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A Study of Short-Run Grain Movements on the Inland Waterway System (Phase 2, Task 5)

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by

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ABSTRACT

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The Army Corps of Engineers (ACE) maintain the nation's waterways. ACE investments in the waterway are, in part, evaluated through complicated planning models. These models make a series of assumptions related to the demand and supply of transportation services and evaluate the costs and benefits through an equilibrium model and associated forecasts of traffic levels. Recent evaluations of the planning models have focused on assumptions related to the treatment of demand, forecasts, and the failure to model modal and market substitution patterns. In part, the assumptions made are for expediency, owing to the complexity of the underlying "true" economic model and to the lack of appropriate data. In this paper, time-series techniques are used to characterize the relationship between river traffic and key economic variables which reflect both modal and market substitution patterns. The model allows for dynamic relationships between variables to be evaluated, an important step because very few studies examine the dynamic relationship between river traffic and economic variables. The approach is to use a vector autoregressive model that includes six categories of variables, lockages, rail deliveries, rail rates, grain bids, ocean freight rates, and barge rates. We evaluate the interrelationships between these variable over time using impulse response functions. Variance decompositions are also constructed and are used to identify the most important variables affecting lockages and other variables in the model at both short and long horizons. Key findings of this study that (i) barge traffic is responsive to both barge and rail rate changes, (ii) barge traffic is responsive to grain bids at different port locations, (iii) barge traffic responds strongly to changes in ocean freight rates, (iv) there are important dynamic adjustment patterns, and (v) the spatial location of locks and related tonnages are central in determining the level and relative importance of changes in key variables.

1. INTRODUCTION

The relationship between river traffic and economic variables such as modal and port prices play a key role in determining the potential benefits of waterway projects to increase the volume of traffic. Generally, these relationships are identified and examined using static structural models, an approach that has been heavily criticized. For example, the National Research Council has noted a number of concerns with Army Corps Planning models relating to the structure of demand and the inherent substitution patterns. In particular, concerns exist over the lack of knowledge of key spatial and time-series relationships between barge and railroad markets, and between downstream prices in various markets and ocean freight rates. In this paper, time-series techniques are used to evaluate substitution patterns and spatial relationships and thereby take a step towards alleviating the concerns expressed by the National Research Council.

The vector autoregressive model used in this paper allows the data to identify important patterns between the level of river traffic and the interrelationship with terminal prices, barge rates, rail rates, rail deliveries, and ocean freight rates. In addition, the model developed here is useful for understanding how the demand for river transportation services is affected by shocks to barge prices and quantities as well as shocks to prices and quantities of products shipped down the river and prices and quantities of competing transportation modes. Demanders of river transportation services often make decisions based upon future expectations of such variables and the model developed here provides a short-run forecasting model capable of uncovering such relationships. This is important because, as recent experience of the Mississippi suggests, changes in variaibles such as ocean freight rates can have large and dramatic influences on river traffic and little is know about how these variables are related. Also, events such as unexpected lock closings can be captured within the model used here and the effects of such closures on prices and quantities of transportation services can be determined.

In the analysis, we use a set of time series techniques that are designed, in part, to address problems with traditional structural forecasting.[1] Forecasts based upon structural models are often poor due to lack of knowledge regarding the true structure and thus uncertainty about how to properly restrict the models, and due to changes in the structure over time that are not incorporated into the model. In the case of river transportation, structural models forecast the demand for river transportation from forecasts of the demand for products that use river transportation such as grains and industrial products.[2] Forecasting the demand for these products requires forecasts for each of the determinants of demand for each of the products that is transported on the river. This is a large and complicated task that often requires questionable simplifying assumptions, a task that is further complicated by the lack of available data on each of the many influences on the demand for each of the products transported on the river. Such models often impose assumptions on the data, explicitly or implicitly, with little theoretical support or based upon theory that has not been thoroughly investigated econometrically. This study proposes an alternative approach that avoids structural

[1] Most forecasting models of river traffic rely on structural modeling. Structural econometric models have as their basic building blocks behavioral equations, equilibrium conditions, and accounting identities derived from theoretical models. This results in restricted models, with the restrictions often in the form of the exclusion of some variables from some equations. Identification restrictions often result in further exclusions, often without theoretical support. Vector autoregressive models do not impose any exclusion restrictions upon the data, instead, they generally rely upon restrictions on contemporaneous causal relationships or assume zero long-run effects of particular types of shocks. Thus, in these models structural shocks are still identified, but through a different set of identifying assumptions that do not involve excluding variables from particular equations.

[2] Two examples are Baumel (2000) and Sparks Companies Inc. (2002).

modeling of complicated real-world behavioral relationships, an approach common in the time-series econometrics literature.

Economists commonly use time-series techniques to understand and forecast variables of interest. These models are used for forecast horizons that extend far into the future and for shorter horizons, as short as days or even minutes in the financial literature. Such techniques often rely upon vector autoregressive (VAR) models. These models are interpreted as general reduced form structural models. The genesis of VAR models[3] arises from the idea that the identification restrictions present in most structural econometric models are arbitrary and not supported by underlying theoretical models. If the identification restrictions used to estimate structural econometric models are suspect, then it is not surprising that these models do not produce reliable forecasts. An alternative is to rely on a different identification scheme and forego the troublesome identification restrictions present in structural econometric models.

This led researchers to consider VAR models as an alternative to structural modeling. Under the VAR approach, a very general reduced form is posited which allows each endogenous variable to depend upon every other endogenous variable in the model as well as any exogenous variables.[4] Estimation of VAR models allows the data to impose restrictions as required to achieve the best fit. This is in contrast to the structural approach where such restrictions are imposed as maintained hypotheses. Forecasts of the endogenous variables can then be derived from the estimated VAR models. More importantly and central to this paper, once the VAR model is estimated, it can be used to simulate the reaction of key variable to shocks to other variables and

[3] A seminal article in this area is Sims (1980).
[4] Thus, there are no exclusion restrictions as would exist under the structural approach.

produce estimates of how key variables are related (impulse response functions) and evaluate the importance of each variable (variance decompositions).

Importantly, VAR models are often called atheoretical models, but this can be misleading. VAR are atheoretic in the sense that variables are not arbitrarily excluded from structural equations to obtain identification, and reduced form rather than behavioral relationships are the focus of the modeling effort. However, identification assumptions are still required in order to identify structural disturbances, and the identification of structural disturbances is a necessary component in estimating and properly interpreting the impulse response functions and variance decompositions used in this paper. In the VAR literature, such restrictions are generally restrictions upon contemporaneous relationships, as in this paper, or restrictions regarding the long-run effects of particular shocks.

In the next section, a nineteen variable VAR model is constructed. The model consists of lockages on the Illinois and Mississippi rivers, rail deliveries of grain to export points, rail rates for grain to export points, the bid price for grain at export points, ocean freight rates from export points, and barge rates on the Illinois and Mississippi rivers. The first two categories, lockages and rail deliveries, involve quantities while the last four, rail rates, grain bids, ocean freight rates, and barge rates, are prices.

The model developed here is used to produce impulse response functions and variance decompositions. These show how particular variables in the model respond to unexpected changes in other variables in the model, and how important each type of shock is in explaining variance of the variables in the model. The central results of both the impulse response functions and variance decompositions are that (i) barge traffic is responsive to both barge and rail rate changes, (ii) barge traffic is responsive to grain bids at different port locations, (iii) barge traffic responds strongly to changes in ocean freight rates, (iv) there are important dynamic adjustment patterns, and (v) the spatial location of locks and related tonnages are central in determining the level and relative importance of changes in key variables. In particular, upriver traffic is sensitive to factors affecting a competing mode of transportation, rail rates and rail deliveries, while downriver traffic is more responsive to barge rates and grain bids. Barge rates also have a large impact on rail deliveries, particularly rail deliveries to the Pacific Northwest. This is noteworthy because many planning models do not allow for a role for barge rates in determining quantity variables such as lockages and rail deliveries.

2. DATA AND ECONOMETRIC MODEL

The VAR model and associated impulse response functions and variance decompositions are constructed as follows.

First, data on river traffic through each lock and prices of commodities from various geographic regions are obtained from the Lock Performance Monitoring System (LPMS) as reported in the USDA's *Grain Transportation Report*. Commodity price and other data are also in the USDA's *Grain Transportation Report* which is available on a weekly basis. The variables used in the analysis are shown in Table 1. The data are available consistently from the first week of 1999 through the 20^{th} week (the last week of May) of 2003.

There are six categories of variables in the model, lockages, rail deliveries, rail rates, grain bids, ocean freight rates, and barge rates. These data, in customary log form, are used to estimate a nineteen variable, one lag VAR model.[5] The order of the variables in the VAR model is the same as in the table, and weekly dummies are added as deterministic variables to capture any seasonal effects over the year. In addition, a dummy for lockages at Mississippi lock #15 is constructed that is equal to one when the lock is open, and zero in the weeks it is closed and the value of lockages is zero.[6] For example, the first equation of the VAR model is Total Lockages on the Illinois at Lock #8 regressed upon a constant, the weekly dummies, the Mississippi lock #15 dummy, and one lag of each of the nineteen variables listed in the table.[7] The second equation is Total Lockages on the Mississippi at Lock #15 regressed upon the same set on independent variables, a constant, the weekly dummies, the Mississippi lock 15 dummy, and one lag of each of the nineteen variables in the model, and so on, until the last equation which has Rail Deliveries to the Pacific as the left-hand side variable.

In order to identify structural shocks in the model, the disturbances must be orthogonalized. The orthogonolization of the shocks in the model is performed in the usual manner using the Choleski decomposition. With this decomposition, the variables

[5] One lag is sufficient to remove evidence of serial correlation in the equations constituting the VAR model. This does not, however, necessarily imply that the effects of shocks are short-lived. That depends upon the magnitude of the coefficients on the lag terms more than it does on the number of terms.

[6] An alternative approach where the time periods where the lock was closed are eliminated from the data does not change the results discussed below. In addition, dropping Mississippi lock 15 from the data set altogether so that only lock 27 on the Mississippi and lock 8 on the Illinois are in the data set produces very similar results. Thus, the results appear robust to how the time periods when lock 15 are closed are treated econometrically.

[7] The variables are Total Lockages on the Illinois at Lock #8, Total Lockages on the Mississippi at Lock #15, Total Lockages on the Mississippi at Lock #27, Rail Deliveries to Texas, Rail Deliveries to Mississippi, Rail Deliveries to the Pacific, the Tariff Rail Rate for Wheat from Kansas City to Houston, the Tariff Rail Rate for Wheat from Kansas City to Portland, the Bid Price for Portland HRW, the Bid Price for Gulf HRW, the Bid Price for Gulf SRW, the Bid Price for LA Corn, the Gulf to Taiwan Ocean Freight Rate for Heavy Grain, the PNW to Taiwan Ocean Freight Rate for Heavy Grain, the Barge Rate for the Mid-Mississippi (Percent of Tariff from Davenport IA), the Barge Rate for the Illinois (Percent of Tariff for the Illinois River, Peoria, IL), the Barge Rate for St. Louis-Cairo (Percent of Tariff from St. Louis) , the Barge Rate for Lower Ohio (Percent of Tariff from Lower Ohio) , and the Barge Rate for Cairo-Memphis (Percent of Tariff from Cairo).

least likely to be affected by contemporaneous shocks to other variables are first in the ordering and those variables most likely to be affected contemporaneously are placed last. The results for variance decompositions are presented by groups so that exact identification of particular shocks within groups is not essential. Note that quantities appear in the model ahead of prices so that one element of the identification assumption used here is, in essence, that prices are sensitive to contemporaneous quantity shocks, but the reverse is not true. Price shocks affect quantities only with a one period or greater lag, which in this model is one week or more.

Under these assumptions, which are that demand shocks affect price contemporaneously but affect quantities with at least a one week lag, and that supply shocks affect both price and quantity contemporaneously, the shocks in the model associated with quantities (i.e. the first two sets of equations for lockages and rail deliveries) can be interpreted as supply shocks and those with prices (i.e. the last four sets of equations) as demand shocks.

The model is estimated using the data described above and the estimated model is used to produce impulse response functions (IRFs) and variance decompositions (VDCs). The IRFs show the impact that an unanticipated structural shock to one variable has on the time path followed by another. For example, an IRF can plot the effect that a change in the barge rate between two points has on the amount of traffic through a particular lock as well as other locks.

Because a shock to any one variable can affect all other variables, there are (19)(19)=361 impulse responses. Thus, this discussion will focus on a subset of the responses.[8] The VDCs complement the IRFs. The IRFs show the pattern over time of the response of one variable brought about by a structural shock to another variable. The VDCs assess the importance of the shock in explaining the variance of the responding variable at each point in time. Thus, the IRFs give the sign and the pattern of the response while the VDCs assess the importance of the structural shock in explaining the variability of a particular variable at each point in time after the shock occurs. The VDCs are also voluminous, so as with the IRFs, only a representative subset is presented.

3. IMPULSE RESPONSE FUNCTIONS

There are six categories of variables in the model, lockages, rail deliveries, rail rates, grain bids, ocean freight rates, and barge rates. As just noted, because the complete set of results is too voluminous to present in its entirety, representative examples from each category are shown. First, IRFs for shocks to quantities (lockages and rail deliveries) are presented and discussed followed by the IRFs for shocks to prices (rail rates, grain bids, ocean freight rates, and barge rates). As noted above, under the identification scheme used here, these are structural supply and demand shocks rather than reduced form shocks (i.e. linear combinations of structural shocks) so that the IRF's can be interpreted as the response to independent structural disturbances.

A. Shocks to Total Lockages

Figure 1a shows how lockages at Illinois lock #8, Mississippi lock #27, and rail deliveries to Mississippi and the Pacific change in response to approximately a 25%

[8] The entire set of responses is available in an appendix.

increase in the supply of lockages on the Mississippi at lock #15.[9] The figures show a 4% drop in lockages at Illinois lock #8 and a quick return to pre-shock levels, though there is a small negative effect that persists. Lockages at Mississippi lock #27 increase 5%, an effect that peaks in the second week and, while the effect is somewhat persistent, the peak tapers substantially and is largely eliminated after around four weeks. Thus, the increase in the supply of lockages at Mississippi lock #15 increases lockages downriver at Mississippi lock #27, though not by as much as the increase at lock #15, and decreases lockages on the Illinois. The increased lockages also cause rail deliveries to the Mississippi to increase around 2.5%, and rail deliveries to the Pacific increase almost 4% at the peak. Both rail responses are slightly noisy at first, but after three to five weeks exhibit a clear positive response to the shock. Thus, the increase in traffic on the river causes a substitution towards rail deliveries.

Figure 1a examines how quantities respond to the shock to lockages. Figure 1b examines the response of prices. The figure shows how the Kansas City-Houston Wheat Rail Rate, the Gulf HRW Price Bid, the Gulf to Taiwan Freight Rate, and the Illinois Barge Rate respond to a shock to the supply of lockages at Mississippi #15. The Kansas City-Houston rail rate exhibits little response to the shock to lockages at Mississippi lock #15, a result common across all shocks and for both rail rates. Thus, rail rates are largely exogenous with respect to the other eighteen variables in the model. To the extent that there is a response to the increase in lockages, it is positive. The Gulf HRW bid price does not respond strongly either. The response is positive and persistent, but only around 1% at its peak. Ocean freight rates show a larger positive response to the increase in the

[9] The size of the shock in all cases is, as usual, one standard deviation. Because lock 15 closes in the winter, there is a large variance in lockages so that a one standard deviation shock is relatively large.

supply of locks of around 1-2%, and the response is persistent. The response of the Illinois barge rate is around the same magnitude and, after a delay of a week or two, shows a clear decline that persists for just over ten weeks. Overall the price responses are not large, at most 1-2%, with barge and ocean rates responding stronger than rail rates and grain bids to the shock to lockages.

The results for shocks to Illinois lock #8 and Mississippi lock #27 (not shown in figure 1, but they are shown in the appendices) are qualitatively identical with two notable exceptions. First, a supply shock to Illinois lock #8 causes lockages at Mississippi lock #15 to decline. Thus, when Lock #15 on the Mississippi receives the shock, lockages at Illinois #8 decline whereas when the shock is to Illinois #8, Mississippi #15 lockages decline. An increase in either decreases the other. Lockages at Mississippi #27 increase in both cases. Second, a supply shock to lockages at Mississippi lock #27 causes barge rates to increase rather than decrease except for the Lower Ohio rate which shows little response. Thus, the effect on barge rates depends upon which lock receives the unanticipated increase in traffic. Upstream lockage shocks lower barge rates while downstream shocks raise barge rates.

B. Shocks to Rail Deliveries

The next example is a supply shock to rail deliveries, in particular a shock of approximately 14% to rail deliveries to the Pacific. With the exceptions noted below, the responses to rail delivery shocks are noisy, particularly in the initial weeks following a shock, and the results in figures 2a and 2b for shock to Pacific rail deliveries reflect this overall characteristic for rail delivery shocks. The figures show a muted response of lockages at Illinois lock #8 which initially increase then, after a delay of three weeks, decline by around 1% then return to pre-shock levels. The response at Mississippi lock #15 is much stronger with an initial decline of around 3% followed by a fairly quick return to pre-shock levels, though there is some evidence of a persistent negative response. As for rail deliveries, rail deliveries to Mississippi and Texas are both initially fairly noisy, then, after three to five weeks, settle down and exhibit a persistent negative effect. Thus, the increase in the supply of rail deliveries to the Pacific causes a decline in lockages at Mississippi lock #15, an uncertain effect on lockages at Illinois lock #8, and effect that is initially positive then negative, and a persistent negative effect on rail deliveries to Texas and Mississippi after an initial turbulent response.

The figures show the response to a supply shock to Pacific rail deliveries. The results differ in two noteworthy ways when the shocks are to Texas and Mississippi rail deliveries rather than to Pacific rail deliveries. First, in both cases, particularly an increase in rail deliveries to Texas, barge rates show a clear and consistent decline for five to ten weeks after the shock. Thus, shocks to rail deliveries to Texas and Mississippi affect barge rates negatively, while shocks to Pacific rail deliveries do not have much impact on barge rates. Second, though the effect is only around 1%, ocean freight rates show a clear positive response to an increase in the supply of Texas and Mississippi rail deliveries, unlike rail deliveries to the Pacific. Thus, shocks to Mississippi and Texas rail deliveries affect barge and ocean freight rates, while shocks to the Pacific do not.

C. Shocks to Tariff Rail Rates

Figures 3a and 3b show how lockages at Illinois lock #8 and Mississippi lock #15, rail deliveries to Texas and the Pacific, the Kansas City-Portland wheat rail rate, the Gulf to Taiwan ocean freight rate, the Portland HRW price, and the Cairo-Memphis barge rate respond to a one standard deviation increase in the Kansas City to Houston rail rate for wheat. Figure 3a shows that a positive demand shock for rail deliveries causing an approximately .5% increase in the tariff rail rate for wheat[10] per ton causes a 3% decline in lockages on the Illinois lock #8, and a 4% increase at lock #15 on the Mississippi, and that the results are persistent with effects lasting beyond fifteen weeks in both cases. The detailed results show that lockages at Mississippi #27 also increase, but not as much and not as persistently. Rail deliveries to Texas decline, both immediately and over a longer time period, though there is an intermediate period at around six weeks where the effects are small. The pattern of the response is an immediate drop of nearly 2%, a return to zero after about six weeks, and then a sustained fall. Rail deliveries the Pacific move in the opposite direction, increasing immediately with the positive effect sustained for many weeks. In this case there is no intermediate period where the effects diminish. Thus, overall, a shock to the rail rate for wheat from Kansas City to Houston causes a substitution towards Mississippi locks #15 and #27 with stronger effects upriver, towards rail deliveries to the Pacific, and away from Illinois lock #8 and rail deliveries to Texas.

Figure 3b shows how prices respond to the rail rate shock brought about by an increase in demand for rail services. The Kansas City to Portland wheat rail rate does not

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[10] The one standard deviation shock is relatively small because the variation in rail rates is small in the sample.

respond strongly nor does the Gulf to Taiwan freight rate. The Portland HRW price does respond, slightly negatively at first, then after a few week delay a positive response of around 1%. The Cairo-Memphis barge rate also responds, falling by around 2% then gradually returning to zero over the course of many weeks.

The additional results in the appendix are generally consistent with the results shown in the figures with one exception. When the demand shock is to the Kansas City to Portland rail rate rather than the Kansas City to Houston rail rate, the quantity responses are almost all in the opposite direction. For example, when the Kansas City to Portland rail rate increases, lockages on the Illinois increase rather than decrease, lockages on the Mississippi decrease at lock #15 rather than increase and show a small positive response downriver at lock #27. Rail deliveries to the Pacific decline rather than increase, rail deliveries to Texas increase initially rather than decreasing. The price responses are all the same, i.e. barge rates decline as in figures 3a and 3b, grain bids increase, and so on.

D. Shocks to Grain Bids

The next example shows the response to a demand shock resulting in increased grain bids. In particular, Figures 4a and 4b presents the response of quantities and prices to a shock to the Portland HRW price of approximately 2%. Figure 4a shows that the response of lockages at Illinois lock #8 is positive and exceeds 2%, while the response of lockages at Mississippi lock #15 is negative with a small and quick decline beginning the second week after the shock followed by a more prolonged decline of similar magnitude several weeks later. The response of Mississippi lock #27 (not shown in the figure) is small and positive. Turning to rail deliveries, the increase in the bid price of HRW in Portland causes a 5% decline in rail deliveries to Texas and a decline of similar magnitude in deliveries to Mississippi (not shown in the figure). Rail deliveries to the Pacific initially decline slightly after a delay of one week, and then show a sustained increase in the weeks that follow. Overall, the results are that an increase in the grain bid price in Portland brought about by an increase in the demand for grain causes lockages on the Illinois to increase at lock #8, to decrease at lock #15 on the Mississippi, and to increase slightly at lock #27 on the Mississippi. The shock also causes rail deliveries to Texas and Mississippi to decline, and rail deliveries to the Pacific to increase.

The response of prices in figure 4b shows that the Kansas City to Houston wheat rail rate does not exhibit a discernible response, which is true for rail rates generally in response to bid prices. The results show that the Gulf HRW increases and follows a pattern very similar to the pattern for the Portland HRW response to its own shock, that after a delay of several weeks the freight rate from Portland to Taiwan increases, and that the Illinois barge rate, and barge rates generally, show a sustained increase due to the increase in the grain bid prices.

The results in the appendices are generally consistent with those in the figures. One exception is the response of rail deliveries to a demand shock that increases the Louisiana bid price for corn. In this case, rail deliveries to Texas fall substantially and for a prolonged time period, and rail deliveries to Mississippi and the Pacific Northwest show a large and sustained increase. When the shock is to the Gulf HRW price, rail deliveries to Texas increase while deliveries to the Pacific Northwest decrease. Deliveries to Mississippi initially decrease as well, and then turn positive after many weeks have passed. Thus, the results indicate that the response of rail deliveries depends upon the particular price that is shocked, with the response differing for shocks to the Portland HRW price, the GUL HRW price, and the price of corn in Louisiana. There is also some evidence that the response of ocean freight rates depends upon the particular grain price that changes, but the difference is not as stark as for rail deliveries.

E. Shocks to Ocean Freight Rates

Figures 5a and 5b examine quantity and price responses to a demand shock for ocean freight deliveries causing an increase in the Gulf to Taiwan ocean freight rate. The quantity responses shown in figure 5a show that lockages at Illinois lock #8 fall for a prolonged period after an initial delay of two weeks, that lockages at Mississippi lock #15 initially increase, then decrease after five to ten weeks, and that lockages at Mississippi lock #27 mirror those at lock #15 but are much more muted (not shown in the figure, see appendix). The figure also shows that Texas rail deliveries are relatively unaffected by the shock to the ocean freight rate, and that Pacific rail deliveries increase after a one week delay. In addition, rail deliveries to Mississippi increase for a substantial period of time after the shock (not shown in the figure, see appendix).

Figure 5b shows the response of prices to the demand shock to the ocean freight rate from the Gulf to Taiwan. As is the case generally, and for all the ocean freight rate shocks and rail rates, there is little noticeable response of the Kansas City to Houston wheat rail rate. The Portland HRW bid price declines in response to the shock, the Pacific Northwest to Taiwan ocean freight rate increases, and the Lower Ohio barge rate increases, each for a substantial period of weeks.

In the expanded results in the Appendix the results are generally the same with two notable differences. First, barge rates decrease when the demand shock is to the Pacific Northwest ocean freight rate, the opposite of the result when the shock is to the Gulf ocean freight rate. Second, the response of quantities, lockages and rail deliveries, depends upon which of the two ocean freight rates is shocked by an increase in demand. When the shock is to the Pacific Northwest ocean freight rate, lockages on the Mississippi, Rail deliveries to Mississippi, and rail deliveries to Texas move in the opposite direction as compared to a shock to the Gulf ocean freight rate, lockages on the Illinois at lock #8 move in the same direction, and once again Texas rail deliveries do not change substantially. Thus, when the shock is to the Pacific Northwest ocean freight rate rather than the Gulf rate, lockages on the Mississippi, rail deliveries to the Mississippi, and Pacific rail deliveries all move in the opposite direction and fall. This indicates that when the Gulf ocean freight rate increases, there is substitution towards the Pacific Northwest, but when ocean freight rates from the Pacific Northwest increase, rail deliveries and lockages fall in all locations except for rail deliveries to Texas, which are unaffected.

F. Shocks to Barge Rates

The final example examines impulse responses to a demand shock for barge services resulting in increased barge rates. The particular example is a shock to the Cairo-Memphis barge rate. The four graphs in Figure 6a show the responses of lockages at lock #8 on the Illinois River, lock #27 on the Mississippi, rail deliveries to Texas, and rail deliveries to the Pacific to a shock to the Cairo-Memphis barge rate. The graphs show that an increase in the barge rate of approximately 3% generates a 2.5% decline in lockages on the Illinois at lock #8, and a 2% decline in lockages on the Mississippi at lock #27. In the expanded results showing demand shocks to all barge rates, this case is noteworthy because the change at lock #27 on the Mississippi is larger than the change at lock #15. In all other cases, when the shock is to barge rates further upriver, the change at lock #27 is generally a muted version of the change at lock #15. The shock brings about a 4% increase in Texas rail deliveries, and a 2% decrease in rail deliveries to the Pacific after a delay of two weeks. This suggests that the increase in barge rates causes a substitution towards rail deliveries to Texas and away from barge transportation.

Figure 6b shows how prices respond to the demand shock to the Cairo-Memphis barge rate. As in previous cases, the response of the wheat rail rates from Kansas City to Houston exhibits little if any response. The response of the Gulf HRW bid price is small and negative after a delay of two weeks, and the response of the ocean freight rate from the Pacific Northwest to Taiwan is positive, but small. The response of barge rates is more substantial, with the Mid-Mississippi barge rate, and barge rates generally, falling in response to the increase in the Cairo-Memphis barge rate. Thus, upriver barge rates fall when downriver barge rates increase.

The results for demand shocks to barge rates shown in the appendices are similar. However, the response of the quantity variables depends upon the particular barge rate shocked. In addition, when the two barge rates furthest downriver, the Lower Ohio and Cairo-Memphis rates, are shocked by a change in demand all barge rates upriver fall. However, when barge rates even further upriver are shocked, barge rates downriver increase, perhaps due to the bypassing of upriver barge transportation through the use of other transportation modes.

4. VARIANCE DECOMPOSITIONS

Impulse response functions document how variables in the model respond over time to their own shocks and to shocks to other variables. However, impulse response functions do not tell us how important the shocks are in explaining variation in the variable under consideration. For example, the left-side of the top half of Figure 6a shows how lockages respond to a shock to the Cairo-Memphis barge rate at various time horizons up to one year after the shock. But among all nineteen shocks identified in the VAR system, how important is this particular shock in explaining variation in lockages at these time horizons? Does a shock to the Cairo-Memphis barge rate cause more or less variation in lockages than, say, a shock to the Portland HRW bid price? Variance decompositions (VDCs) can be used to answer these and other questions.

A. Variance Decompositions for Lockages

Variance decompositions decompose the variance of a particular variable, say lockages at Mississippi lock #15, at each forecast step (from one to fifty-two in the figures) into the fraction of the variance attributable to shocks to each of the seventeen variables in the model. The first set of numbers in Table 2 present variance decompositions for one of the lockage variables, Mississippi lock #15, at steps of 1, 2, 4, 8, 12, 20, 26, 40, and 52.[11] The VDCs have been accumulated by category of variable.

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[11] Space does not permit listing the complete set of variance decompositions for all seventeen variables in the model or for every one of the 52 steps. Representative VDCs for each category are presented and any

For example, consider the entry of .11 under the heading Rail Rates for step 12 of the decomposition for Mississippi Lock #15. This indicates that 11% of the variance in lockages after 12 weeks can be explained by the combined effect of supply shocks to rail rates, where the combined effect is the sum of the individual VDC entries for the two rail rate variables.

Several conclusions emerge from examination of the VDCs. First, the largest factor affecting the variance of lockages is shocks to lockages. This is the usual outcome for VDCs, i.e. that the largest fraction of the variability at all horizons is explained by a variables' own shocks. Second, setting aside the fraction of the variance of lockages explained by shocks to lockages, rail deliveries and rail rates each account for approximately 10% at the 52 week horizon, while grain bids, ocean rates, and barge rates each account for around 5%. Thus, none of these variables has a dominating influence individually, but their combined effect is large, e.g. rail rates and barge rates account for 17% of the total variation at the one year time horizon. At shorter horizons such as two weeks, the most important factors are rail deliveries and barge rates which account for 12% of the variation. As time passes, rail rates and ocean rates become more important.

The more detailed results in the appendices show that the results are generally very similar across the three lockage variables. One notable difference is that the sensitivity of lockages at Mississippi lock #27 to rail rates and rail deliveries is smaller than for Mississippi lock #15 and Illinois lock#8 while the effect of other variables is larger. Thus, rail rates and rail deliveries affect upriver lockages more than downriver lockages. For instance, after 12 weeks, shocks to rail rates and rail deliveries explain

notable differences from the results in the appendices are explicitly noted. As with the IRFs, the complete set of VDCs can be obtained in a appendix available from the authors.

20% (9% plus 11%) of the variation in lockages at Mississippi lock #15, and 14% of the variation at Illinois lock #8, but only 6% of the variation at Mississippi lock #27. Grain bids and barge rates, which account for 6%+8% = 14% of the variation at this horizon, are more important.

Thus, from the results in Figures 1a and 1b along with the results in the Appendix F show that upriver lockages are most sensitive to factors affecting rail deliveries and rail rates while downriver lockages are more sensitive to shocks to barge rates and grain bids. The result that barge rates are as important as other factors in explaining downriver lockages is noteworthy because river transportation planning models assume that lockages are invariant to changes in barge rates brought about by changes in the demand for barge deliveries.

This is also consistent with the results from the IRFs. Recall there is only one case, a supply shock to a downriver barge rate, where the response downriver at Mississippi lock #27 exceeds the response to the shock upriver. In all other cases, the upriver response at Mississippi lock #15 and at Illinois lock #8 is larger than the response downriver at Mississippi lock #27. Downriver lockages are affected more by downriver barge rates than those further upriver.

B. Variance Decompositions for Rail Deliveries

At short time horizons, e.g. two weeks, the most important factors explaining the variance of rail deliveries are lockages at 14%, grain bids at 5%, and barge rates at 6%. At four weeks, the numbers are 14%, 10%, and 16% so that these three variables, lockages, grain bids, and barge rates, account for 40% of the total variation. At longer horizons, e.g. one year, the most important variables are lockages at 15%, rail rates at 9%, grain bids at 16%, and barge rates at 25%.

The detailed results for rail deliveries to Mississippi, Texas, and the Pacific are generally consistent. However, it is worth noting that rail deliveries to the Pacific are more responsive to changes in barge rates and ocean rates than are rail deliveries to Texas and Mississippi, and that the variables in the model do not explain as much of the variability in Mississippi rail deliveries as the other two rail delivery variables. That is, Mississippi rail deliveries are much more invariant to shocks than the other two rail delivery variables. But even in this case the price variables explain 24% of the total variation at the one year horizon.

Overall, lockages, rail rates, grain bids, and barge rates all play a role in determining the variability in rail deliveries, with the role for barge rates in explaining rail deliveries of particular note due to its absence in many planning models.

C. Variance Decompositions for Rail Rates

The third set of numbers in Table 2 shows the VDC for the Kansas City-Houston wheat rail rate, which is very similar to the VDC for the Kansas City-Portland rate. In the short-run, lockages play the largest role, explaining 15% at the one week horizon, followed closely by rail deliveries at 11%. Thus, changes in quantity variables caused by supply shocks explain most of the variation at this horizon. As the horizon is increases, the quantity variables become less important and changes in price variables due to demand shocks become more important so that, at the 52 week horizon, lockages and rail deliveries explain 18% of the variation, down from a peak of 32% at the two seek horizon, and prices explain 30% with grain bids at 16%, ocean rates at 4%, and barge rates at 10%. Ocean freight rates have very little impact on variation in rail rates at any horizon.

D. Variance Decompositions for Grain Bid Prices

In the short-run, at one or two weeks, only rail rates have a notable impact on grain bid prices, explaining 17% of the variation at the two week horizon. As the horizon increases, river lockages, rail deliveries, rail rates in particular, and barge rates have an effect on the variation in the bid price explaining 11%, 9%, 37%, and 12% of the total variance at the 52 week horizon. Ocean rates do not have a large impact at any horizon.

The more detailed results for the other grain bids are very similar. The only difference is a smaller role for rail rates, e.g. around 27% rather than 37%, at the 52 week horizon, but this still indicates a substantial role for rail rates.

E. Variance Decompositions for Ocean Freight Rates

The results for the two ocean freight rates are very similar with no notable differences. The results in the table show that the Gulf to Taiwan ocean freight rate is relatively unaffected by anything other than its own shocks until the four week horizon, though at the two week horizon lockages, rail deliveries, and grain bids account for over 15% of the total variation. At the four week horizon, lockages explain 10% of the variation, rail deliveries explain 11%, and barge rates 7%. At longer horizons, e.g. 52 weeks, two variables emerge as dominant, lockages and grain bids which together account for more than 60% of the variation. Also important are rail deliveries at 12% and rail rates at 20%. These four variables, lockages, grain bids, rail deliveries, and rail rates, explain over 85% of the total variation at the 52 week horizon. Barge rates do not affect ocean freight rates substantially at any horizon.

F. Variance Decompositions for Barge Rates

There are five barge rates examined and the results are surprisingly similar across the five rates. The results in table 2, for the St. Louis-Cairo barge rate, show that in the short-run, rail deliveries, grain bids, and ocean rates exert the most influence explaining 14%, 10%, and 7% of the variance. As the horizon progresses to 52 weeks, river lockages become increasingly important explaining 10%, rail deliveries falls slightly to 11% from a peak of 15%, rail rates become more important as do grain bids which increase to 14% and 16%, and the percentage explained by ocean rates stays fairly steady and is 9% at 52 weeks. Overall, the variation at the 52 week horizon not explained by its own shocks, which is 60% of the variation, is explained fairly evenly by the other five categories of variables in the model so that 12% for each is a fairly good approximation of the outcome. This is true generally in the detailed results except that ocean rates are generally a percentage or two lower and grain bids three or four percentage points higher.

5. CONCLUSIONS

This paper uses time-series techniques, in particular impulse response functions and variance decompositions, to characterize the short-run relationships among nineteen variables in a VAR model designed to trace the short-run interconnections among variables impacting lockages on the Mississippi and Illinois rivers. The model contains six categories of variables, lockages, rail deliveries, rail rates, grain bids, ocean freight rates, and barge and long horizons.

The results in this paper are useful for illuminating the causal relationships among variables in the model and for understanding the behavioral relationships present in the data, and can be used to guide short-run and long-run planning models. For example, the results of both the impulse response functions and variance decompositions show that the location of a lock on the river is an important factor in determining its response to shocks. In particular, upriver traffic is sensitive to factors affecting a competing mode of transportation, rail rates and rail deliveries, while downriver traffic is more responsive to barge rates and grain bids, particularly downriver barge rates. Barge rates also have a large impact on rail deliveries, particularly rail deliveries to the Pacific Northwest. This is noteworthy because many planning models do not allow for a role for barge rates in determining quantity variables such as lockages and rail rates. Variance decompositions and impulse response functions are constructed which identify the most important variable affecting lockages and other variables at both short deliveries.

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TABLE 1 Weekly Data from 1999:01 through 2003:20 Collected from the USDA's Grain Transportation Report Used in the VAR Model

A. Lockages

Total Lockages on the Illinois at Lock #8
Total Lockages on the Mississippi at Lock #15
Total Lockages on the Mississippi at Lock #27

B. Rail Deliveries

Rail Deliveries to Texas
Rail Deliveries to Mississippi
Rail Deliveries to the Pacific

C. Tariff Rail Rates

The Tariff Rail Rate for Wheat from Kansas City to Houston
The Tariff Rail Rate for Wheat from Kansas City to

D. Grain Bid Prices

The Bid Price for Portland HRW
The Bid Price for Gulf HRW
The Bid Price for Gulf SRW
The Bid Price for LA Corn Portland

E. Ocean Freight Rates

The Gulf to Taiwan Ocean Freight Rate for Heavy Grain
The PNW to Taiwan Ocean Freight Rate for Heavy Grain

F. Barge Rates

Barge Rates for the Mid-Mississippi (Percent of Tariff from Davenport IA)
Barge Rates for the Illinois (Percent of Tariff for the Illinois River, Peoria, IL)
Barge Rates for St. Louis-Cairo (Percent of Tariff from St. Louis)
Barge Rates for Lower Ohio (Percent of Tariff from Lower Ohio)
Barge Rates for Cairo-Memphis (Percent of Tariff from Cairo)

TABLE 2 Variance Decompositions

Mississippi Lock #15

Step	River Locks	Rail Deliv.	Rail Rates	Grain Bids	Ocean Rates	Barge Rates
1	1.00	.00	.00	.00	.00	.00
2	.85	.08	.03	.01	.00	.04
4	.79	.07	.06	.02	.01	.04
8	.72	.08	.10	.03	.02	.05
12	.69	.09	.11	.03	.02	.06
20	.67	.10	.11	.03	.03	.07
26	.66	.10	.11	.03	.03	.07
40	.65	.10	.11	.04	.04	.06
52	.64	.10	.11	.06	.04	.06

Pacific Rail Deliveries

Step	River Locks	Rail Deliv.	Rail Rates	Grain Bids	Ocean Rates	Barge Rates
1	.13	.87	.00	.00	.00	.00
2	.14	.73	.02	.05	.00	.06
4	.14	.51	.04	.08	.01	.21
8	.12	.40	.06	.09	.04	.28
12	.12	.36	.07	.10	.06	.29
20	.14	.32	.08	.13	.06	.27
26	.15	.30	.08	.15	.06	.26
40	.15	.28	.09	.16	.06	.25
52	.15	.28	.09	.16	.06	.25

Kansas City-Portland Rail Rate

Step	River Locks	Rail Deliv.	Rail Rates	Grain Bids	Ocean Rates	Barge Rates
1	.15	.11	.74	.00	.00	.00
2	.21	.11	.62	.03	.00	.03
4	.21	.08	.59	.06	.00	.06
8	.16	.07	.56	.11	.01	.09
12	.14	.06	.54	.14	.02	.10
20	.12	.06	.53	.17	.03	.10
26	.11	.06	.53	.17	.03	.10
40	.12	.05	.52	.16	.04	.10
52	.13	.05	.51	.16	.04	.10

Portland HRW Bid Price

Step	River Locks	Rail Deliv.	Rail Rates	Grain Bids	Ocean Rates	Barge Rates
1	.01	.02	.10	.87	.00	.00
2	.02	.02	.17	.76	.00	.03
4	.06	.06	.21	.60	.01	.06
8	.11	.09	.22	.49	.02	.06
12	.14	.10	.23	.44	.03	.06
20	.14	.10	.27	.36	.04	.09
26	.14	.10	.30	.32	.03	.10
40	.12	.10	.35	.30	.03	.11
52	.11	.09	.37	.29	.03	.12

Gulf to Taiwan Ocean Freight Rate

Step	River Locks	Rail Deliv.	Rail Rates	Grain Bids	Ocean Rates	Barge Rates
1	.03	.04	.03	.05	.85	.00
2	.04	.06	.02	.05	.80	.03
4	.10	.11	.01	.03	.69	.07
8	.17	.17	.02	.04	.52	.09
12	.22	.18	.02	.09	.41	.08
20	.28	.16	.04	.19	.28	.06
26	.29	.15	.05	.24	.22	.05
40	.29	.13	.07	.31	.16	.04
52	.29	.12	.08	.32	.14	.04

St. Louis-Cairo Barge Rate

Step	River Locks	Rail Deliv	Rail .Rates	Grain Bids	Ocean Rates	Barge Rates
1	.00	.01	.02	.10	.12	.75
2	.04	.14	.04	.10	.07	.60
4	.05	.15	.06	.08	.05	.59
8	.10	.13	.12	.09	.07	.50
12	.11	.11	.15	.09	.08	.46
20	.10	.11	.15	.13	.08	.43
26	.10	.10	.14	.16	.08	.41
40	.10	.10	.14	.16	.09	.40
52	.10	.11	.14	.16	.09	.39

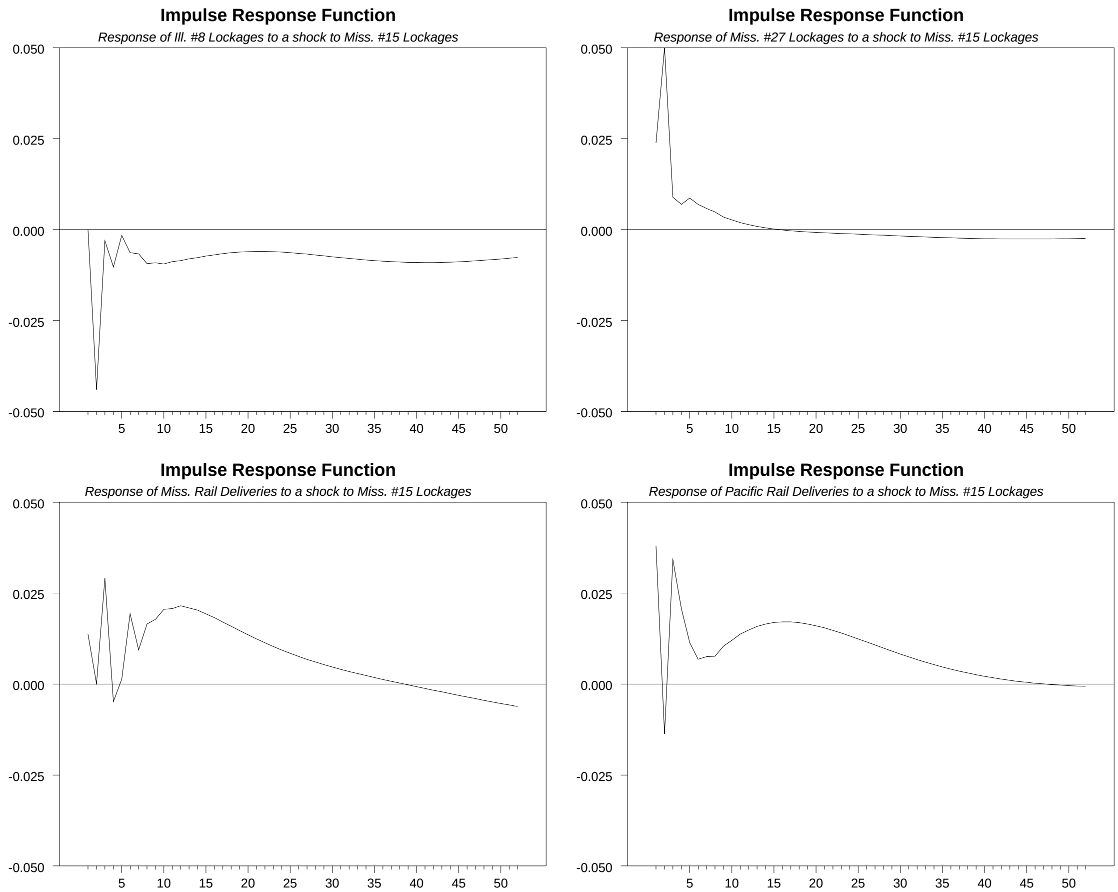

FIGURE 1a Responses of Lockages at Illinois #8, the Cairo-Memphis Barge Rate, and Rail Deliveries to Mississippi and the Pacific to a Shock to Lockages at Mississippi #15

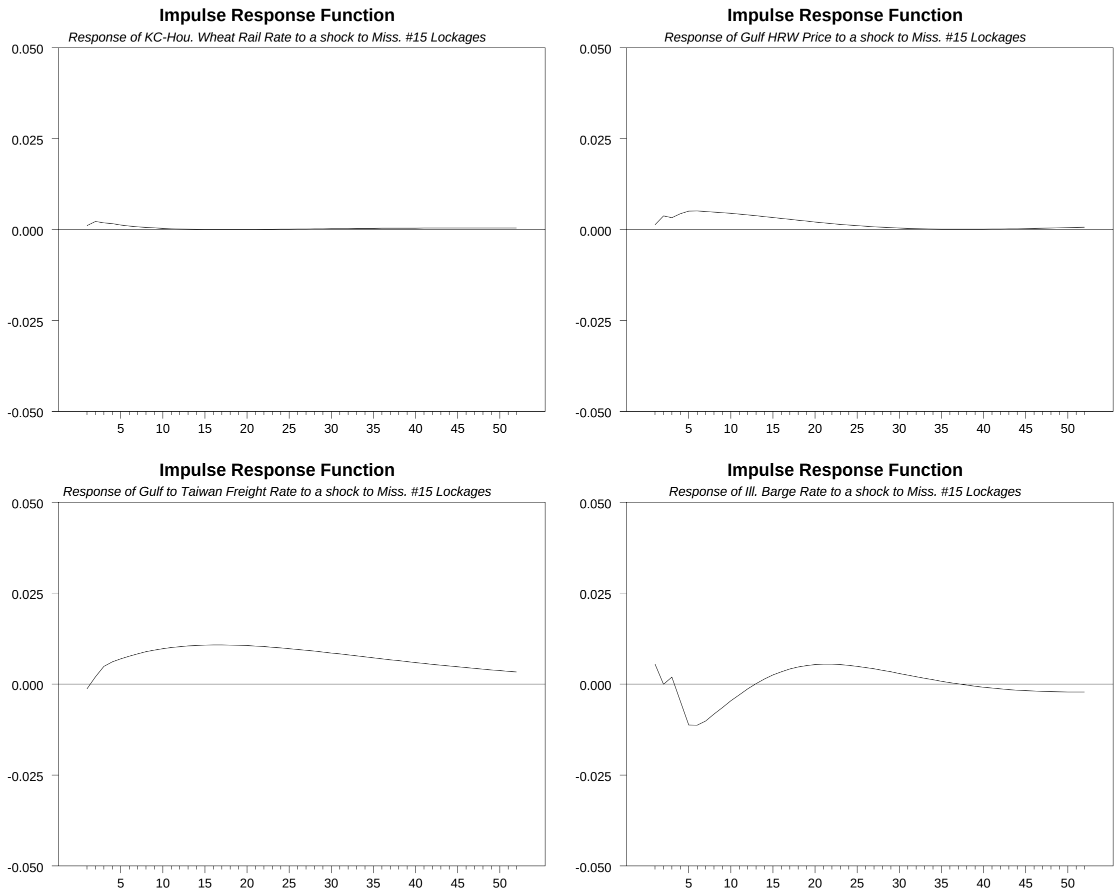

FIGURE 1b Responses of the KC-Houston Wheat Rail Rate, the Gulf HRW Price Bid, the Gulf to Taiwan Freight Rate, and the Illinois Barge Rate to a Shock to Lockages at Mississippi #15

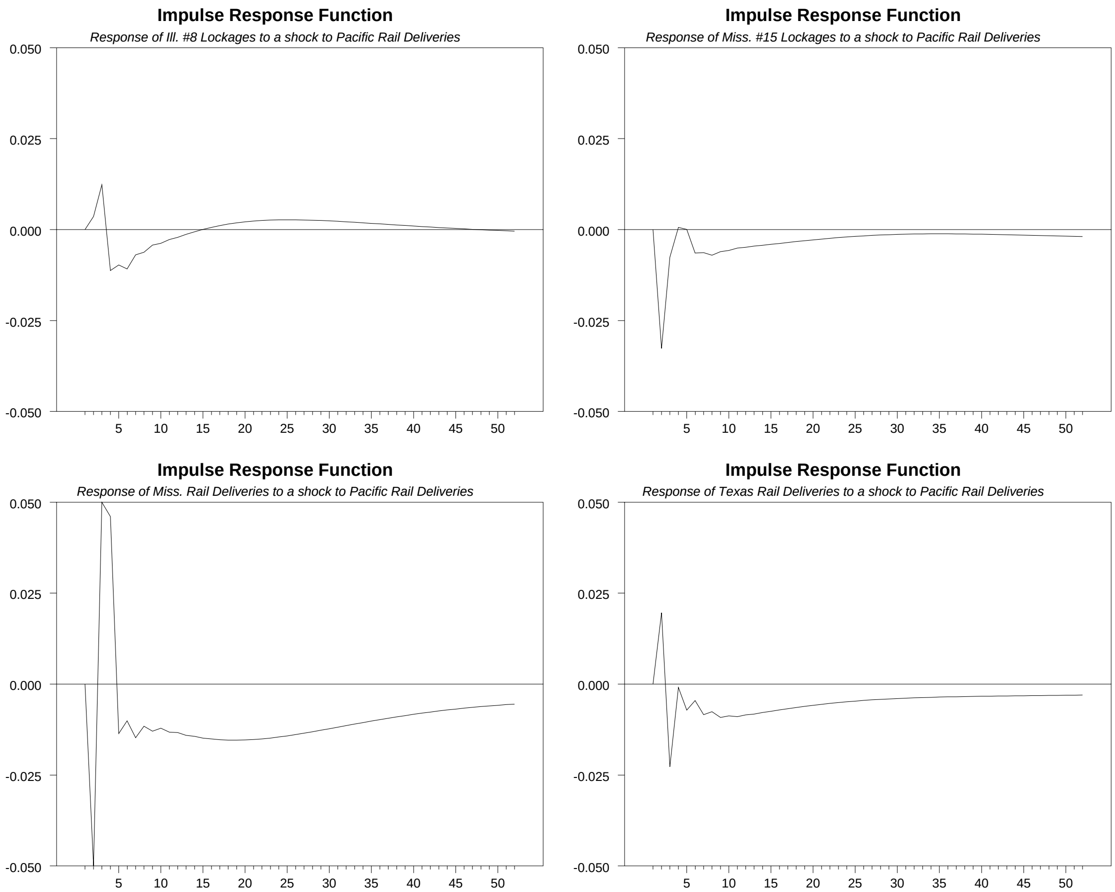

FIGURE 2a Responses of Lockages at Illinois #8, Mississippi #27, and Rail Deliveries to Mississippi and Texas to a Shock to Pacific Rail Deliveries

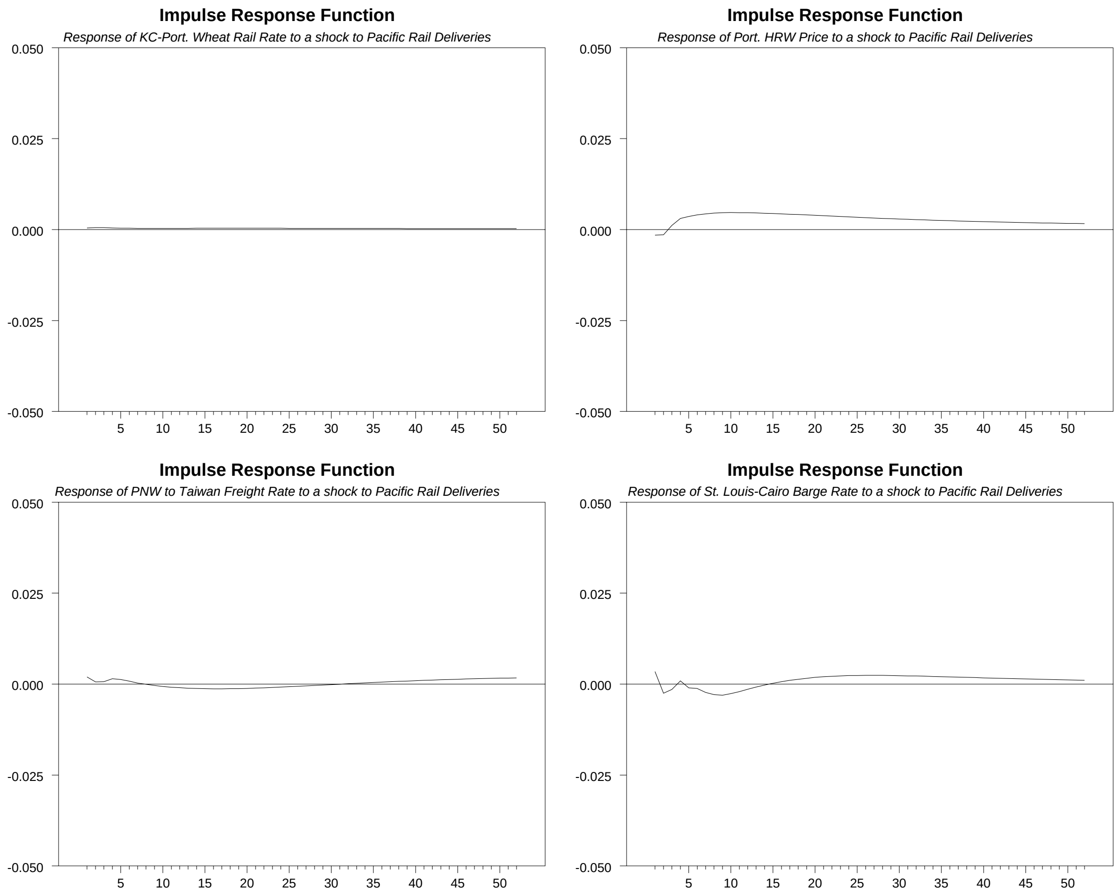

FIGURE 2b Responses of the KC-Portland Wheat Rail rate, the Portland HRW Bid Price, the PNW to Taiwan Freight Rate, and the St. Louis-Cairo Barge Rate to a Shock to Pacific Rail Deliveries

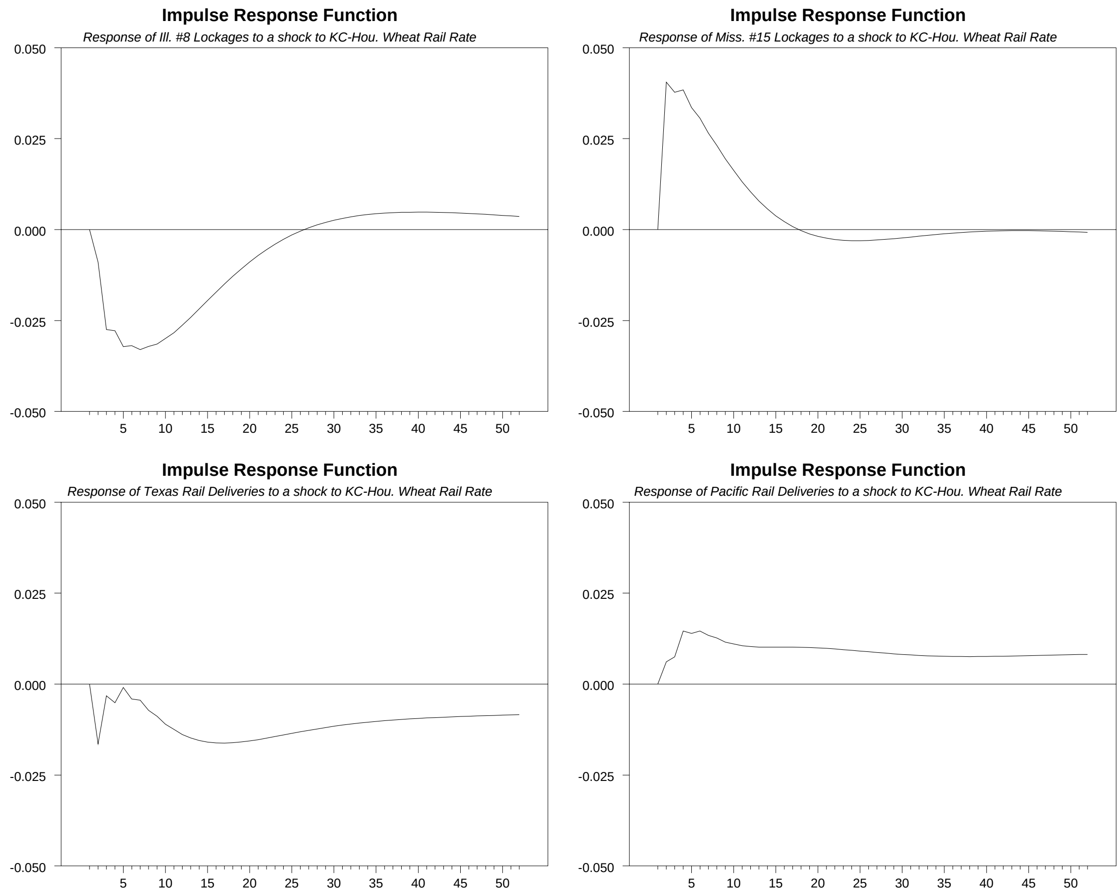

FIGURE 3a Responses of Lockages at Illinois #8, Mississippi #15, and Rail Deliveries to Texas and the Pacific to a Shock to the Kansas City-Houston Rail Rate for Wheat

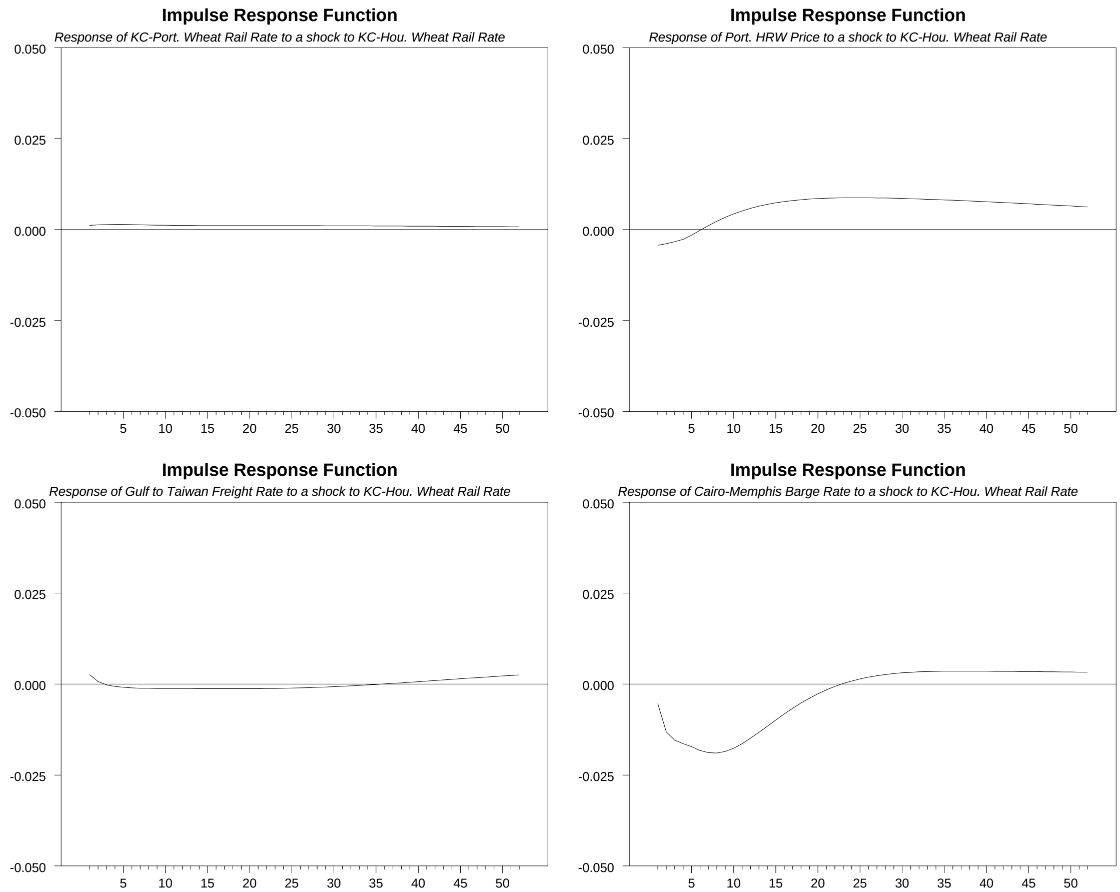

FIGURE 3b Responses of the KC-Portland Wheat Rail rate, the Portland HRW Bid Price, the Gulf to Taiwan Freight Rate, and the Cairo-Memphis Barge Rate to a Shock to the KC-Houston Wheat Rail Rate

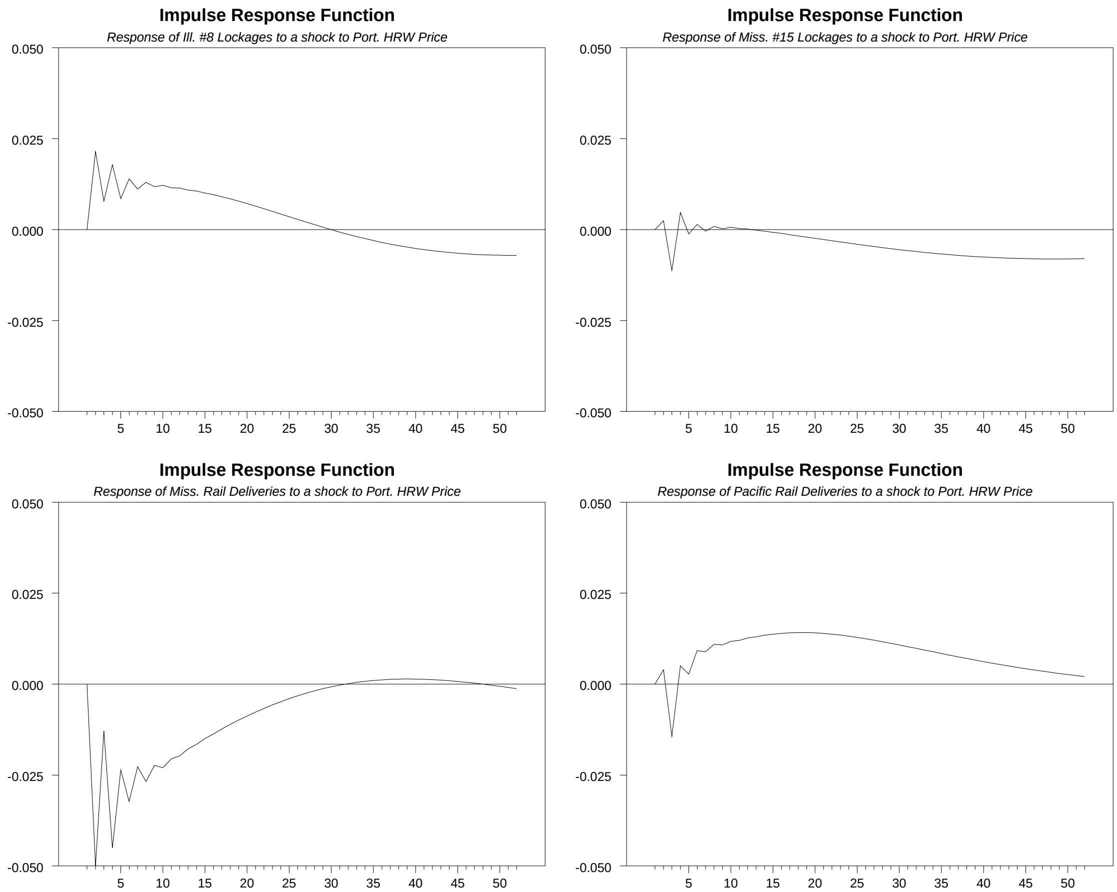

FIGURE 4a Responses of Lockages at Illinois #8, Mississippi #15, and Rail Deliveries to Mississippi and the Pacific to a Shock to the Portland HRW Price

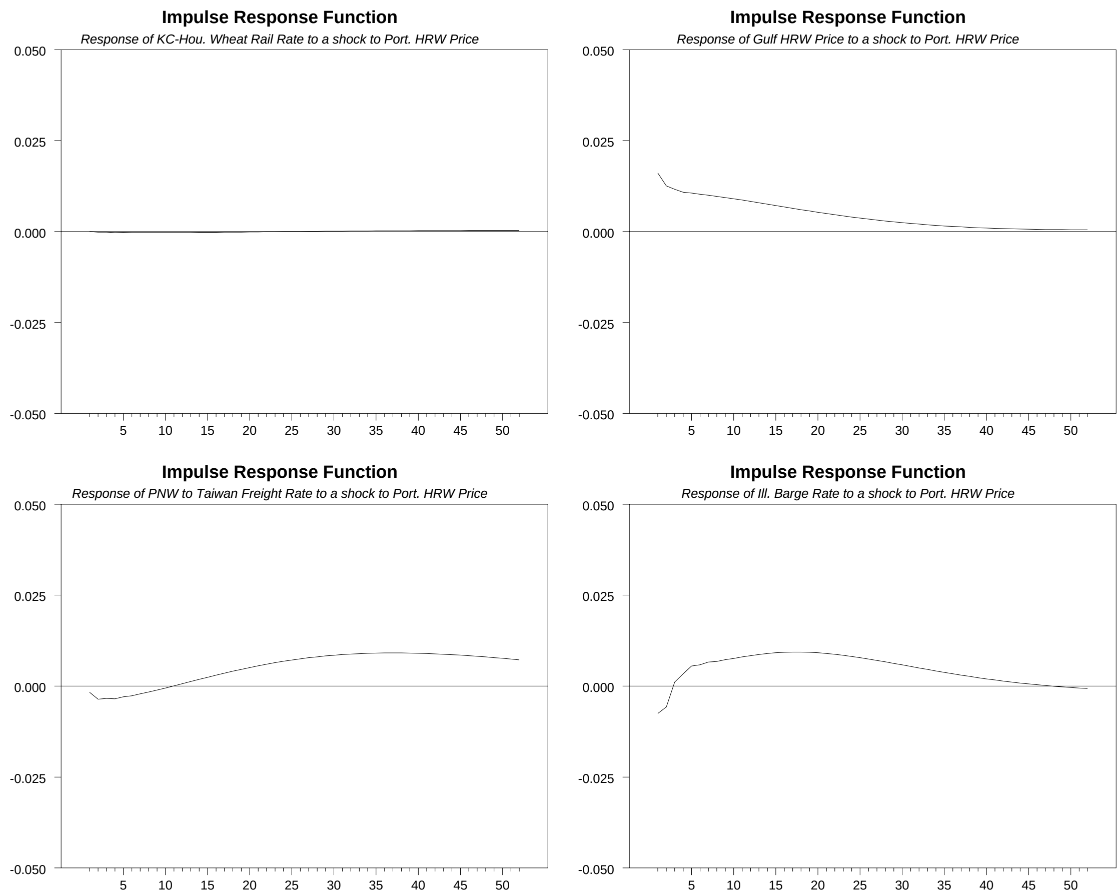

FIGURE 4b Responses of the KC-Houston Wheat Rail rate, the Gulf HRW Price, the PNW to Taiwan Freight rate, and the Illinois barge rate to a Shock to the Portland HRW Price

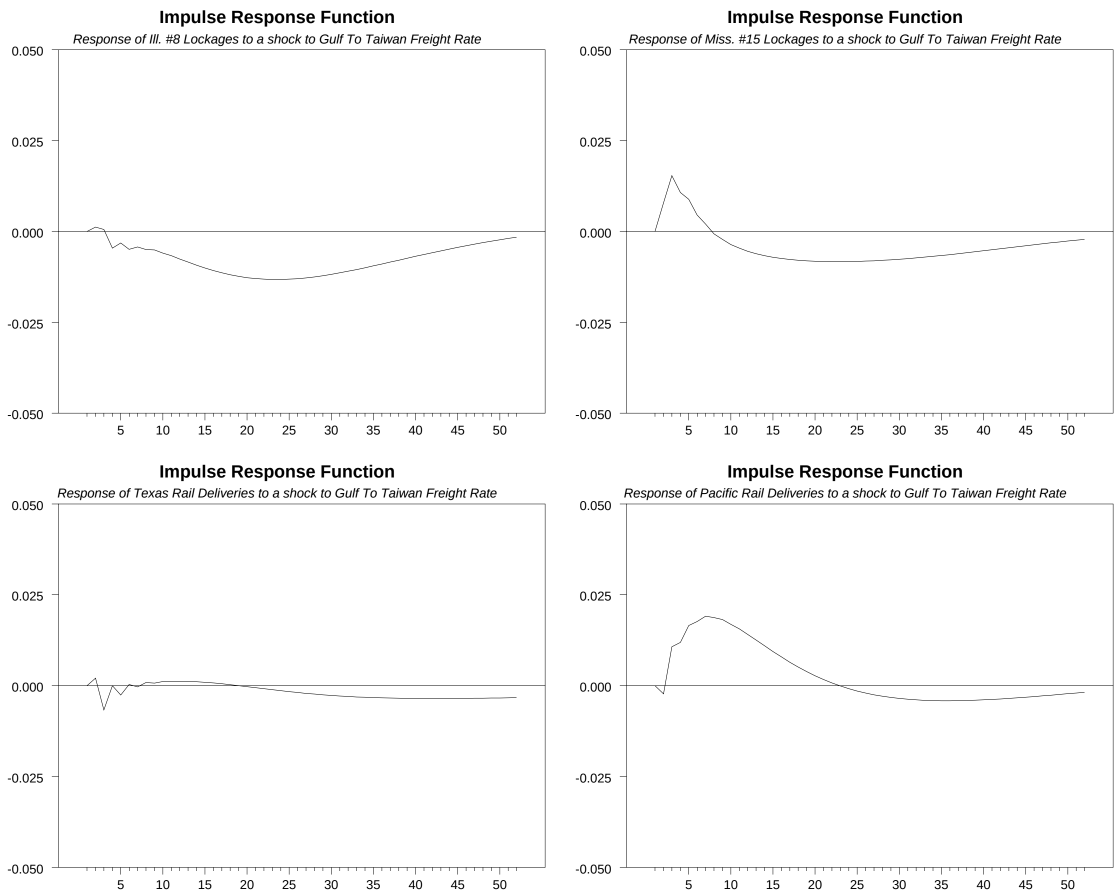

FIGURE 5a Responses of Lockages at Illinois #8 and Mississippi #15, and Rail Deliveries to Texas and the Pacific to a Shock to the Gulf to Taiwan Freight Rate

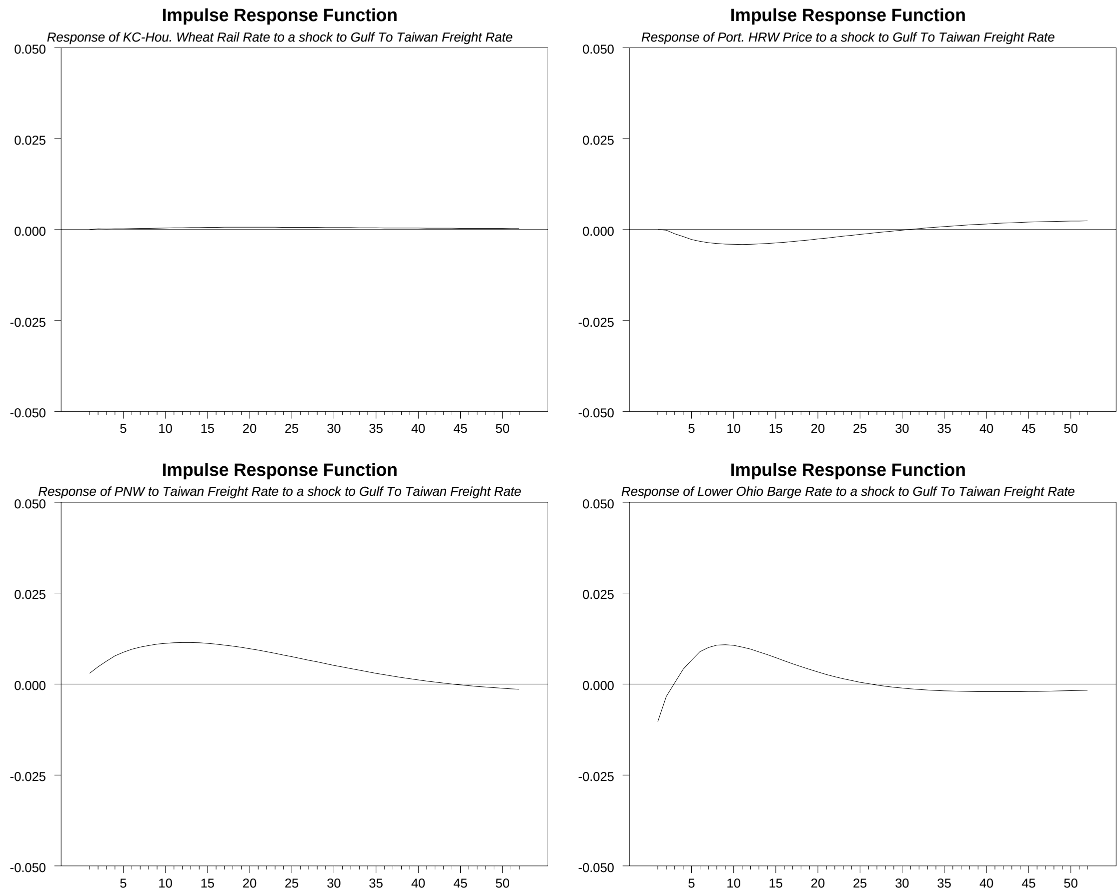

FIGURE 5b Responses of the KC-Houston Wheat Rail Rate, the Portland HRW Price, the PNW to Taiwan Freight Rate, and the Lower Ohio Barge Rate to a Shock to the Gulf to Taiwan Freight Rate

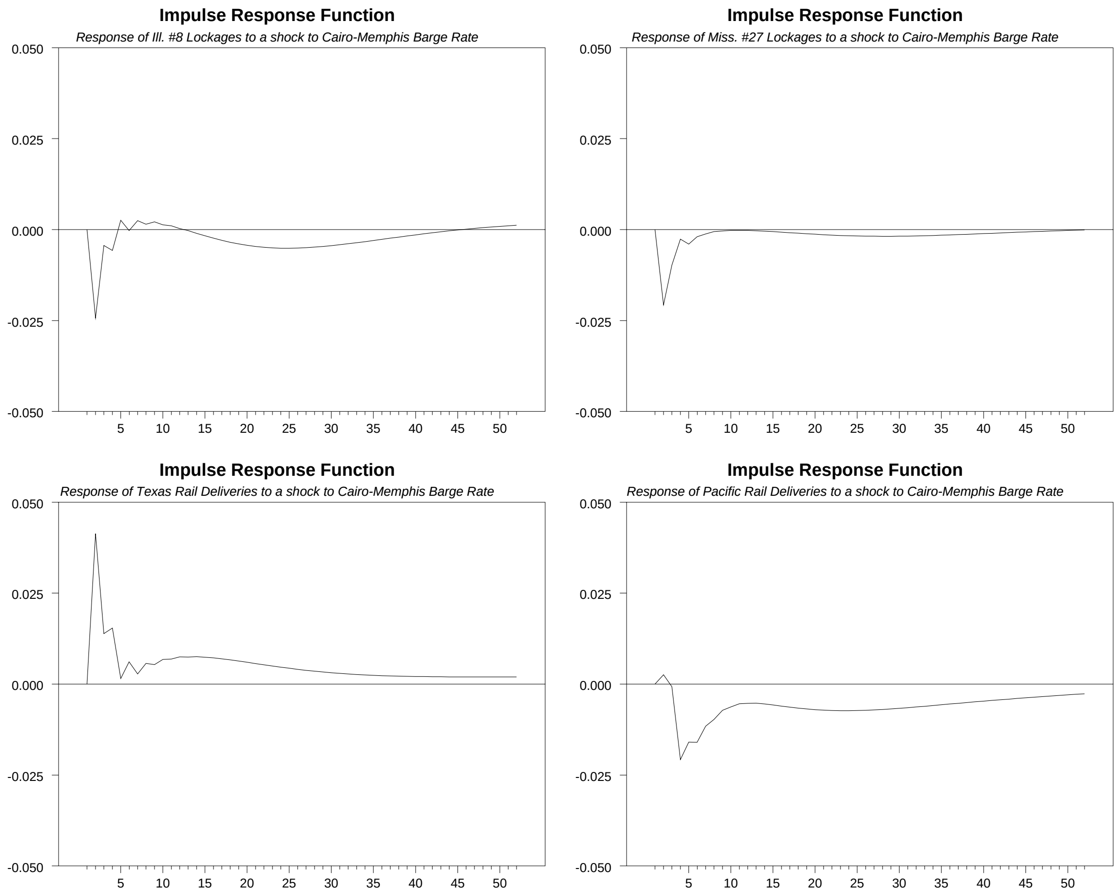

FIGURE 6a Responses of Lockages at Illinois #8, Mississippi #27, and Rail Deliveries to Texas and the Pacific to a Shock to the Cairo-Memphis Barge Rate

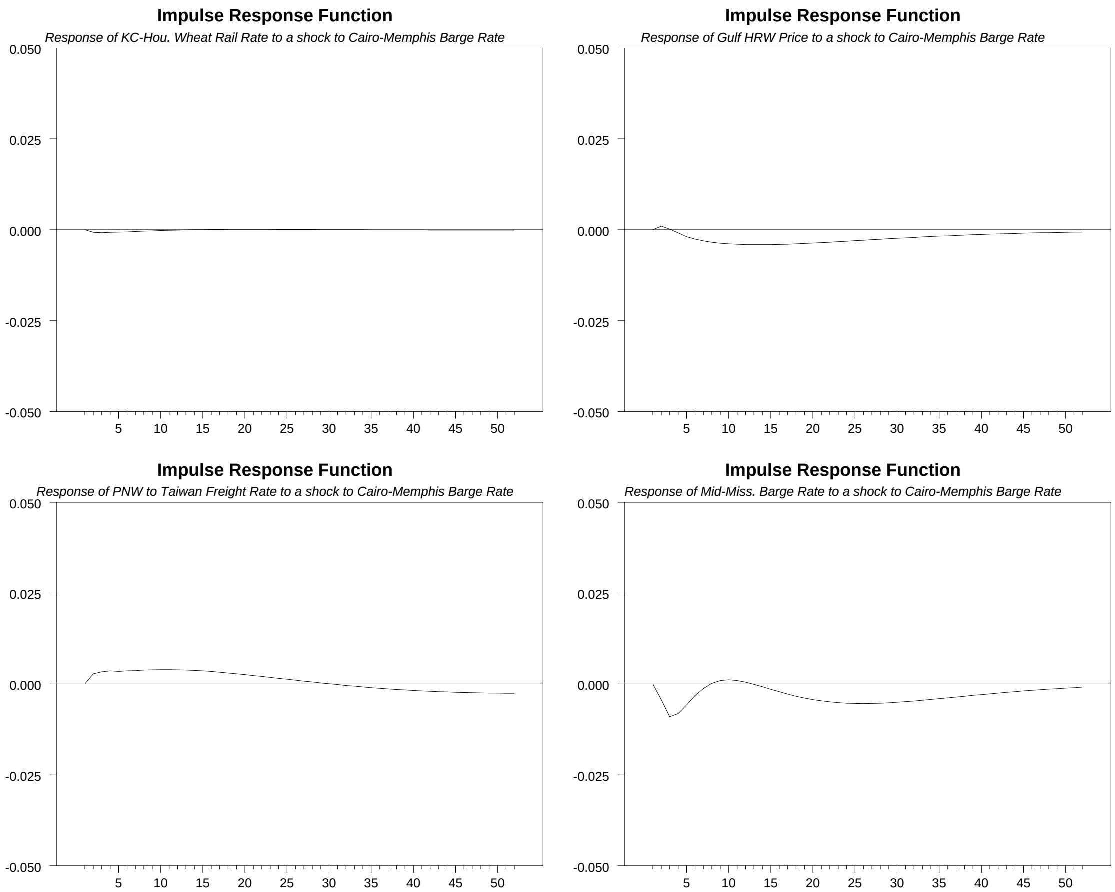

FIGURE 6b Responses of the KC-Houston Wheat Rail Rate, the Gulf HRW Bid Price, the PNW to Taiwan Ocean Freight Rate, and the Mid-Mississippi Barge Rate to a Shock to the Cairo-Memphis Barge Rate