When Are Supply And Demand Determined Recursively Rather Than Simultaneously?

Kathryn Graddy
Brandeis University
and
Peter Kennedy
Simon Fraser University

Corresponding author contact: kennedy@sfu.ca

RRH: When are Supply and Demand Determined Recursively?

Abstract: When supply and demand are recursive, with uncorrelated cross-equation errors, least squares estimation has no simultaneous equation bias. 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 adequate explanation, as coming from a market in which price and quantity are determined simultaneously. We provide the missing explanation, and in doing so reveal some issues about simultaneity that deserve better coverage in our textbooks and fuller consideration by applied econometricians.

Keywords: simultaneity, inventories, Fulton fish market

JEL Codes: A20, C3, L6

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, several papers in the literature using these data, Graddy [1995], Angrist, Graddy, and Imbens [2000], 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."

Previous work has demonstrated that OLS gives biased elasticity estimates when applied to the Fulton fish market data, but without an explanation as to why the estimates are biased. In this paper we offer one 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, demand shocks can affect both price and total (including inventory change) supply to the market. An unexpectedly high demand, for example, will put upward pressure on price but at the same time in part be met through inventory depletion, creating a standard simultaneous equation scenario.

Furthermore, we show that under one scenario, the recursive model may be appropriate for days in which there are only small inventory changes, whereas a simultaneous equations model is required on days with moderate to large inventory changes. Our regression results are consistent with this scenario. A final contribution of this paper is to note that if inventory changes do occur 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 modelled 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. In previous work, Graddy (1995 and 2006) and Angrist, Graddy and Imbens (2000) demonstrate that OLS estimates of demand at the Fulton fish market suffer from simultaneous equations bias.

For our purposes and for tractability, we first assume that sellers are price takers. Although Graddy (1995) demonstrated that price discrimination and thus some price setting behavior exists at the market, there is no evidence that sellers manipulate inventories in order to influence price. Rather, sellers respond to unexpected demand shocks by adding to or depleting their inventories.

We assume that for small unexpected demand shocks dealers are happy to add to or deplete inventories in order to meet demand for that day, but for large shocks dealers only partially adjust their inventories – the remainder of the shock is induces price changes. This reflects the reasoning that for large positive unexpected demand shocks, dealers fear stocking out, and for large negative demand shocks, dealers fear potential spoilage as fish only have a finite life.

Here is a tractable model to illustrate this phenomenon.[1] Each day, the expected equilibrium price P_{te} before the market opens is the price at which the current day's market is expected to clear: the price such that last night's catch exactly equals today's expected demand. We model the previous night's catch as

(1) $Catch_{t-1} = \alpha + \eta W_{t-1} + u_{t-1}$

where W_{t-1} is the previous night's weather and u_{t-1} is a traditional error term. Demand is written as

(2) $Q_{dt} = \gamma + \delta P_t + \varepsilon_t$

so that the opening market price, P_{te} is determined from

(3) $Catch_{t-1} = \gamma + \delta P_{te}$

Now consider the unexpected demand shock, ε_t. For small ε_t sellers accommodate the demand shocks through inventory changes. So total supply, Q_{st}, which includes inventory change, is

(4) $Q_{st} = \alpha + \eta W_{t-1} + \varepsilon_t + u_{t-1}$

In this case there is no simultaneity, because price does not change with the demand shock and hence correlation of P_t and ε_t in equation (2) above is zero.

Alternatively, suppose there is a large demand shock. Firms meet some of this excess demand out of inventory or absorb some of the excess supply into inventory, but not all:

(5) $Q_{st} = \alpha + \eta W_{t-1} + \theta\varepsilon_t + u_{t-1}$

where θ is less than one. In this case, prices also rise or fall in order to equate supply with demand. There is simultaneity, because prices change with the demand shock, and hence the correlation of P_t and ε_t in equation (2) above is not equal to zero.

The main consequence of all this is that whenever inventory changes are small, corresponding to θ=1 in equation (5), the recursive system given by equations (2) and (5) does not suffer from simultaneous equations bias. Equation (2) can be estimated unbiasedly by regressing Q_t on P_t using OLS, and equation (5) can be estimated unbiasedly by regressing Q_t on W_{t-1} using OLS. 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. We report on this later.

With other models of inventory change, it is not the case that the recursive model is appropriate for observations with only small inventory changes. For example, if sellers are price setters, the sellers could be manipulating price upwards by not changing inventories even on days with small positive demand shocks, and hence P_t and ε_t could be correlated for all observations.

The presence of inventories is a generic explanation for simultaneity; it applies to any high-frequency market in which inventory changes play a role in determining actual supply on a market. 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 (error terms are suppressed for expositional ease in what follows) $QS_{producer} = \kappa + \lambda P$ where λ measures the change in the amount produced by the producer in response to a price change. Now suppose that the sellers in this market allow inventories to adjust in the manner described earlier, namely change in inventories is given by $\theta(QS_{producer} - Q_d)$ where Q_d is the demand. Actual quantity supplied on the market consequently is $Q_s = \kappa + \lambda P - \theta(QS_{producer} - Q_d)$.

Substituting in for demand from equation (2), identifying Q_s with $QS_{producer}$, and reducing, we get

(6) $Q_s = (\kappa + \theta\gamma)/(1+\theta) + [(\lambda + \theta\delta)/(1+\theta)]P$

Estimation using traditional simultaneous equation estimation techniques produces an asymptotically unbiased estimate of $(\lambda + \theta\delta)/(1+\theta)$, not an estimate of λ. This estimate is a weighted average of the producer response and the demand response to price change, with the weight depending on the extent to which excess demand/supply is met by inventory change. 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.

THE FULTON FISH MARKET DATA

Graddy [2006] provides a very good description of the Fulton fish market data.[2] These are 111 daily observations on price and quantity of whiting in 1991-2, along with weather information serving as an instrumental variable. 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).

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. Following Graddy [1995], 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.

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 approximately half 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 4,040 pounds), or by 1.4% of the quantity sold. This amount is likely to be unrecorded sales or shrinkage. Average daily fish sales during this period was 6335 pounds, with an average absolute value of daily inventory change of 1740 pounds. Despite the perishable nature of this product, average inventory holdings were at least 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, this daily difference, the inventory change, is quite variable. The big upward spike took place on Friday, March 13, during Lent, when an unusually large quantity of fish was received.[3] 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.

<< Figure 1 here>>

For the purposes of our estimation below, we define days in which inventory change is “small” as follows. We took the standard deviation of daily inventory changes (3021 pounds), arbitrarily trimmed it by five percent, and chose to define “small” as twenty percent of this figure. This gave rise to 34 “small” inventory change days, and 77 days with “large” inventory change. (Our results are robust to the exact definition of “small” 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 here >>

As can be seen from the table, there are no substantive or 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 behavior is in essence cushioning price changes, concealing the relationship between price and inventory adjustment. The only statistically significant differences in the subsamples are that the quantity received is significantly larger on days in which there are inventory additions rather than depletions.

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

$$\ln q_t^d\left(p\right) = \beta_o + \beta_1 \ln(p) + \beta_2 x + \varepsilon_t^d$$

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 binary variable “stormy” as an instrument.

<< Table 2 here >>

When using all the data, as reported in columns 1 and 2 of Table 2, the IV estimates of the price elasticity of demand contrast sharply with the ordinary least squares estimates. These columns match results reported by Graddy [2006]. Together with the small p value for the Hausman test statistic, this suggests that there is considerable simultaneity in these data.

As explained earlier in our specific model, 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 “small”, as described earlier, and days in which the inventory change is “large.”[4]

The results in Table 2 are striking. In the regressions using only the data with “large” 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 “small” inventory change the Hausman test p value of 0.997, suggests that in these data there is no simultaneity.

Furthermore, we find, as anticipated, that when using only data for which there are “small” inventory changes, the OLS estimate of the demand elasticity is comparable to the IV estimates. This latter evidence is more convincing; the Hausman test is sensitive to sample size.

As a final check, we used the OLS estimated coefficients from the “small” change data (column 5 of Table 2) to predict quantity demanded for the “large” 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 inventory changes motivate price 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 and price changes move together 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, inventory changes must not have any influence on prices changes. In our model, which was consistent with the Fulton Fish market data, we showed that small inventory chances do not have any influence on price, but that moderate to large inventory changes do.

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 produces biased estimates of long-run producer response to a price change, the bias depending in a complicated way on producer reactions to price changes, consumer reactions to price changes, and the role of inventory changes.

Acknowledgement

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Notes

1 This model, and the ensuing empirical work, have deliberately been kept simple, to focus on the contribution of this paper, namely the role played by inventories in creating simultaneity in high-frequency markets. We leave for further work more sophisticated modelling of inventory behavior, and its joint estimation with associated demand and supply parameters.

2 These data were gathered by Graddy over a four-month period in 1991-2. They are available at http://people.brandeis.edu/~kgraddy/data.html.

3 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].

4 It is not necessarily the case that large inventory changes always identify simultaneous equations bias. Some large inventory changes may correspond to no simultaneous equations bias; these inventory changes may be desired because sellers

need to adjust inventories to compensate for large inventory changes experienced the day before. That is, the expected equilibrium price for the day, before the day's demand shock, already takes into account a desired inventory change. Note, however, that this phenomenon should shrink the difference between the OLS results using "small" inventory change data and those using "large" inventory change data. This bias works against our empirical hypothesis and so is not of consequence here.

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Table 1 Summary Statistics for the Fulton fish market data

	Full Sample		Small change		Large Change			Large Change Subsample				
								Depletions		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
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		

Table 2 OLS and IV Regressions with Covariates
Dependent variable: lnquantity

	1	2	3	4	5	6
	Full Sample		Large Change		Small Change	
	OLS	IV	OLS	IV	OLS	IV
lnprice	**-0.545**	**-1.223**	**-0.422**	**-1.137**	**-0.958**	-0.97
	(0.175)	**(0.506)**	**(0.185)**	**(0.375)**	**(0.451)**	(4.100)
day1	0.032	-0.033	0.286	0.284	-0.748	-0.75
	(0.207)	(0.215)	(0.219)	(0.213)	(0.513)	(0.779)
day2	**-0.493**	**-0.533**	-0.362	-0.38	-0.789	-0.789
	(0.204)	**(0.209)**	(0.224)	(0.219)	(0.427)	(0.462)
day3	**-0.539**	**-0.576**	-0.413	-0.39	**-0.892**	-0.894
	(0.206)	**(0.211)**	(0.232)	(0.227)	**(0.414)**	(0.858)
day4	0.095	0.118	0.255	0.383	-0.401	-0.404
	(0.201)	(0.205)	(0.233)	(0.234)	(0.403)	(0.987)
cold	-0.062	0.068	-0.029	0.135	-0.194	-0.193
	(0.134)	(0.164)	(0.147)	(0.162)	(0.306)	(0.532)
rainy	0.067	0.072	-0.073	-0.061	0.365	0.365
	(0.177)	(0.181)	(0.203)	(0.198)	(0.358)	(0.397)
Constant	**8.617**	**8.442**	**8.57**	**8.288**	**8.759**	**8.759**
	(0.162)	**(0.205)**	**(0.194)**	**(0.229)**	**(0.291)**	**(0.373)**
Hausman p-value		0.146		**0.033**		0.997
obs	111	111	77	77	34	34
R-squared	0.22	0.2	0.26	0.3	0.33	0.22

Standard errors in parentheses

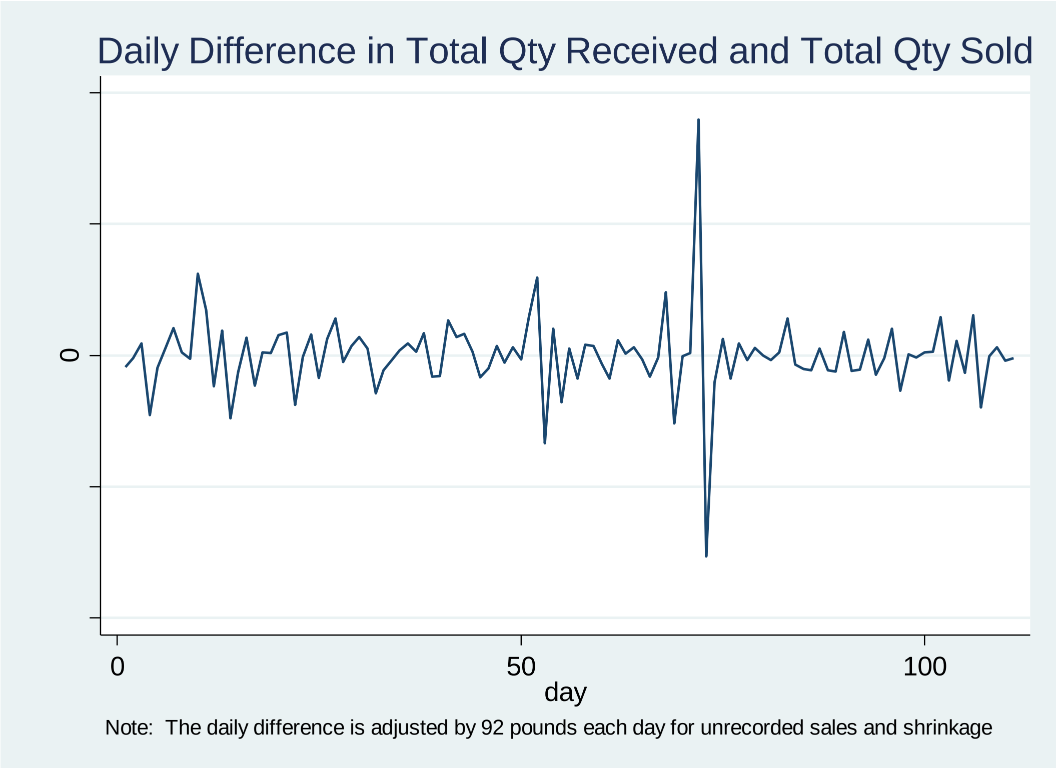

Figure 1 Daily inventory change