventory change. Further, we divided the subsample of inventory change days into days in which the inventory changes were positive, and days in which the changes were negative. In Table 1 below we present summary statistics for the full samples and subsamples.

Table 1
Summary Statistics

	Full Sample		No change		Change			Change Subsample: Depletions		Change Subsample: Additions		
	mean	s.d.	mean	s.d.	mean	s.d.	t-test p-value	mean	s.d.	mean	s.d	t-test p-value
price	0.88	(0.34)	0.95	(0.31)	0.86	(0.34)	0.19	0.84	(0.36)	0.87	(0.33)	0.75
qty sold	6335	(4040)	5685	(3898)	6621	(4093)	0.26	5749	(3540)	7428	(4438)	0.07
qty received	6427	(4981)	5783	(3976)	6711	(5364)	0.37	3356	(2839)	9815	(5299)	0.00
stormy	0.29	(0.46)	0.18	(0.39)	0.34	(0.48)	0.09	0.38	(0.49)	0.30	(0.46)	0.47
mixed	0.31	(0.46)	0.44	(0.50)	0.25	(0.43)	0.04	0.24	(0.43)	0.25	(0.44)	0.95
Monday	0.19	(0.39)	0.12	(0.33)	0.22	(0.42)	0.20	0.14	(0.35)	0.30	(0.46)	0.08
Tuesday	0.21	(0.41)	0.18	(0.39)	0.22	(0.42)	0.60	0.30	(0.46)	0.15	(0.36)	0.12
Wednesday	0.19	(0.39)	0.21	(0.41)	0.18	(0.39)	0.77	0.11	(0.31)	0.25	(0.44)	0.11
Thursday	0.21	(0.41)	0.24	(0.43)	0.19	(0.40)	0.63	0.27	(0.45)	0.13	(0.33)	0.11
Friday	0.21	(0.41)	0.26	(0.45)	0.18	(0.39)	0.33	0.19	(0.40)	0.18	(0.38)	0.87
cold	0.50	(0.50)	0.41	(0.50)	0.55	(0.50)	0.41	0.51	(0.51)	0.58	(0.50)	0.65
rainy	0.16	(0.37)	0.21	(0.41)	0.14	(0.35)	0.20	0.16	(0.37)	0.13	(0.33)	0.59
observations	111		34		77			37		40		

As can be seen from the table, there are no significant differences in prices in inventory depletion or inventory addition days, than from other days. This result carries through if we divide the full sample into days in which the inventory change is greater than zero and days in which it is less than zero, or if we divide the full sample into days in which the inventory change is greater than or less than 92. Prices are similar on these days because inventory adjustment behaviour is in essence cushioning price changes, concealing the relationship between price and inventory adjustment. The only statistically significant differences in the subsamples regarding price and quantity are that the quantity received is significantly larger on days in which there are inventory additions rather than depletions**,** consistent with the story we are telling.

Estimation with the Fulton fish market data

The supply curve for the Fulton fish market is not identified, so we cannot look at that side of the market. On the demand side, the demand equation can be written as

$$\ln q_t^{\,d}\,(p) = \beta_o + \beta_1 \ln(p) + \beta_2 x + \varepsilon_t^{\,d}$$

where the x are exogenous dummy variables representing days of the week and the weather onshore. Table 2 presents estimates of this equation. The IV estimates result from using the variable “stormy” as an instrument and the variables “stormy” and “mixed” as instruments.

Table 2: OLS and IV Regressions with Covariates

Dependent variable: quantity

	1	2	3	4	5	6	7	8	9
	Full Sample			Change			No Change		
	OLS	IV	IV	OLS	IV	IV	OLS	IV	IV
		stormy	stormy/mixed		stormy	stormy/mixed		stormy	stormy/mixed
price	**-0.545**	**-1.223**	**-0.947**	**-0.422**	**-1.137**	**-0.892**	**-0.958**	-0.97	-1.233
	(0.175)	**(0.532)**	**(0.410)**	**(0.185)**	**(0.425)**	**(0.380)**	**(0.451)**	(3.789)	(1.133)
day1	0.032	-0.033	-0.007	0.286	0.284	0.284	-0.748	-0.75	-0.785
	(0.207)	(0.226)	(0.215)	(0.219)	(0.241)	(0.229)	(0.513)	(0.720)	(0.535)
day2	**-0.493**	**-0.533**	**-0.517**	-0.362	-0.38	-0.374	-0.789	-0.789	-0.788
	(0.204)	**(0.220)**	**(0.210)**	(0.224)	(0.247)	(0.235)	(0.427)	(0.427)	(0.430)
day3	**-0.539**	**-0.576**	**-0.561**	-0.413	-0.39	-0.398	**-0.892**	-0.894	**-0.942**
	(0.206)	**(0.222)**	**(0.212)**	(0.232)	(0.256)	(0.243)	**(0.414)**	(0.793)	**(0.457)**
day4	0.095	0.118	0.108	0.255	0.383	0.34	-0.401	-0.404	-0.461
	(0.201)	(0.216)	(0.207)	(0.233)	(0.265)	(0.250)	(0.403)	(0.913)	(0.465)
cold	-0.062	0.068	0.015	-0.029	0.135	0.079	-0.194	-0.193	-0.166
	(0.134)	(0.173)	(0.155)	(0.147)	(0.183)	(0.171)	(0.306)	(0.491)	(0.326)
rainy	0.067	0.072	0.07	-0.073	-0.061	-0.065	0.365	0.365	0.371
	(0.177)	(0.190)	(0.182)	(0.203)	(0.224)	(0.213)	(0.358)	(0.367)	(0.362)
Constant	**8.617**	**8.442**	**8.513**	**8.57**	**8.288**	**8.384**	**8.759**	**8.759**	**8.746**
	(0.162)	**(0.215)**	**(0.191)**	**(0.194)**	**(0.259)**	**(0.240)**	**(0.291)**	**(0.345)**	**(0.298)**
Hausman p-value		0.146	0.266		**0.033**	0.133		0.997	0.795
obs	111	111	111	77	77	77	34	34	34
R-squared	0.22	0.11	0.11	0.26	0.10	0.10	0.33	0.33	0.33

Standard errors in parentheses; boldface type indicates significance at the 5% level.

When using all the data, as reported in columns 1 through 3 of Table 2, the IV estimates of the price elasticity of demand contrast sharply with the ordinary least squares estimates. Together with the small p value for the Hausman test statistic, this suggests that there is considerable simultaneity in these data.

As explained earlier, we have reason to believe that OLS should exhibit very little simultaneity bias if it is applied using only observations for which inventory changes are small. To investigate this we separated the data into days in which the inventory change is close to zero (the “no change” data), as described earlier, and days in which the inventory change is substantive.

The results in Table 2 are striking. In the regressions using only the data with inventory changes, the p-value for the Hausman test drops dramatically, suggesting that in these data there is considerable simultaneity going on. And in the regressions using only the data with no/small inventory change the large Hausman test p value suggests that in these data there is no simultaneity.

Furthermore, we find, as anticipated, that when using only data for which there are no/small inventory changes, the OLS estimate of the demand elasticity is comparable to the IV estimates.

As a final check, we used the OLS estimated coefficients from the no inventory change data (column 7 of Table 2) to predict quantity demanded for the inventory change data. We find that the predicted demand exceeds the quantity of fish received on 27 out of 37 days in which inventory fell, and that predicted demand is smaller than the quantity of fish received on 35 out of 40 days in which inventory rose.

Conclusion

The Fulton fish market at first glance appears to be recursive because current price cannot affect the previous night's catch. We have shown, however, that this market is actually a good example of a simultaneous market. Our explanation recognizes that the relevant supply in this market is not the previous night's catch, but rather includes inventory changes. Because current price affects inventory changes, there is simultaneous determination of supply and demand. Textbook explanations of simultaneous equations bias should make note of this phenomenon.

This explanation is not unique to the Fulton fish market. Any high-frequency market in which inventory changes are affected by price changes is subject to the simultaneity feature we have identified. To be a recursive market, a market must satisfy two criteria. First, the frequency of observation must be sufficiently short that institutional constraints prohibit feedback from current price to traditional producer supply. And second, something not spelled out in the simultaneous equations literature, price changes must not influence inventory changes that can affect the supply actually appearing on the market. Markets without substantive inventories, such as would be the case for an extremely perishable product, would satisfy this requirement.

Finally, we have also noted that whenever inventory changes are influenced by price in a high-frequency market, estimation of the supply price elasticity must be reinterpreted to encompass supply changes due to inventory adjustment. Traditional estimation overstates long-run producer response to a price change.

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Footnotes

[1] Despite these empirical regularities we were unable successfully to estimate the precise role of inventory change; all models did not survive a sensitivity analysis. These data are not able to speak loudly about the supply side of this market except to say that inventories play a major role.

[2] Overall during lent, more fish was both received and sold than at other times, with Mondays and Thursdays being especially big days. This is consistent with what would be expected (see Bell (1968)).