Causality in Structural Vector Autoregressions: Science or Sorcery?

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Abstract

This paper presents the structural vector autoregression (SVAR) as a method for estimating dynamic causal effects in agricultural and resource economics. We have a pedagogical purpose; we aim the presentation at economists trained primarily in microeconometrics. The SVAR is a model of a system, whereas a reduced-form microeconometric study aims to estimate the causal effect of one variable on another. The system approach produces estimates of a complete set of causal relationships among the variables, but it requires strong assumptions to do so. We explain these assumptions and describe similarities and differences with the classical instrumental variables (IV) model. We demonstrate that the population analogue of the Wald IV estimator for a particular causal effect is identical to the ratio of two impulse responses from an SVAR. We further demonstrate that incorrect identification assumptions about some components of the SVAR do not necessarily invalidate the estimated causal effects of other components. We present an SVAR analysis of global supply and demand for agricultural commodities, which was previously examined using IV (Roberts and Schlenker, 2013). We illustrate the additional economic insights that the SVAR reveals, and we articulate the additional assumptions upon which those insights rest.

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... though large-scale statistical macroeconomic models exist and are by some criteria successful, a deep vein of skepticism about the value of these models runs through that part of the economics profession not actively engaged in constructing or using them.

— Christopher Sims, *Econometrica*, 1980

Almost forty years ago, Sims (1980) proposed the structural vector autoregression (SVAR) model to replace empirical macroeconomic models that had lost credibility. SVARs have become the staple method for generating causal estimates from time series, but skepticism lurks among many applied economists. One may argue that the above quote from Sims' paper now applies to the SVAR. The goal of this paper is two-fold. First, we aim to demystify SVARs for applied microeconomists. Second, we illustrate the framework through an SVAR analysis of global agricultural commodity markets and thereby examine the dynamic relationship between the key determinants of global agricultural demand and supply.

The SVAR identifies each of the causal relationships among the variables in the model. In this sense, it is a model of a system. In contrast, a typical reduced-form microeconometric study aims to estimate the causal effect of only one variable on another. The system approach allows researchers not only to estimate the effect of a particular X on a particular Y, but also to estimate the other factors that drive Y, thereby gaining deeper economic insights. However, these additional estimates rely on stronger assumptions. Our goal here is to carefully explain these assumptions, compare them with the linear IV assumptions and illustrate the implications of their violation in the context of a demand and supply system. Most notably, we illustrate that, when using the most common identification scheme, the estimated causal effects of a subset of variables are robust to incorrect identification assumptions about the effects of the other variables. Thus, a reader can believe the exogeneity of some variables and use the resulting estimates even if they reject the assumptions in other parts of the model.

We begin by providing a simple presentation of SVARs to show how they can address causal questions in time series that do not fit neatly into the potential outcomes framework with a discrete treatment variable (Rubin, 1974; Imbens, 2014).[1] Non-discreteness does not create problems for causal inference as long as sufficient assumptions can be imposed. In theory, if a non-discrete treatment variable is exogenous and the linear model is correctly specified, then ordinary least squares can consistently estimate an average causal effect. If the treatment variable is endogenous but a valid instrument exists, then an average treatment effect may be consistently estimated in a linear model by two stage least squares. In practice,

[1] Section B in the supplementary appendix discusses some examples of time series applications that fit in the potential outcomes framework.

linear (or flexible parametric) models are used as approximations, but to make our discussion of causal effects in a linear SVAR precise, we emphasize the role of correct specification.

Serial correlation, on the other hand, complicates causal inference in time series, because it implies that treatments and responses persist for multiple periods. If a serially correlated treatment variable jumps above its mean one period and remains above the mean for several periods, then we expect economic agents to respond as though they received a single treatment that lasted multiple periods rather than a sequence of independent treatments. Put differently, we expect them to respond to the *treatment path*. In addition to the treatment potentially lasting for multiple periods, the responses to treatment may also play out over multiple periods. For example, in response to a crop price increase (treatment), farmers may convert pasture to cropland if they expect prices to remain high for a long period, but they will not do so if they expect the price increase to be shortlived.[2] Thus, the response of agricultural supply to price varies depending on the persistence of the price change. Moreover, for a price change of a given duration, the producer responses will vary over time. Some producers may respond to a persistent price change by converting land immediately; others will wait and convert later. The SVAR provides a way to extract treatment paths and dynamic responses from a set of variables.

In an overwhelming majority of time series applications, there are multiple continuous variables that are serially correlated and potentially mutually dependent. Without further restrictions, we cannot disentangle the effect of any one of the variables on another. The SVAR imposes structure on those variables. This structure consists of restrictions on the contemporaneous dependence between them, while accounting for their time series dependence. The goal behind these restrictions is to extract sources of exogeneous variation from this vector of endogenous variables, which are referred to as "shocks". These shocks mark the beginning of treatment paths and play the role of "randomly assigned" treatments (Ramey, 2016). Impulse response functions (IRFs) quantify the effects of each shock on each variable in the model over time, and are hence referred to as "dynamic causal effects" (Stock and Watson, 2018). As such, IRFs show the short- and long-run effects and therefore give a richer view of the relationship between the shocks and the variables in the system than a single treatment effect.

We compare triangular SVARs and linear IV models to illustrate important similarities

[2] Bojinov and Shephard (2017) propose a model-free approach to identification, estimation and inference on causal effects of treatment paths in time series. Inspired by a large experiment by a quantitative hedge fund, they show how to extend the potential outcomes framework to define treatment paths and potential outcomes in order to achieve a completely model-free approach to causal inference solely relying on random assignment of treatment paths. Their approach is specific to the case of a large number of randomly assigned treatment paths.

and differences between the two models.[3] We formalize their similarity by showing that the population analogue of the Wald IV estimator is identical to a ratio of two contemporaneous impulse responses from an SVAR under certain conditions. Connections between SVARs and IV have been noted in previous work. For instance, in seminal work, Hausman and Taylor (1983) point out that the assumptions in a triangular SVAR allow residuals to be viewed as instruments. Both models hence share a common goal, which is to extract exogenous variation from endogenous variables.

Despite the commonalities between the two methods, we emphasize that a structural approach like SVAR that identifies an entire system of equations necessarily rests on stronger assumptions than the reduced-form IV approach. The SVAR extracts exogenous variation from all variables in the system, whereas the IV approach focuses on exogenous variation from a single variable. The validity of the SVAR assumptions depends on the empirical context. We thus proceed to illustrate the nuances of these assumptions and assess their validity in an empirical application revisiting Roberts and Schlenker (2013), henceforth RS2013.

We present an SVAR analysis of global demand and supply of agricultural commodities. Following RS2013, the variables in the SVAR are calorie-weighted aggregates of global yield, acreage, inventory and price for corn, wheat, rice and soybeans, which constitute about 75% of calories consumed by humans. The identification strategy for the SVAR analysis exploits the natural sequence of events in the agricultural growing season to motivate exclusion restrictions that lead to a triangular SVAR system. Farmers plant crops at the beginning of the growing season, then weather events affect yields, which subsequently influence wholesale traders' inventory decisions and result in an equilibrium price. From the four observed variables, the SVAR extracts two supply shocks and two demand shocks. The supply shock associated with yield is more easily defended as exogenous than the other shocks. It is essentially this shock that RS2013 use in their IV estimation.

When we look at the IRF of each shock on itself, we find that different shocks have different durations. The first supply shock, which is the exogenous component of acreage and may reflect a change in cost or productivity, tends to persist for multiple years. The second supply shock is weather-induced and only affects production for a single year. The inventory demand shock is short-lived, whereas the consumption demand shock has a longer run.

To identify supply elasticities, we focus on two different sources of price changes: shocks

[3]More recently, external instruments have been used in SVARs to provide more credible identification. However, we focus on the classical IV model in this paper. See Stock and Watson (2018) for a review of external instruments in SVARs.

to consumption demand and prior-year weather shocks.[4] The latter was also used by RS2013. We find that producers have a smaller initial response but a larger cumulative response to a consumption demand shock. Their response to a shock induced by poor weather last year tends to be larger initially, but it drops to zero in subsequent years. This finding reflects the fact that consumption demand shocks are more persistent than weather shocks and suggests that producers respond accordingly, perhaps by making capital investments in response to consumption demand shocks that they would not make in response to a one-year weather shock. In contrast, demand responds similarly to one-year supply changes as to longer-run supply changes, although the response to longer-run supply changes is estimated imprecisely.

The SVAR results provide several insights on the IV results in RS2013. The SVAR further illustrates that the weather shocks are short-lived, which raises concern that the IV estimates of demand elasticity may not reflect consumer response to long-lived shocks such as those caused by climate change or changes in government policy. This concern is however alleviated by the similarity in the estimate of demand elasticities identified from weather shocks and the longer-lived acreage shock. This suggests that consumer response is not affected by the horizon of the shock. On the other hand, the estimated supply elasticities do vary depending on the persistence of the shocks used to identify them as producers may respond to long-lived shocks by making capital investments to increase production. They are less likely however to make such investments if a price shock is expected to only last for a single year.

Finally, we conclude our empirical application by discussing the consequences of violations of the key identification assumption of our baseline SVAR specification, which is the triangular structure. We first consider violations of the assumptions pertaining to the demand equations. We illustrate empirically that changing the assumptions in this part of the model only affects the IRFs of the demand, but not the supply shocks. This is due to the latter preceding the former in the temporal ordering of the system, and it means the estimates of the effects of the supply shocks are robust to the assumptions about the demand shocks. In addition, we examine the potential violation of the exogeneity of the two supply shocks and present some falsification tests that suggest that the bias due to such violations is likely small.

This analysis of agricultural commodity markets builds on an older literature on SVARs in agricultural economics. For instance, Orden and Fackler (1989) and Adamowicz, Armstrong, and Lee (1991) use SVAR methodology to examine the impact of monetary shocks on

[4] Inventory demand shocks have no statistically significant effect on price, so we cannot use it to identify a supply elasticity.

agricultural markets and the relationship between macroeconomic factors and agricultural markets, respectively. More recently, Hausman, Auffhammer, and Berck (2012) exploit the timing in the agricultural growing season to inform their SVAR analysis of the impact of biofuel production on food crop prices. Carter, Rausser, and Smith (2017) use an SVAR model of corn inventory dynamics to estimate the effect of biofuel policies on corn prices, and Janzen, Smith, and Carter (2018) used an SVAR to study commodity price comovement and the effects of financial speculation on cotton prices. Finally, the findings on agricultural supply dynamics build on previous work on the response of acreage and yield to price shocks (Haile, Kalkuhl, and von Braun, 2014, 2016).

Before we proceed, we emphasize that we focus on triangular SVARs in this paper to adhere to our goal of a simple presentation of SVARs. However, the literature has several recent innovations that allow for identification and inference under weaker assumptions (e.g. Baumeister and Hamilton, 2017; Montiel-Olea, Stock, and Watson, 2016; Gafarov, Meier, and Olea, 2018). A systematic review of this literature is beyond the scope of this paper and can be found in Stock and Watson (2016) and Ramey (2016). A comprehensive textbook treatment of the topic is also provided in Kilian and Lütkepohl (2017).

The paper is organized as follows. We first introduce the SVAR system as a model for identifying causal effects when treatment variables are continuous. As a result, we introduce SVAR terminology before we can explain it in a manner that is accessible to an applied microeconomist. We then compare and contrast the SVAR to the IV model and address the question of when we can interpret IRFs as causal parameters. Next, we present a triangular analysis of global supply and demand of agricultural commodities. Finally, we discuss potential violations of the triangular structure and their consequences for our analysis.

The Structural Vector Autoregression

To elucidate the SVAR and compare it to IV, we use the example of global demand for agricultural commodities. This model is simpler than the full supply and demand SVAR that we specify later in the paper, which makes it easier to comprehend. Furthermore, the variables in this demand model are identical to those used to estimate demand elasticities in RS2013. This allows us to augment our analytical comparison of SVARs and IV with data.

Our data set contains global annual prices, quantities, and yield (production per unit of land) for corn, wheat, rice and soybeans from 1962-2013.[5] Following RS2013, we construct calorie-weighted indexes of price, quantity demanded, and yield across the four commodities.

[5]RS2013 used data from 1962-2007. We update the data through 2013. The raw data on area, production

The SVAR Model

To estimate the elasticity of demand, RS2013 regress log quantity demanded (q_t) on log price (p_t) using detrended yield (w_t) as an instrumental variable. We use the same three variables here. A triangular SVAR with ℓ lags is given by the following

$$\begin{aligned} w_t &= \qquad\qquad\qquad\quad \rho_{11}Y_{t-1} + \rho_{12}Y_{t-2} + \cdots + \rho_{1\ell}Y_{t-\ell} + f_w(t) + v_{wt} \quad (1) \\ p_t &= \beta_{21}w_t + \qquad\quad\;\; \rho_{21}Y_{t-1} + \rho_{22}Y_{t-2} + \cdots + \rho_{2\ell}Y_{t-\ell} + f_p(t) + v_{pt}, \quad (2) \\ q_t &= \beta_{31}w_t + \beta_{32}p_t + \rho_{31}Y_{t-1} + \rho_{32}Y_{t-2} + \cdots + \rho_{3\ell}Y_{t-\ell} + f_q(t) + v_{qt}. \quad (3) \end{aligned}$$

where $Y_t \equiv (w_t, p_t, q_t)'$ and ρ_{ij} is a 3-dimensional row vector for all i and j. The terms $f_w(t)$, $f_p(t)$, and $f_q(t)$ are fixed functions of time and capture any deterministic components in the above variables. The model is triangular because, conditional on the deterministic components and the lags of each variable, p_t and q_t are omitted from the yield equation and q_t is omitted from the price equation.

Using the standard SVAR terminology, we refer to the elements of v_t as “shocks”. The shocks represent the part of the observed variables that (i) cannot be predicted using past observations $(Y_{t-1}, ..., Y_{t-\ell})$ and (ii) is not affected by other contemporaneous variables. As such, they constitute new information that arrives in period t. Based on this view, we see how the SVAR disentangles sources of exogenous variation from the observed endogenous variables. Importantly, the errors are white noise and uncorrelated with each other, i.e., $v_t = (v_{wt}, v_{pt}, v_{qt})'|Y_{t-1}, Y_{t-2}, \dots, Y_{t-\ell} \sim WN(0, D)$, where D is a diagonal matrix. In the next subsection, we show how the uncorrelatedness of the shocks allow us to identify impulse response functions and discuss how this assumption rules out the presence of any omitted variables that enter multiple equations.

The three equations of the SVAR can be written in matrix notation as follows

$$A_0Y_t = A_1Y_{t-1} + A_2Y_{t-2} + \cdots + A_\ell Y_{t-\ell} + f(t) + v_t, \quad (4)$$

and yield are obtained from the Food and Agricultural Organization (FAO). Production of maize, rice, soybeans and wheat are measured in tons, then converted into calories using calorie weights from RS2013. We hence convert production from tons into calories. We then divide by 365*2000, the number of calories consumed by the average person in a year. Hence, the units of production in our analysis is in millions of people as in RS2013. Yield is production per area and is measured in bushels per *ha*. The raw price data is obtained from Quandl, and it includes spot and futures prices. The spot and futures price we use are calorie-weighted averages of the individual commodity prices. For more details on the data, see Section A of the supplementary appendix.

where A_0 is a lower-triangular matrix,

$$A_0 = \begin{bmatrix} 1 & 0 & 0 \\ -\beta_{21} & 1 & 0 \\ -\beta_{31} & -\beta_{32} & 1 \end{bmatrix}. \tag{5}$$

Multiplying through by A_0^{-1}, we can write the reduced form of the above model, which is a VAR(ℓ),

$$Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_\ell Y_{t-\ell} + g(t) + \varepsilon_t \tag{6}$$

where $g(t) = A_0^{-1} f(t)$, $\Pi_j = A_0^{-1} A_j$ for $j = 1, \dots, \ell$ and $\varepsilon_t = A_0^{-1} v_t$.[6] The parameters in (6) can be estimated consistently by ordinary least squares (Hamilton, 1994).

Impulse response functions (IRF) characterize the response of the observed variables to a shock, which is defined as the partial derivative of Y_{t+h} for some $h \geq 0$ with respect to each element of v_t. To derive the IRF, we can invert (6) to express Y_t in vector MA(∞) form as a linear function of current and past structural errors, v_t,

$$Y_t = m(t) + \sum_{j=0}^{\infty} \Psi_j v_{t-j}, \tag{7}$$

where $m(t) = (I - \Pi_1 L - \ldots - \Pi_\ell L^\ell)^{-1} g(t)$.[7] The MA coefficients are square summable (i.e., $\sum_{j=0}^{\infty} \|\Psi_j\|^2 < \infty$) if Y_t is covariance-stationary (see Hamilton (1994) for technical conditions). Hence, the triangular SVAR allows us to decompose a vector of endogenous time series variables into a trend plus a weighted sum of uncorrelated white-noise shocks. The IRFs are $\partial Y_{t+j} / \partial v_t' = \Psi_j$; the i^{th} column of Ψ_j equals the effect of shock i on each of the variables j periods in the future.

To provide a simple illustration of how IRFs correspond to the structural parameters in

[6]The above VAR does not impose any zero restrictions on the elements of $\Pi_1, \ldots, \Pi_L$. It is worth noting here that in a bivariate VAR, when one variable (y_2) does not Granger-cause the other (y_1), then it implies the following zero restrictions on the coefficient matrix on the lagged vectors (Hamilton, 1994). Specifically,

$$\begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = g(t) + \begin{bmatrix} \pi_1^{(11)} & 0 \\ \pi_1^{(21)} & \pi_1^{(22)} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \cdots + \begin{bmatrix} \pi_\ell^{(11)} & 0 \\ \pi_\ell^{(21)} & \pi_\ell^{(22)} \end{bmatrix} \begin{bmatrix} y_{1,t-\ell} \\ y_{2,t-\ell} \end{bmatrix} + \varepsilon_t.$$

In our analysis of the SVAR as a causal tool, we allow the matrices of the lags of Y_t to be completely unrestricted.

[7]L denotes the backshift, or lag, operator. The MA Coefficients Ψ_j are functions of the parameters in (6) and can be estimated consistently using a plug-in estimator. Most econometrics software packages have built-in routines to compute these estimates. Alternately, they can be estimated using the local projections method of Jorda (2005).

A_0, we consider a static version of the above model, which excludes the control variables, i.e., the trends and $Y_{t-1}, \ldots, Y_{t-\ell}$. We re-introduce these elements in our full SVAR model of agricultural supply and demand. The static model is:

$$\begin{bmatrix} 1 & 0 & 0 \\ -\beta_{21} & 1 & 0 \\ -\beta_{31} & -\beta_{32} & 1 \end{bmatrix} \begin{bmatrix} w_t \\ p_t \\ q_t \end{bmatrix} = \begin{bmatrix} v_{wt} \\ v_{pt} \\ v_{qt} \end{bmatrix} \tag{8}$$

where $v_t \sim WN(0, \Sigma)$ and Σ is diagonal as in the above. In this simple model, we can express the dependent variables as a linear combination of uncorrelated shocks as follows

$$\begin{bmatrix} w_t \\ p_t \\ q_t \end{bmatrix} = \underbrace{\begin{bmatrix} 1 & 0 & 0 \\ \beta_{21} & 1 & 0 \\ \beta_{31} + \beta_{32}\beta_{21} & \beta_{32} & 1 \end{bmatrix}}_{\partial Y_t / \partial v_t'} \begin{bmatrix} v_{wt} \\ v_{pt} \\ v_{qt} \end{bmatrix}. \tag{9}$$

Because this model has no autocorrelation, the IRFs are zero for all $h > 0$.

The elements of the matrix on the right-hand side of (9) give the contemporaneous impulse responses. For instance, β_{21} is the impulse response of a yield shock on contemporaneous price ($\partial p_t / \partial v_{wt}$), β_{32} is the impulse response of other supply shocks on contemporaneous quantity ($\partial q_t / \partial v_{pt}$), and $\beta_{31} + \beta_{32}\beta_{21}$ is the impulse response of a yield shock on contemporaneous quantity ($\partial q_t / \partial v_{pt}$). IRFs give the change in the predicted value of the dependent variables due to a unit or marginal change in the individual shocks.

Identification of IRFs

Next, we illustrate how uncorrelatedness of the shocks in an SVAR produces identification of the three IRFs in (9). First, consider $\partial p_t / \partial v_{wt} = \beta_{21}$. If $cov(v_{pt}, v_{wt}) = 0$, then

$$cov(p_t, w_t) \equiv cov(\beta_{21} w_t + v_{pt}, v_{wt}) = \beta_{21} var(w_t). \tag{10}$$

It follows that $\beta_{21} = cov(p_t, w_t)/var(w_t)$, the slope coefficient from a simple regression of p_t on w_t. Thus, assuming $var(w_t) > 0$, zero correlation between v_{pt} and v_{wt} identifies the first impulse response.

To identify $\partial q_t / \partial v_{wt}$, we not only require that $cov(v_{pt}, v_{wt}) = 0$, but also $cov(v_{qt}, v_{wt}) = 0$, which implies

$$cov(q_t, w_t) = \beta_{31} var(w_t) + \beta_{32} cov(p_t, w_t) = (\beta_{31} + \beta_{32}\beta_{21}) var(w_t). \tag{11}$$

Thus, given the two uncorrelatedness conditions, $\beta_{31} + \beta_{32}\beta_{21}$ is identified from the slope coefficient of a simple OLS regression of q_t on w_t.[8] The third impulse response parameter is β_{32}. If $cov(v_{wt}, v_{pt}) = cov(v_{wt}, v_{qt}) = cov(v_{pt}, v_{qt}) = 0$, then it is straightforward to show that β_{32} is identified from the coefficient on p_t in an OLS regression of q_t on w_t and p_t.

The block-triangular structure of A_0 implies that impulse responses to the shocks in the first block are unaffected by assumptions about the second block.[9] For example, if we were to define

$$A_0 = \begin{bmatrix} 1 & 0 & 0 \\ -\beta_{21} & 1 & -\beta_{32} \\ -\beta_{31} & 0 & 1 \end{bmatrix}, \tag{12}$$

or, equivalently keep a triangular A_0 but re-order the variables as $Y_t \equiv (w_t, q_t, p_t)'$, then the response to a v_{wt} shock would be unchanged. This can be seen in (10) and (11), which imply that the first two impulse responses can be computed from univariate regressions of p_t and q_t on w_t and are thus unaffected by any assumptions on the structural interpretation of the correlation between p_t and q_t.

Finally, we emphasize that the uncorrelatedness of the shocks rules out any omitted variables that enter multiple shocks.[10] For instance, if there were a control variable, x_t, that was mistakenly omitted from the SVAR in (8), then

$$\begin{bmatrix} 1 & 0 & 0 \\ -\beta_{21} & 1 & 0 \\ -\beta_{31} & -\beta_{32} & 1 \end{bmatrix} \begin{bmatrix} w_t \\ p_t \\ q_t \end{bmatrix} = \begin{bmatrix} \tilde{v}_{wt} \\ \tilde{v}_{pt} \\ \tilde{v}_{qt} \end{bmatrix} \tag{13}$$

where $\tilde{v}_{wt} = \gamma_w x_t + v_{wt}$, $\tilde{v}_{pt} = \gamma_p x_t + v_{pt}$ and $\tilde{v}_{qt} = \gamma_q x_t + v_{qt}$. If γ_w, γ_p, and γ_q are non-zero, then the covariances of the shocks in (13) are non-zero, which introduces bias into the IRF estimation. It is possible however that this omitted variable is not relevant in all equations. In this case, the unbiasedness of some of the IRF estimators may be unaffected by its omission. For instance, if $\gamma_w = 0$, and $cov(x_t, v_{wt}) = 0$, then we can identify β_{21}, even though the remaining structural parameters may not be identifiable.

Triangular SVAR vs. Instrumental Variables

[8] Note that if $cov(v_{pt}, v_{wt}) = 0$ but $cov(v_{qt}, v_{wt}) \neq 0$, then β_{21} is identifiable, even though $\beta_{31} + \beta_{32}\beta_{21}$ is not.

[9] We prove this separation result in the general case in the supplementary appendix as we are not aware of any written proofs elsewhere.

[10] For an accessible discussion of omitted variable bias in SVARs as well as an important example from macroeconomics, see Stock and Watson (2001).

In the previous sections, we explain how the uncorrelateness between shocks in an SVAR allows us to identify the IRFs of exogenous shocks on different variables in the system. IV models also assume uncorrelateness-type assumptions to identify causal parameters. In this section, we compare and contrast the SVAR and IV models and show that the Wald estimand is identical to the ratio of two impulse responses formally and empirically.

Figure 1 presents the triangular system in (8) alongside the IV model of demand in RS2013. The second equation in the IV setup is the 'first stage regression' and the third equation is the equation of interest.[11] In both systems, w_t is purely a shock that is uncorrelated with other shocks, since they are driven primarily by weather as mentioned above. Specifically, in the IV model the yield deviation is $w_t = u_{wt}$ and in the triangular system the yield deviation is $w_t = v_{wt}$. There are two differences between the systems. First, the IV model excludes w_t from the q_t equation, whereas the triangular model does not. Second, the IV model allows the price and quantity shocks (u_{pt} and u_{qt}) to be correlated (σ_{23} is unrestricted), whereas the triangular structure imposes that the variance-covariance matrix of the shocks is diagonal.

Figure 2 illustrates the identification assumptions graphically. Panel A shows that the parameter b_{32} in the IV model is the elasticity of demand; it is the change in log quantity given a unit change in log price holding demand constant. This parameter is identified econometrically by the instrumental variable w_t, which is valid because it affects price ($b_{21} \neq 0$) but not the demand curve ($b_{31} = 0$), and because it is exogenous to price and quantity ($b_{12} = b_{13} = \sigma_{12} = \sigma_{13} = 0$). In this model, a positive weather shock increases supply, which reduces price and increases quantity demanded. The potential correlation between the first stage error (u_{pt}) and the error in the demand equation means that price may be endogenous to demand.

Panel B of Figure 2 illustrates the responses to a weather shock in the SVAR. A unit weather shock changes price by β_{21}, and it changes quantity by $\beta_{31} + \beta_{32}\beta_{21}$ (see (9)). The parameter β_{21} represents the coefficient on w_t in a least squares regression of p_t on w_t (see equation (2)). The parameters β_{31} and β_{32} represent the coefficients on w_t and p_t in a least squares regression of q_t on w_t and p_t (see equation (3)). Thus, the response of quantity to a weather shock equals the sum of a direct effect (β_{31}) and an indirect effect that works through price ($\beta_{32}\beta_{21}$). This is also the coefficient one would obtain from a regression of q_t

[11] This presentation of the IV model is closely related to the SVAR approach using "external instruments" (Montiel-Olea, Stock, and Watson, 2016). In this example, the external instrument would be w_t, which is correlated with p_t ($b_{21} \neq 0$), but not with q_t directly ($b_{31} = 0$). According to Montiel-Olea, Stock, and Watson (2016), we can identify b_{32} using w_t as an "external" instrument in the two-equation SVAR of p_t and q_t.

on w_t only.

Next, we show a close connection between the Wald IV estimand and the impulse responses from an SVAR. Due to the assumptions of the IV model, specifically the exclusion of w_t from the q_t equation and the uncorrelatedness of $w_t = v_{wt}$ and v_{qt}, it follows that

$$cov(q_t, w_t) = b_{32} cov(p_t, w_t). \tag{14}$$

Solving for b_{32}, we can show that this Wald IV estimand is equal to the ratio of the impulse responses of quantity and price to a yield shock.

$$b_{32} = \frac{cov(q_t, w_t)/var(w_t)}{cov(p_t, w_t)/var(w_t)} = \frac{\beta_{31} + \beta_{32}\beta_{21}}{\beta_{21}}, \tag{15}$$

where the first equality following from multiplying and dividing by $var(w_t)$ and the second equality follows from (10) and (11). Now note that the population analogue of the Wald estimator equals the ratio of two impulse responses in

$$\frac{\beta_{31} + \beta_{32}\beta_{21}}{\beta_{21}} = \frac{cov(q_t, w_t)/var(w_t)}{cov(p_t, w_t)/var(w_t)}, \tag{16}$$

This equivalence between the Wald estimand and impulse response ratios also holds when the models include control variables such as trends or lags, but only if the two models contain the *same* controls. Moreover, in the presence of control variables, the IV estimator uses shocks (i.e., regression residuals) for identification just like the SVAR.

To see the equivalence in the presence of controls, note that the IV estimator can be implemented in two stages. First, the user purges the controls using a regression of w_t on the control variables. Then, the residuals from the first stage are used as instruments for price in a second stage IV regression that excludes the controls.[12] Thus, the population analogue of the IV estimator can be expressed as

$$b_{32} = \frac{cov(q_t, u_{wt})}{cov(p_t, u_{wt})}, \tag{17}$$

where u_{wt} denotes the population errors from a regression of w_t on the control variables. The weather equations are identical across the SVAR and IV specifications, so $u_{wt} \equiv v_{wt}$ even in the presence of controls. For the triangular SVAR, we can apply similar algebra as in

[12] This approach employs the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963). This is different from standard two-stage least squares, in which the *predicted values* from the first stage are used in a second stage OLS regression that *includes* the controls. The point estimates from these two procedures are identical.

(10) and (11) to obtain $cov(p_t, v_{wt}) = \beta_{21} var(v_{wt})$ and $cov(q_t, v_{wt}) = (\beta_{31} + \beta_{32}\beta_{21}) var(v_{wt})$. Then, we can write

$$b_{32} = \frac{cov(q_t, u_{wt})/var(u_{wt})}{cov(p_t, u_{wt})/var(u_{wt})} = \frac{\beta_{31} + \beta_{32}\beta_{21}}{\beta_{21}}. \tag{18}$$

As above, the population analogue of the Wald estimator equals the ratio of two impulse responses.

Table 1 presents IV and SVAR estimates of the models in Figure 1 using the updated RS2013 data. To enable comparison with RS2013, we model the trend using cubic splines with four knots and we include no lags. Column (1) reports that the IV estimate of the demand elasticity is −0.063, which is similar to the analogous estimate of −0.055 in RS2013 (Column (1b) of their Table 1). Columns (2) and (3) of Table 1 illustrate how to obtain estimates of the parameters in the coefficient matrix of the triangular SVAR, specifically β_{21}, β_{31} and β_{32}, from OLS regressions.[13] The estimated response of quantity to a weather shock is presented in Column (4) and equals 0.306, which could also be constructed from coefficients in Columns (2) and (3). The demand elasticity computed from the SVAR as in (16) is $-0.306/4.856 = -0.063$.

We have shown in this section that, under the RS2013 assumption that yield deviations constitute supply shocks and are exogenous to price and quantity, the IV and SVAR methods produce identical demand elasticity estimates. The interpretation of these estimates differs slightly. As shown in Figure 1, b_{32} is *the* demand elasticity, whereas in the SVAR, the ratio $(\beta_{31} + \beta_{32}\beta_{21})/\beta_{21}$ is *a* demand elasticity. The SVAR captures the demand elasticity with respect to a weather shock, which may differ from a demand elasticity with respect to a different supply shock. This elasticity could be used to estimate the welfare effects of a weather shock on this market as in Thurman and Wohlgenant (1989).

In the IV formulation, the supply elasticity is not identified because there is no instrumental variable that shifts the demand curve holding the supply curve constant. Put differently, IV does not identify supply because the errors in the price equation are not necessarily supply shocks. In contrast, the SVAR identifies supply based on an assumption that it is perfectly elastic. The two approaches produce the same demand elasticity estimates, and the SVAR also produces a supply elasticity because it includes an additional identification assumption.

If we were instead to assume perfectly inelastic supply in the SVAR as in (12), then the estimate of the demand elasticity would be unchanged. The estimated demand elasticity is unaffected by a change in the identifying assumption about the supply elasticity. As we

[13]Column (2) is also the first stage regression in the IV model.

explain above, this property stems from the block triangular structure of A_0 in (5). Thus, a reader can believe the exogeneity of the first shock and use the resulting estimates even if they reject the assumptions in other parts of the model.

The above analysis illustrates the close connection between IV and SVARs. To simplify illustration, we imposed the assumption of perfectly elastic supply, which had no effect on the estimated demand elasticity. In the next section, we construct an SVAR of global supply and demand for agricultural commodities that relaxes this assumption and re-introduces lags and time trends.

Before we proceed, we note that to provide a presentation of the SVAR that is accessible to applied microeconomists, we point to its similarities to IV. However, this comparison does not imply that the two methods rely on equally strong assumptions. As a structural approach, the SVAR imposes stronger assumptions than IV precisely to identify the entire system of equations. We discuss the restrictions these assumptions impose on the supply and demand system and assess their validity in the context of our empirical application.

SVAR Analysis of Supply and Demand of Agricultural Commodities

In this section, we model commodity supply and demand using a triangular SVAR. We present the model under a set of baseline identifying assumptions, and then in the next section we explore the validity of these assumptions and the implications if they fail.

Quantity supplied is determined by farmer decisions about how much cropland to plant, i.e. acreage, and by weather realizations that ultimately determine yield. The difference between quantity supplied and quantity demanded is the change in inventories. Consumption exceeds production in years when inventory is depleted and production exceeds consumption in years when inventory accumulates. Thus, the decision on how much inventory to hold across crop years is an important driver of prices. Moreover, storage arbitrage links prices across crop years; the expected value of next year's price equals this year's price plus the price of storage.[14]

We exploit the natural annual sequence of these economic decisions, illustrated in Figure

[14] The price of storage includes interest costs, physical storage costs and a convenience yield. The convenience yield is negative and it represents the flow of benefits to firms that hold a commodity in storage. The price of storage need not be constant over time; convenience yield tends to be large when inventories are small (Carter, Rausser, and Smith, 2017)

3, to propose a triangular SVAR identification strategy.[15] In the spring (February-April), Northern Hemisphere farmers choose the amount of land to cultivate (acreage, a_t). Through storage, traders can arbitrage the commodity over time, so last year's price (p_{t-1}) is linked to the expected price in the following year ($E_{t-1}(p_t)$), and is therefore a good proxy for the information on which farmers base their planting decisions. Weather realizations over the summer determine the yield (y_t), which in turn determines the size of the harvest in the early fall. Wholesale traders then decide on the amount they will sell to consumers and how to change inventory (i_t). These decisions jointly determine the price (p_t), which we measure in November and December. This narrative omits the fact that farmers also plant crops in the Southern Hemisphere, where the seasons are opposite to the north. Results in Hendricks, Janzen, and Smith (2014) suggest that the potential bias due to violations of this assumption is small.

While some research questions are better answered with commodity-specific or country-specific analysis, the questions posed in this application are better answered using aggregate data. Since we are interested in global food supply and demand, general equilibrium considerations matter. Corn, rice, soybeans and wheat are substitutes in supply and demand, so if the price of one commodity increases, then the prices of the others will also increase. Modeling the aggregates across commodities accounts for any substitution across commodities.[16] When aggregating across commodities, however, it is not obvious how best to weight them. RS2013 use calorie weights on the grounds that the aggregates represent the number of calories available for human consumption. We also use calorie weights to facilitate comparison with their results. However, consumers value calories differently across the four commodities. As a whole, they prefer to eat animals that were fed by corn rather than eating corn, but they are happy to eat rice. An alternative would be to weight the commodities by a measure of dollar value. To this end, we re-estimated the model using value-weighted data. Specifically, we weighted by the average price of the four commodities from 1986-2013 (these are the years for which we have prices for all four commodities). The relative weights on the four commodities are 0.63 for corn, 1.09 for rice, 1.45 for soybeans and 0.83 for wheat (scaled so the average weight equals one). This means that a bushel of soybeans is worth almost twice as much as a bushel of corn, for example. The calorie weights are 0.98 for corn, 0.83 for rice, 1.32 for soybeans and 0.87 for wheat. Thus, the main difference is that value

[15] For discussion on the role of information delays and physical constraints as sources of identifying restrictions in SVARs, see Chapter 8.3 in Kilian and Lütkepohl (2017).

[16] To model global supply and demand, a researcher could either estimate all the cross-price elasticities between the four commodities, or use aggregate data. The former approach demands much more of the data and the model specification. In their Table 8, RS2013 show IV estimates from a commodity-specific analysis. However, their instruments are weak because the prices of the four commodities move closely together making it difficult to identify the cross-price elasticities separately. Thus, aggregating provides more robust results.

weights place more emphasis on rice and less on corn compared to calorie weights.[17]

It is good practice in time series analysis to plot the data. Such plots may be viewed as the counterpart of summary statistics tables for microeconomic data. The left panels of Figure 4 present the time series plots for all variables in our SVAR using our updated version of the dataset of RS2013. Yield and acreage display increasing trends and price displays a decreasing trend. These patterns are consistent with long-run technological progress that improved land productivity thereby increasing production and reducing prices. The right panels of Figure 4 show each of these series after removing the trend using a cubic spline with 4 knots following the trend specification in RS2013.

Baseline Identifying Assumptions for IRFs

The timeline of events in Figure 3 motivates the following SVAR

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 \\ \alpha_{21} & 1 & 0 & 0 \\ \alpha_{31} & \alpha_{32} & 1 & 0 \\ \alpha_{41} & \alpha_{42} & \alpha_{43} & 1 \end{bmatrix}}_{A_0} \underbrace{\begin{bmatrix} a_t \\ y_t \\ i_t \\ p_t \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} \rho_{11} & \rho_{12} & \rho_{13} & \rho_{14} \\ \rho_{21} & \rho_{22} & \rho_{23} & \rho_{24} \\ \rho_{31} & \rho_{32} & \rho_{33} & \rho_{34} \\ \rho_{41} & \rho_{42} & \rho_{43} & \rho_{44} \end{bmatrix}}_{A_1} \underbrace{\begin{bmatrix} a_{t-1} \\ y_{t-1} \\ i_{t-1} \\ p_{t-1} \end{bmatrix}}_{Y_{t-1}} + \Gamma X_t + \underbrace{\begin{bmatrix} v_{at} \\ v_{wt} \\ v_{it} \\ v_{dt} \end{bmatrix}}_{v_t} \tag{19}$$

where X_t is a vector of cubic spline time trends. The above SVAR includes the first lags of all variables.[18]

We maintain the assumption that $var(v_t) = \Sigma$, a diagonal matrix. All variables are measured in logs. We define i_t as the log difference between production and consumption, i.e., a log-linearized estimate of the percentage change in inventory. To compare the variables in our model to those in RS2013, we note that production (quantity supplied) equals acreage times yield, hence its log equals $a_t + y_t$. The supply model in RS2013 is a regression of $(a_t + y_t)$ on an expected price (for which we use p_{t-1}), yield (y_t), and the trend.[19] Their demand equation is a regression of $(a_t + y_t - i_t)$ on p_t and the trend.

[17]We present the relevant SVAR results in Figure A2 and Table A2 of the supplementary appendix. The impulse response functions and elasticities are almost identical.

[18]Both the Akaike and Schwarz information criteria select the model with the first lag only. We further examine the robustness of our results to incorporating further lags in the SVAR in Section E in the supplementary appendix.

[19]RS2013 do not use actual yield y_t as a control variable in their supply equation. Rather, they use a yield shock, which is log yield minus a trend. Because the supply model controls for trends, these two specifications are identical if the model used to detrend log yield is the same as the trend specification in the supply equation. Hendricks, Janzen, and Smith (2014) show that the supply elasticity estimates are almost identical across the two specifications.

We label the shocks as follows: (i) v_{at} is an acreage supply shock, (ii) v_{wt} is a weather-driven supply shock, (iii) v_{it} is an inventory demand shock, and (iv) v_{dt} is a consumption demand shock. We begin by explaining these labels and stating the assumptions underlying them. Then, we present the impulse responses and supply and demand elasticities estimated under these baseline assumptions. In a subsequent section, we explore the validity of the baseline assumptions, the implications if they fail to hold, and the robustness of the results to alternative assumptions.

The zeroes in the first row of A_0 imply that acreage (a_t) is a function of lagged variables, the trends, and the first shock (v_{at}), but it is unaffected contemporaneously by any of the other three shocks (v_{wt}, v_{it}, or v_{dt}). This assumption relies on the sequencing of events. When making planting decisions, farmers may be responding to demand shocks that determined last season's price, but they are not responding to as yet unobserved weather or demand shocks. Once they observe this year's weather and demand shocks, they can use that information to determine next year's planted acreage, but they cannot go back in time to change this year's acreage. Thus, we interpret the difference between actual and predicted acreage as a shock to supply (v_{at}) caused by, for example, a change in cost or productivity or by weather events prior to planting.

The second row of A_0 reveals that yield (y_t) is a function of lagged variables, the trends, current acreage, and the second shock (v_{wt}). We assume that farmers do not take actions to increase yield in response to contemporaneous shocks in inventory or consumption demand. This assumption follows arguments in RS2013 pointed out above that yield deviations from trend are driven by weather shocks. This is why we label v_{wt} a weather-driven supply shock.

The zero in the third row of A_0 implies that v_{it} is the part of inventory that is not predicted by lagged variables, the trends, or quantity supplied (a_t and y_t). Importantly, inventory does not respond to contemporaneous demand shocks, which means that inventory demand is perfectly inelastic with respect to price (holding supply constant). Thus, we interpret any difference between actual inventory and the amount predicted by quantity supplied, lags of all variables and trends as an exogenous change in inventory demand. Such changes may reflect speculation about future supply and demand. Finally, the fourth equation expresses prices as a function of all the other variables, lags and trends. Given the quantity supplied and the quantity put into storage, neither of which respond contemporaneously to prices, the price adjusts to equilibrate the market. Thus, this equation is a demand function and its error, v_{dt}, is a consumption demand shock.

IRF Results under Baseline Assumptions

Figure 5 shows the estimated impulse responses along with pointwise 95% confidence intervals estimated using the residual-based bootstrap. It contains 16 plots, each showing the dynamic effect on one of the four variables to a one standard deviation shock in one of the four treatments. Table 2 lists the estimated impulse responses to both a one-standard-deviation and a one-unit change in the shocks.

The first row of Figure 5 shows that an acreage supply shock increases acreage by 0.9% and decays to zero two years later.[20] This shock raises expected yield by 0.6% and inventory by 1.3%. The effect of acreage supply shocks on yield is not statistically significant. The magnitude of the inventory response to this shock implies that much of the supply increase is saved as inventory, which in turn implies that the shock has a long lasting effect on prices. The contemporaneous price response is a statistically insignificant 3.8% decrease and the effect decays to zero by year four.

The second row of Figure 5 shows the effects of a weather supply shock, which is the shock that RS2013 use to identify both supply and demand elasticities. The plot in the second row, second column shows that a typical weather shock raises yield by 2.1% and lasts only one year. Because production equals acreage times yield and acreage is determined before the weather shock is observed, this shock implies a 2.1% increase in production. In response, inventory increases by 1.7% and price decreases by 8.0%. In the next year after a weather supply shock, farmers respond to the resulting lower price by planting 0.5% fewer acres and obtaining 0.1% lower yield, which implies a production decrease of 0.6% (see Table 2 and the second row of Figure 5).

The third row of Figure 5 shows the response to an inventory demand shock. This shock dissipates to zero by the second year and has no significant effect on the other variables. Thus, shocks to inventory demand appear not to be a major driver of global agricultural supply and demand. This result suggests that speculation about future supply and demand has little effect on prices. However, using a partially identified SVAR of the corn market, Carter, Rausser, and Smith (2017) find that inventory demand shocks affect United States corn prices significantly. Later, we investigate whether our result could be due to differing identification assumptions.

The bottom row of Figure 5 shows the responses of all variables to a consumption demand shock. The bottom right figure shows that an average consumption demand shock raises the price by 13.5% and dissipates to zero by about the third year after the shock. By assumption, current-year acreage, yield, and inventory are determined before price, so they

[20]Throughout, we describe changes in the log of variables as a percentage change. Thus, we describe a log-acreage increase of 0.009 as a 0.9% increase.

are not affected contemporaneously by this shock. In the following year, however, producers respond to this price by increasing acreage by 0.52%. The estimated yield response is close to zero and statistically insignificant, so the supply response is determined almost entirely by land use change rather than a change in intensity. The negligible yield response is consistent with the identifying assumption that yield shocks are weather driven. If farmers do not increase yield in response to demand shocks from the previous year, then it is unlikely that they would increase yield in response to current-year demand shocks.

Estimated Demand and Supply Elasticities under Baseline Assumptions

In addition to the standard SVAR analysis, we now compute demand and supply elasticities using our IRF estimates. We specifically can identify two distinct demand and supply elasticities, which we report in Table 3 in addition to the quantiles of their respective residual-based bootstrap distribution using 1,000 bootstrap replications. These quantiles can be used to construct 5% and 10% confidence bands for our elasticity estimates.

From the SVAR results, we can identify two demand elasticities using the two supply shocks we have, specifically acreage and weather supply shocks. To illustrate how these estimates are obtained, consider the acreage supply shock. The ratio of the contemporaneous response of price and quantity to the acreage supply shock estimate a demand elasticity. Recalling that quantity demanded equals $(a_t + y_t - i_t)$, the current-year demand elasticity is therefore

$$\frac{\partial q_{dt}/\partial v_{at}}{\partial p_t/\partial v_{at}} = \frac{\partial a_t/\partial v_{at} + \partial y_t/\partial v_{at} - \partial i_t/\partial v_{at}}{\partial p_t/\partial v_{at}} = \frac{0.0090 + 0.0061 - 0.0131}{-0.0380} = -0.053. \quad (20)$$

This is very similar to the demand elasticity estimated using the IV strategy in RS2013 in Table 1. However, it is identified by shocks to land use (acreage supply) rather than the weather supply shocks used in RS2013. The residual-bootstrap quantiles, however, imply wide confidence intervals, which implies that this demand elasticity is estimated imprecisely.

Using weather supply shocks, we can also identify the contemporaneous demand elasticity, which is given by

$$\frac{\partial q_{dt}/\partial v_{wt}}{\partial p_t/\partial v_{wt}} = \frac{\partial y_t/\partial v_{wt} - \partial i_t/\partial v_{wt}}{\partial p_t/\partial v_{wt}} = \frac{0.0211 - 0.0170}{-0.0803} = -0.051. \quad (21)$$

This elasticity is statistically significant at the 5% level based on the bootstrap quantiles in Table 3. Moreover, our construction of the demand elasticity allows us to understand the component-wise response. The above estimate specifically suggests that the relatively small demand elasticity can be explained by the fact that most of the yield change due to the shock is incorporated into greater inventory.

The implied demand elasticity due to yield shocks (21) is almost identical to the one due to acreage shocks (20), even though acreage shocks are more long-lived than yield shocks. The plot in the second row, second column Figure 5 shows that a typical weather shock raises yield for only one year, whereas the plot in the top left of the same figure shows that an acreage-supply shock affects supply for two years.

Next we turn to estimating supply elasticities. Using lagged weather shocks and noting that farmers respond to the spot price with a one-year lag, we can obtain the following supply elasticity

$$\frac{\partial q_{s,t+1}/\partial v_{wt}}{\partial p_t/\partial v_{wt}} = \frac{\partial a_{t+1}/\partial v_{wt} + \partial y_{t+1}/\partial v_{wt}}{\partial p_t/\partial v_{wt}} = \frac{0.0049 + 0.005}{0.0803} = 0.067. \tag{22}$$

This estimate is statistically significant at the 5% level. Using consumption demand shocks, we can identify another supply elasticity, which is solely composed of the acreage response, since yield does not respond to consumption demand shocks as implied by Figure 5,

$$\frac{\partial(a_{t+1} + y_{t+1})/\partial v_{dt}}{\partial p_t/\partial v_{dt}} = \frac{0.0052}{0.1354} = 0.038, \tag{23}$$

which is statistically significant at the 10% level and just over half the elasticity identified from weather shocks.[21]

Consumption demand shocks are much more persistent than weather shocks. The plot in the second row, last column Figure 5 shows that a typical weather shock reduces price for only one year, whereas the plot in the bottom right of the same figure shows that a consumption demand shock affects price for two years. Over the first five years, the cumulative acreage response to a weather shock is

$$\begin{aligned}\frac{\sum_{j=1}^{5} \partial a_{t+j}/\partial v_{wt} + \partial y_{t+j}/\partial v_{wt}}{\partial p_t/\partial v_{wt}} &= \frac{0.0049 + 0.0023 + 0.0005 - 0.0004 - 0.0006}{0.0803} \\ &\quad + \frac{0.0005 - 0.0007 + 0.0000 + 0.0002 + 0.0002}{0.0803} \\ &= 0.086. \end{aligned} \tag{24}$$

Thus, for every 1% rise in price from a weather shock, farmers produce an additional amount

[21] As noted in RS2013, government programs in many countries affect supply. For example, prior to 1996 the U.S. government would direct farmers to reduce acreage in years with low prices. In this sense, our estimated elasticities incorporate the collective responses of farmers and governments.

equal to 0.086% of production. This estimate is only slightly greater than the first year elasticity of 0.067, which means that almost all the response occurs in the first year. This is reasonable given that the yield shock only lasts for one year.

The cumulative acreage response to the consumption demand shock over the first five years is

$$\frac{\sum_{j=1}^{5} \partial a_{t+j}/\partial v_{dt}}{\partial p_t/\partial v_{dt}} = \frac{0.0052 + 0.0053 + 0.0035 + 0.0015 + 0.0002}{0.1354} = 0.116. \tag{25}$$

Yield does not respond to v_{dt} at any horizon, so this estimate also equals the total production response, and it is substantially larger than the first-year elasticity of 0.038. Thus, for every 1% rise in price from a consumption demand shock, farmers produce an additional amount equal to 0.116% of production but they spread this increase over several years. This finding reflects the fact that consumption demand shocks affect price for multiple years.

Overall, these results suggest that demand responds to a price increase similarly regardless of the duration of the shocks used, whereas suppliers' contemporaneous and future response varies depending on the nature of the shocks. Specifically, commodity buyers respond in a similar way to one-year supply changes as to longer-run supply changes. Since both supply shocks affect price only in the contemporaneous year, the demand response in future years is insignificantly different from zero. The shocks used to identify supply response however have a longer run impact on price, and hence we can identify the dynamic supply response. We find that producers have a smaller initial response but a larger cumulative response to a consumption demand shock. Their response to a shock induced by poor weather last year tends to be larger initially, but it drops to zero in subsequent years.

Assessing the Identifying Assumptions

Consistent estimation of dynamic causal effects in an SVAR requires correct specification of the model, as is the case in IV settings. This requirement encompasses a functional form assumption, namely that the expected value of each variable conditional on the past is linear in the lags of the variables in the model, and a set of identification assumptions, which are embodied in the matrix A_0. We do not explore nonlinear specifications in this application, but these could be incorporated using, for example, the local projections estimator of Jorda (2005). The number of lags we include in our baseline SVAR is determined by using the Akaike and Schwarz information criteria. We examine the robustness of our results to incorporating further lags in Section E in the supplementary appendix. In this section, we focus our discussion on potential violations of the main identification assumptions.

As mentioned above, the identification of the baseline SVAR parameters relies on the validity of the triangular structure of A_0 in (19).[22] We define two blocks in this matrix, the first contains the two supply shocks (acreage and weather) and the second contains the two demand shocks (inventory and consumption). We first illustrate that the assumptions made to identify the two demand shocks do not affect the responses to the two supply shocks, as per our discussion of (12). Then, we discuss potential violations of the restrictions on the two supply shocks, yield and acreage.

What if the Acreage and Yield Shocks are the Only Plausibly Exogenous Shocks?

Suppose we accept the argument that the acreage and yield shocks are exogenous but are skeptical about other parts of the model, specifically the exclusion restriction on price in the inventory equation in ($\alpha_{34} = 0$ in Eq. 19). This assumption implies that inventory does not respond to contemporaneous demand shocks, which means that inventory demand is perfectly inelastic with respect to price, conditional on quantity supplied. This assumption appears at face value to be false; we would expect inventory holders to be less interested in stocking up on the commodity if high consumption demand pushes up prices.

In our data, the correlation between price and inventory is close to zero after conditioning on acreage, yield and all the lags. We know this from Figure 5, in which we estimate a small response of price to inventory demand shocks, and we assume a zero contemporaneous response of inventory to consumption demand shocks ($\alpha_{34} = 0$). In general, the two demand shocks imply conditional correlations between inventory and prices of opposite signs. For example, Carter, Rausser, and Smith (2017) study an inventory demand shock from a biofuel mandate that increased future demand for agricultural commodities and therefore increased inventory levels as the market prepared for higher future demand. Such a shock raises the price and inventory levels. In contrast, a positive shock to current demand increases price and consumption, which means it decreases inventory levels. Based only on the near zero conditional correlation between price and inventory, we cannot tell whether the two variables are unresponsive to each other or whether they are responsive in equal and opposite ways, i.e., positive price responses to inventory demand shocks cancel negative inventory responses to consumption demand shocks.

To illustrate this point empirically, we consider alternative specifications in which we fix α_{34} to take one of three non-zero values: 0.1, 0.25 and 0.5. These values of α_{34} are motivated

[22]We discuss the implied restrictions in detail when presenting the baseline specification in the previous section.

by the baseline estimates. Specifically, the baseline model identifies two non-zero inventory demand elasticities. First, the ratio of the inventory and price responses to the acreage supply shock is $0.0131/(-0.0380) = -0.345$. Second, the ratio of the inventory and price responses to the weather supply shock is $0.0170/(-0.0803) = -0.212$. These elasticites are components of the total demand elasticities in (20) and (21). Thus, if price changes because of a change in supply, the baseline model allows an inventory response within the same crop year, but if price changes because of a change in consumption demand, then it allows no response. By setting $\alpha_{34} = 0.25$, we impose that the inventory demand elasticity as identified by consumption demand shocks equals -0.25, which is similar to the two elasticities identified in the baseline model. The smaller value ($\alpha_{34} = 0.1$) implies a smaller response of inventory to demand shocks than to supply shocks, which may be reasonable because inventory levels have a whole crop year to respond to supply shocks, whereas it may only have part of the year to respond to a demand shock. The larger value ($\alpha_{34} = 0.5$) provides an upper bound.

Figure 6 presents the IRF graphs when we fix $\alpha_{34} = 0.25$.[23] Because the acreage and yield shocks occur earlier in the temporal ordering implied by (19), their IRFs do not depend on the value of α_{34}, unlike the two demand shocks. As a result, the IRFs for the acreage and yield shocks are identical to the baseline results. This feature of the model is important because it means a lack of identification of the inventory demand shock does not invalidate the identification of the earlier shocks. Readers can believe the responses identified by the acreage and yield shocks in the baseline model even if they do not think the inventory- and consumption demand shocks are well identified.

The IRFs for inventory and consumption demand shocks are however quite different from the baseline model results in Figure 5. The baseline results indicate that consumption demand shocks have persistent price effects, and inventory demand shocks have negligible price effects. In contrast, Figure 6 shows that consumption demand shocks have small price effects and inventory demand shocks have large price effects over a longer horizon. The latter result is more consistent with Carter, Rausser, and Smith (2017), who find significant price effects from inventory demand shocks. In their model, an example of an inventory demand-shock is a biofuel mandate that will increase future demand for agricultural commodities and therefore increase inventory levels as the market prepares for higher future demand.[24]

Based on the IRFs in Figure 6, and as we stated above, the supply elasticity identified by consumption demand shocks increases when we allow α_{34} to be non-negative. It increases

[23]Table A7-A8 in the supplementary appendix contains the IRF results for $\alpha_{34} = 0, 0.1, 0.25, 0.5$.

[24]A noteworthy observation is that yield does not respond to either of the demand shocks at any horizon whatever values we choose for α_{34}. This is consistent with the intuition in RS2013 that yield deviations from the cubic spline trends are driven by weather shocks.

from 0.038 in (23) to 0.061, which is similar to the estimate of 0.067 in (24) that we identified using weather supply shocks. The long-run elasticity increases from 0.116 in (25) to 0.201. Whether a reader believes these estimates, the baseline estimates, or neither depends on what assumptions they are willing to make about the inventory demand elasticity and does not affect the interpretation of parameters identified by the yield shocks. If we were to be agnostic about whether $\alpha_{34} = 0$ or $\alpha_{34} = 0.25$ is a better assumption, we would conclude that demand shocks (i.e., variation in prices is uncorrelated with yield and acreage) have persistent effects on price, but we would not identify the relative roles of consumption and inventory demand shocks.[25]

In sum, depending on the assumed short-run elasticity of inventory demand, the dynamic effects of the two types of demand shocks change, but the dynamic effects of the two supply shocks are unaffected since they occur earlier in the temporal ordering in the system.

What if Farmers Anticipate Future Shocks When Choosing Acreage?

The exogeneity of the acreage shock relies on the validity of the exclusion of contemporaneous yield, inventory and consumption demand from its equation. The implication of the resulting zeroes in the top row of (19) is that producers make planting decisions based on prior-year yield, inventory and price and do not incorporate information on the current-year values of those variables beyond what can be predicted from their lags. These assumptions would fail if farmers anticipate shocks that are unanticipated by the markets that set the prior-year price. For example, if farmers anticipate good growing-season weather and therefore increase acreage, the model would interpret the resulting shock as an acreage shock rather than a yield shock.

Because we measure price in November and December, which is a few months before planting, a natural check of this potential source of bias is to see whether our results change if we use March prices instead. If new information arrives in the months between November/December and March that significantly affects acreage and other variables in the system, then the baseline model would have an omitted variable and a violation of the triangular SVAR assumptions as we discuss in (13). As a result, the baseline results would be biased, and we would expect the results to change when we use March prices instead.

We conduct this falsification test by re-estimating our baseline model using March prices instead of November/December. The IRFs look very similar.[26] The implied demand elas-

[25] This agnosticism can be incorporated formally using partial identification as in, for example, Carter, Rausser, and Smith (2017).

[26] See Figure A3 and Table A3 in the supplementary appendix for results.

ticities are -0.044 and -0.059, compared to -0.053 and -0.051 in (20) and (21) from our baseline specification. We obtain supply elasticities of 0.075 and 0.039, compared to 0.067 and 0.038 in (24) and (23). Thus, the results are not sensitive to using March prices, providing suggestive evidence that the bias from this potential violation of the assumptions on the acreage equation is negligible.

Another possible violation of the exclusion restrictions in the acreage equation would be if farmers can better anticipate growing-season price shocks than commodity traders. Farmers would use this information in making acreage decisions. Such a mechanism would induce a positive relationship between acreage and the post-harvest price. We expect such an effect to be small because most of the shock to the post-harvest price stems from factors such as weather shocks that market participants, including farmers, do not predict. If a large segment of the market knew a price shock was coming, then it would already be incorporated into the pre-planting price.

The baseline estimates show a weak negative effect of acreage on price within a crop-year. Under the baseline assumptions, this correlation reflects a relationship between acreage and price—an increase in acreage constitutes an increase in supply, which causes the equilibrium price to decline. This relationship underlies the demand elasticity estimate in equation (20). Table 3 shows that this estimate has very wide confidence intervals, reflecting the weakness of the relationship, and suggesting point estimates from the acreage supply shocks should be interpreted with caution.

What about the Exogeneity of the Yield Shock?

The yield shock (v_{wt}) is analogous to the shock that RS2013 use as an instrument. They argue that yield shocks are driven primarily by weather and are therefore exogenous to agricultural markets. They note that yield shocks exhibit little correlation over time or between countries. We impose this assumption on our model by excluding both contemporaneous inventory and consumption from the second equation of (19). These restrictions imply that, conditional on current acreage and the past values of all variables, crop-year-ending inventory and the post-harvest price do not cause yield.

This assumption on yield shocks would fail if growing-season shocks that change inventory or price were to cause changes in yield. For example, suppose demand were to increase during the growing season causing an increase in expected price. If farmers responded to such a shock by increasing fertilizer use or making other changes that materially affect yield, then yield shocks would be correlated with price shocks and our assumption would fail.

We do not assume that yield is exogenous to contemporaneous acreage in our SVAR, i.e., we allow α_{21} to be a free parameter in (19). Moreover, the presence of lagged variables in the SVAR implies that prior-year observables may affect yield, for example if farmers were to change inputs such as fertilizer in response to a previous-period price shock or if weather is autocorrelated. In the language of regression, we are using current acreage and the lagged variables as controls to identify the effect of yield. In the language of SVARs, we identify the effect of yield shocks rather than detrended yield *per se*.[27]

In this application, the controls make little difference. The IRFs in Figure 5 indicate that prior-year shocks have no effect on yield in the current year and that contemporaneous acreage shocks have a small but statistically insignificant effect. This is consistent with RS2013, who point out that the detrended yield is uncorrelated over time.

Conclusion

This paper explains the most common method to identify causal effects in time series econometrics (SVAR) to agricultural and resource economists primarily trained in microeconometrics. We illustrate the method with an application to the global supply and demand for agricultural commodities. Our presentation highlights important differences in objectives between SVAR analysts and proponents of reduced-form causal inference, but also reveals important similarities. SVAR models decompose variation in the data into "exogenous" components, whereas reduced-form causal models estimate the effect of only one component. Nonetheless, we show that the standard IV estimate of the effect of this component is identical to the ratio of two impulse responses in the SVAR.

We focus on the triangular identification scheme in our exposition and application, and we illustrate how a triangular structure may be justified from the timing of events. However, the triangular structure may be hard to justify in many empirical settings. Alternative identification and inference procedures that rely on weaker conditions (Stock and Watson, 2016, 2018, 2017; Montiel-Olea, Stock, and Watson, 2016; Gafarov, Meier, and Olea, 2018; Paul, 2020) would be more appropriate in those cases. Moreover, the linear functional form of the SVAR may not fit in all settings and methods. Kilian and Lütkepohl (2017) present numerous examples of nonlinear SVAR models, including those with regime switching, time-varying coefficients, threshold transitions, and asymmetric responses. In some

[27] Equivalence of these two views stems from the Frisch-Waugh-Lovell theorem (Frisch and Waugh, 1933; Lovell, 1963). The coefficient on X in a regression of Y on X and Z is the same as the coefficient on v in a regression of Y on v, where v denotes the residuals from a regression of X on Z.

cases, nonlinearities can be exploited to obtain identification, as proposed in Rigobon (2003) and applied to cotton prices in Janzen, Smith, and Carter (2018). Flexible specifications could be accommodated using a nonlinear parametric model or semi-parametrically using the local projection estimator (Jorda, 2005).

Our main points carry over to different identification schemes, model specifications, and estimators. Time series settings typically contain multiple continuous variables that are serially correlated and potentially mutually dependent. Causal analysis of such data requires the analyst to consider the persistence of the "treatments" (i.e., identify treatment paths) and to estimate the dynamic effects of these treatments. These points also extend to panel data settings, especially those with a long time series dimension.

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Figure 1: Instrumental Variables vs. Triangular SVAR: Demand Elasticity

Panel A: IV

$$\begin{bmatrix} 1 & 0 & 0 \\ -b_{21} & 1 & 0 \\ 0 & -b_{32} & 1 \end{bmatrix} \begin{bmatrix} w_t \\ p_t \\ q_t \end{bmatrix} = \begin{bmatrix} u_{wt} \\ u_{pt} \\ u_{qt} \end{bmatrix}, \qquad \Omega = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & \sigma_{23} \\ 0 & \sigma_{23} & \sigma_3^2 \end{bmatrix}.$$

Panel B: Triangular System (Static SVAR)

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 \\ -\beta_{21} & 1 & 0 \\ -\beta_{31} & -\beta_{32} & 1 \end{bmatrix}}_{A_0} \underbrace{\begin{bmatrix} w_t \\ p_t \\ q_t \end{bmatrix}}_{Y_t} = \underbrace{\begin{bmatrix} v_{wt} \\ v_{pt} \\ v_{qt} \end{bmatrix}}_{v_t}, \qquad \Sigma = \begin{bmatrix} \sigma_w^2 & 0 & 0 \\ 0 & \sigma_p^2 & 0 \\ 0 & 0 & \sigma_q^2 \end{bmatrix}.$$

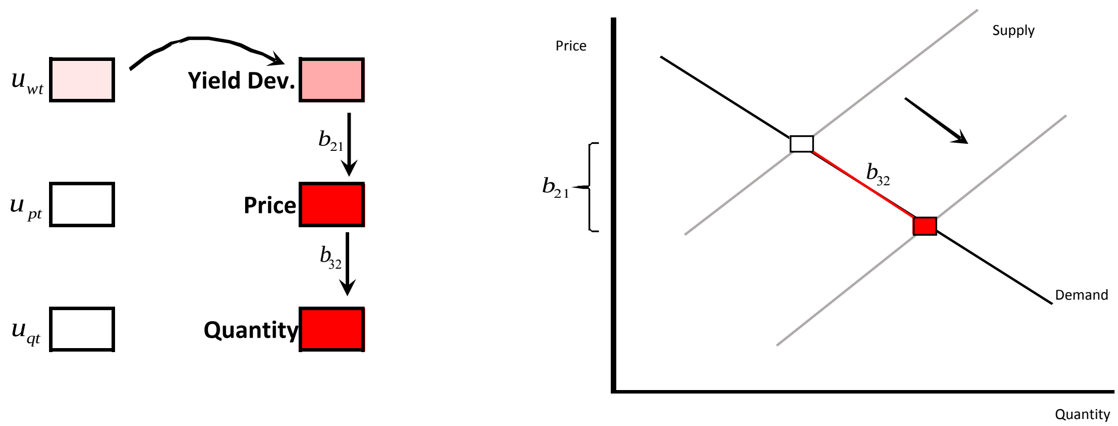
Table 1: Demand Elasticity: Triangular System vs. IV

	IV	SVAR		
	(1)	(2)	(3)	(4)
Dependent Variable:	q_t	p_t	q_t	q_t
p_t	-0.063		$\overbrace{0.002}^{\hat{\beta}_{32}}$	
	(-2.22)		(0.22)	
w_t		$\overbrace{-4.856}^{\hat{\beta}_{21}}$	$\overbrace{0.317}^{\hat{\beta}_{31}}$	$\overbrace{0.306}^{\widehat{\beta_{31}+\beta_{32}\beta_{21}}}$
		(-5.35)	(2.18)	(2.28)
Sample Size	52	52	52	52

Notes: (1) is estimated using 2SLS with w_t as the instrument. (2)-(4) are estimated using OLS. All regressions include flexible time trends modeled using cubic splines with four knots as in RS2013. The t statistics in parentheses are computed using Newey-West standard errors to correct for heteroskedasticity and first-order autocorrelation. Sample: 1962-2013.

Figure 2: Triangular SVAR vs. IV

Panel A: IV



Panel B: SVAR

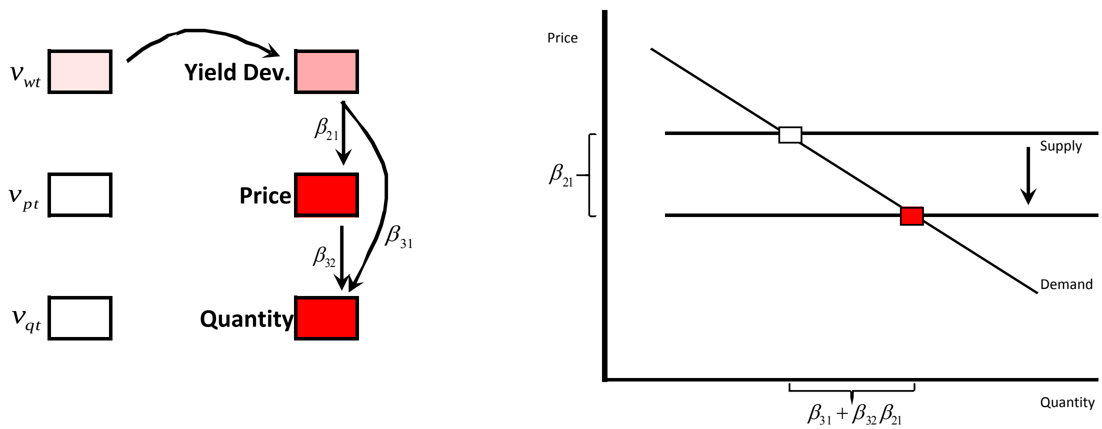


Figure 3: Time Line

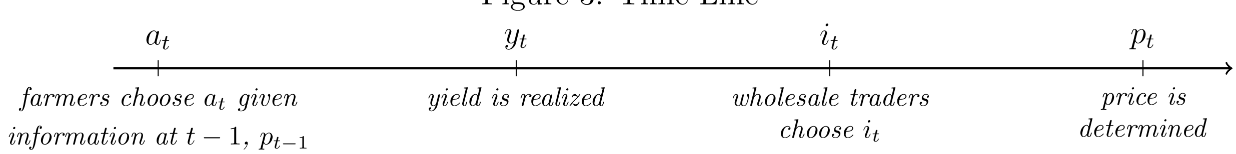


Figure 4: Time Series Plots of Acreage, Yield, Inventory and Consumption Price

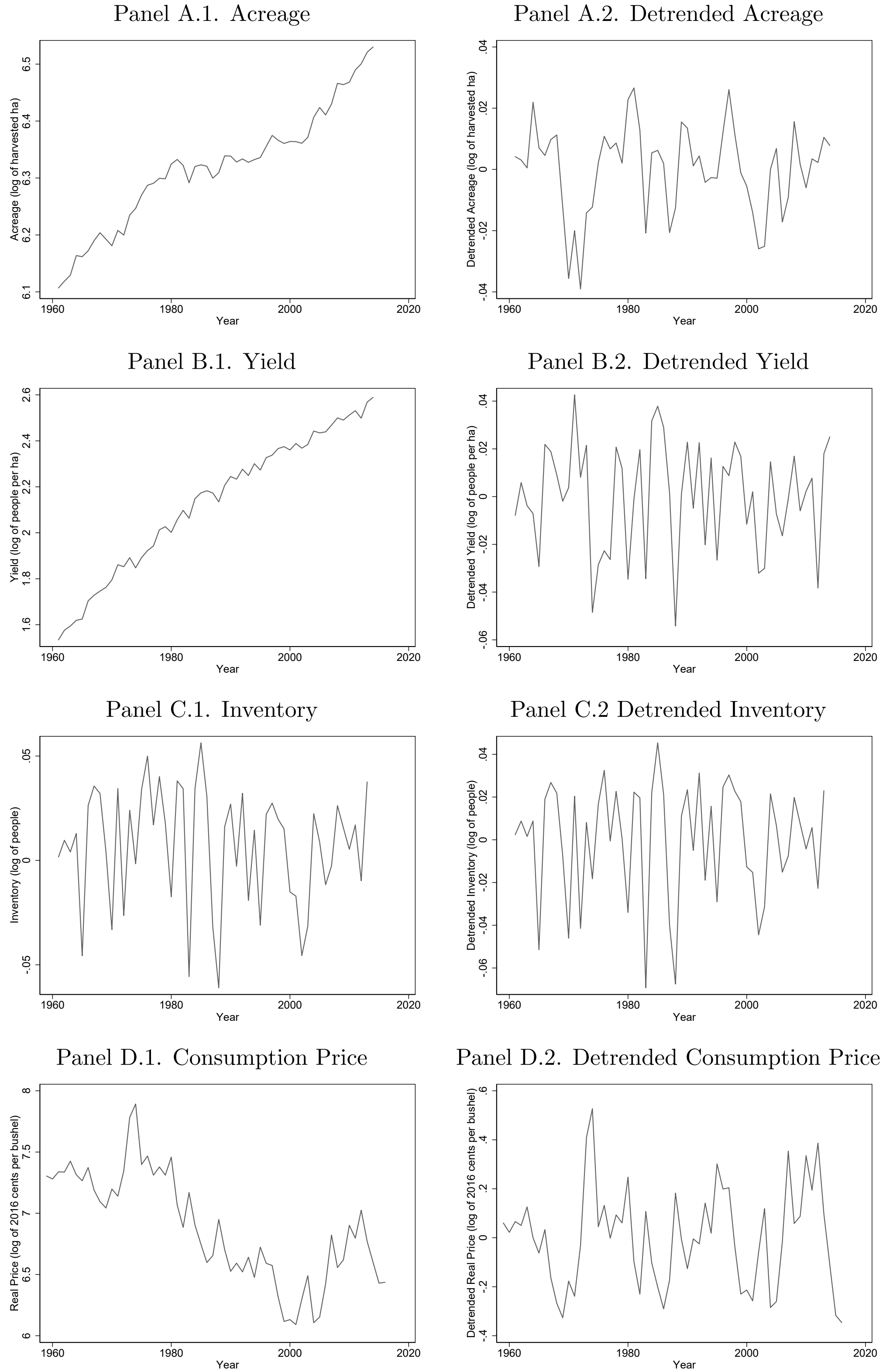
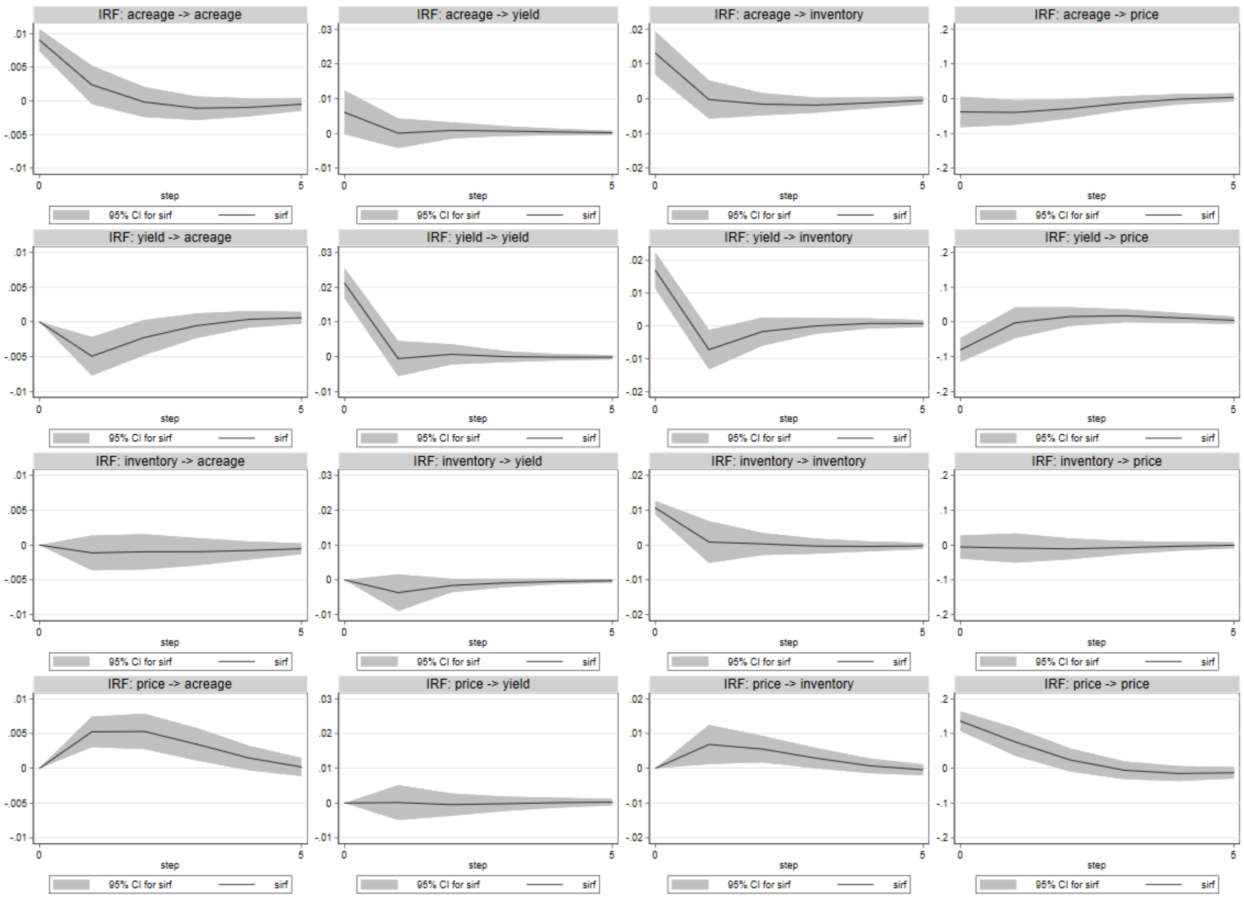


Figure 5: SVAR Analysis of RS2013: Impulse Response Functions



Notes: The above figure presents the impulse response functions over 5 years for the SVAR given in (19). The exact values of the impulse response functions are given in Table 2. In the first row, v_{at} is increased by its standard deviation and the response of all variables is presented. Similarly, in the second, third and fourth rows, v_{wt}, v_{it}, and v_{dt} are increased by their standard deviations, respectively. The plots in each column are presented on the same scale because they show the response of the same variable to different shocks. The impulse response functions (sirf) are plotted in solid lines and their 95% bootstrap confidence intervals are shaded in gray (1000 bootstrap replications).

Table 2: SVAR Analysis of RS2013: Impulse Response Functions

		Response to S.D. Change				*Response to Unit Change*			
Impulse	h	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}
v_{at}	0	0.0090	0.0061	0.0131	-0.0380	1	0.670	1.447	-4.204
	1	0.0024	0.0001	-0.0003	-0.0395	0.265	0.007	-0.029	-4.372
	2	-0.0002	0.0009	-0.0016	-0.0288	-0.018	0.097	-0.176	-3.185
	3	-0.0011	0.0007	-0.0019	-0.0127	-0.120	0.076	-0.206	-1.409
	4	-0.0010	0.0004	-0.0012	-0.0014	-0.106	0.048	-0.134	-0.153
	5	-0.0005	0.0002	-0.0005	0.0037	-0.055	0.022	-0.053	0.405
v_{wt}	0	0	0.0211	0.0170	-0.0803	0	1	0.803	-3.804
	1	-0.0049	-0.0005	-0.0072	-0.0026	-0.234	-0.026	-0.343	-0.121
	2	-0.0023	0.0007	-0.0017	0.0152	-0.107	0.032	-0.081	0.722
	3	-0.0005	0.0000	0.0000	0.0176	-0.026	0.000	0.000	0.832
	4	0.0004	-0.0002	0.0008	0.0114	0.018	-0.008	0.037	0.542
	5	0.0006	-0.0002	0.0008	0.0045	0.028	-0.008	0.037	0.214
v_{it}	0	0	0	0.0107	-0.0056	0	0	1	-0.523
	1	-0.0011	-0.0037	0.0009	-0.0085	-0.105	-0.344	0.082	-0.797
	2	-0.0010	-0.0016	0.0003	-0.0108	-0.090	-0.152	0.031	-1.013
	3	-0.0010	-0.0009	-0.0003	-0.0073	-0.090	0.081	-0.029	-0.686
	4	-0.0008	-0.0004	-0.0004	-0.0032	-0.073	-0.042	-0.035	-0.304
	5	-0.0005	-0.0003	-0.0002	-0.0004	-0.049	-0.024	-0.023	-0.041
v_{dt}	0	0	0	0	0.1354	0	0	0	1
	1	0.0052	0.0001	0.0068	0.0758	0.039	0.001	0.051	0.560
	2	0.0053	-0.0005	0.0055	0.0241	0.039	-0.003	0.041	0.178
	3	0.0035	-0.0002	0.0029	-0.0058	0.026	-0.001	0.021	-0.042
	4	0.0015	0.0001	0.0007	-0.0152	0.011	0.001	0.005	-0.112
	5	0.0002	0.0003	-0.0004	-0.0129	0.001	0.002	-0.003	-0.095

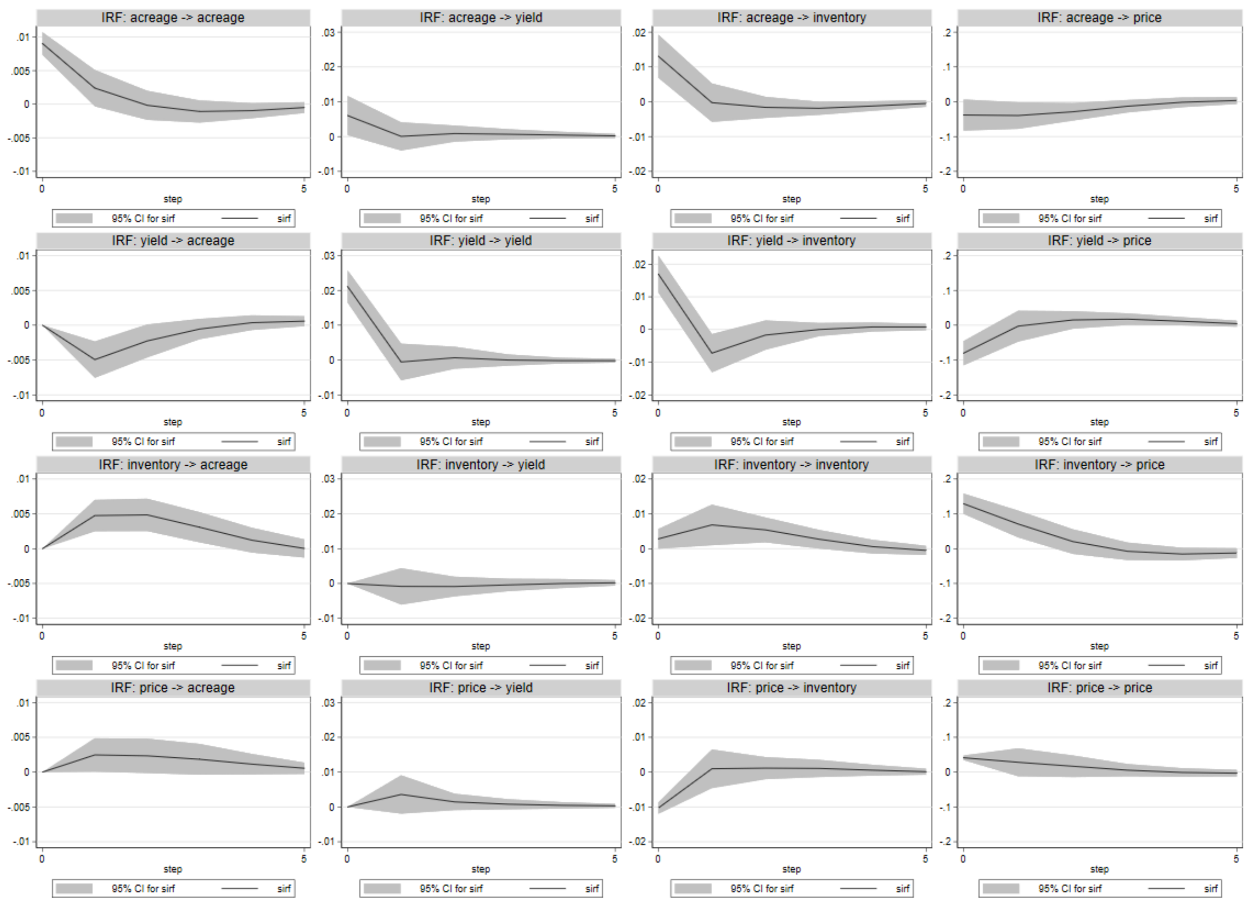
Notes: The above table presents the impulse responses to a standard deviation (S.D.) as well as a unit change in each shock on all variables in the system h-steps ahead for the SVAR given in (19). Sample: 1962-2013.

Table 3: Estimates of Demand and Supply Elasticities in Response to SVAR Shocks

	Elasticity	Quantiles of the Bootstrap Distribution			
		0.025	0.05	0.95	0.975
Demand Elasticity					
in response to v_{at}	-0.053	-0.492	-0.296	0.087	0.254
in response to v_{wt}	-0.051	-0.129	-0.114	-0.013	-0.006
Supply Elasticity					
in response to $v_{w,t-1}$	0.067	0.010	0.022	0.198	0.225
in response to v_{dt}	0.038	-0.009	0.000	0.082	0.090

Notes: The quantiles of the bootstrap distribution are obtained from a residual-based bootstrap described in Hamilton (1994) using 1,000 replications.

Figure 6: SVAR Results with Nonzero Coefficient on Price in Inventory Eqn. ($\alpha_{34} = 0.25$)



Notes: The above figure presents the impulse response functions over 5 years for the SVAR given in (19) using cubic spline trends but allowing $\alpha_{34} = 0.25$ instead of $\alpha_{34} = 0$. The exact values of the impulse response functions are given in Tables A7-A8 in the supplementary appendix for $\alpha_{34} = 0.25$ in addition to other choice of this parameter. In the first row, v_{at} is increased by its standard deviation and the response of all variables is presented. Similarly, in the second, third and fourth rows, v_{wt}, v_{it}, and v_{dt} are increased by their standard deviations, respectively. The plots in each column are presented on the same scale because they show the response of the same variable to different shocks. The impulse response functions (sirf) are plotted in solid lines and their 95% bootstrap confidence intervals are shaded in gray (1000 bootstrap replications).

AJAE Appendix for Causality in Structural Vector Autoregressions: Science or Sorcery?

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September 14, 2021

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List of Figures

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List of Tables

A Data

We construct a time series data set from 1962-2013 that includes global production, acreage, inventory and spot prices for corn, wheat, rice and soybeans. We obtain area, production, inventory changes (storage variation) and yield data by country from the Food and Agricultural Organization (FAO) statistics. Similar to RS2013, we construct calorie-weighted global production of the four crops (quantity supplied). Production of maize, rice, soybeans and wheat are measured in tons, then converted into calories using calorie weights from RS2013. We specifically convert production tons into calories and then divide by 365*2000, the number of calories consumed by the average person in a year. Acreage is the total area planted to these crops. Yield is the ratio of production to acreage. Quantity demanded is quantity supplied minus inventory changes. The spot prices for the individual commodities are obtained from Quandl and aggregated using the same calorie weights used to aggregate production. The spot price is also deflated using the CPI to 2016 U.S. dollars. Using our updated dataset, we replicate the IV estimate of the demand elasticity in RS2013 as illustrated in the main paper. We are also able to reproduce very similar IV estimates of supply elasticities, see Table A1.

B Defining the Treatment in Time Series Applications

The potential outcomes framework, also known as the Rubin Causal Model, has become the standard lens through which microeconometricians view causality. Time series settings rarely generate treatments that fit neatly in the potential outcomes framework. A neat fit would require that only a subset of the observations are treated and that the treatment timing and magnitude is exogenous to the outcome variable.

In typical time series applications, treatments are not randomly assigned across observations; every observation is "treated" and the magnitude and persistence of the treatment varies by observation. Defining treatments and disentangling causal effects may require more structure and assumptions in these settings. In this section, we first present two time series examples that fit neatly in the existing potential outcomes framework. These two examples clarify how the typical time series setting differs from a typical potential outcomes setting.

B.1 A Discrete Treatment Event

The event study literature provides a close time-series analog to the potential outcomes framework (MacKinlay, 1997). An event study focuses on a single treatment, or event, that occurs at a point in time such as an earnings announcement or a scandal. The researcher uses pre-event data to estimate counterfactual values of the outcome variable if the event had not occurred.[1] For example, Carter and Smith (2007) examine the price effect of a food scare caused by genetically modified StarLink corn. StarLink corn is a genetically modified (GM) variety that was only approved for animal feed and non-food industrial products. In 2000, it was found in taco shells and other foods.

To place Carter and Smith (2007) in the potential outcomes framework, denote by t^* the date the food scare occurred. Then, define a binary treatment variable D_t that equals one for $t = t^*$ and zero otherwise. Thus, there is a single treatment applied on a single date: July 18, 2000. The outcome variable y_t is the logarithm of the relative price of corn to sorghum.[2] Figure A1 plots daily y_t before and after the food scare. The two horizontal red lines indicate the estimates of $E[Y_t|t \geq t^*]$ and $E[Y_t|t < t^*]$. The difference between them is -0.13, the question is whether that difference estimates a causal effect.

Define Y_t^0 as the potential log relative price in the absence of the food scare, and Y_t^1 as the potential log relative price in the presence of the food scare. The event study approach of Carter and Smith (2007) estimates the causal effect of StarLink contamination if

$$E[Y_t|t \geq t^*] - E[Y_t|t < t^*] = E[Y_t^1 - Y_t^0|t \geq t^*].$$

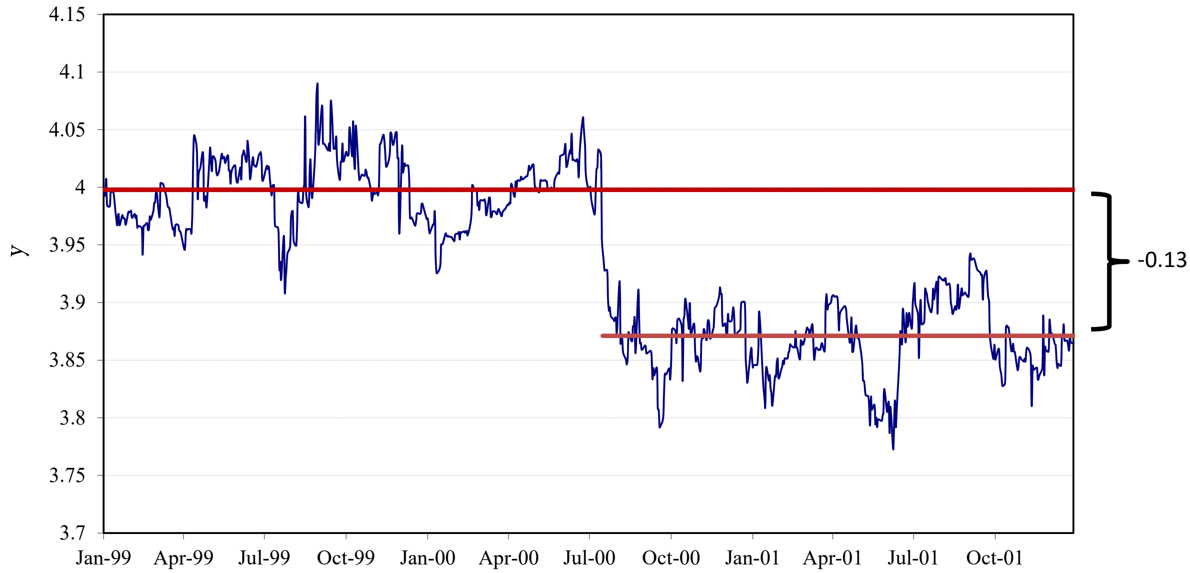
The term on the right hand side is the difference between the log relative price in the presence and absence of the food scare in the same period averaged over the periods after the food scare; it is the treatment on the treated.[3] The treatment was an unexpected event,

[1] Event studies are sometimes referred to as regression discontinuity in time.

[2] Sorghum is a substitute for corn with no GM varieties.

[3] The assumption of stationarity here is of course critical to causal inference. For the above equality to hold, we must have $E[Y_t^0|t \geq t^*] = E[Y_t^0|t < t^*]$, which is implied by stationarity. Suppose that Y_t was not stationary, e.g. $E[Y_t^d|t = \tau] = \mu_\tau(d)$ is time-varying, then to obtain a causal effect, we have to be able to observe $\mu_\tau(0)$ and $\mu_\tau(1)$ simultaneously, which is not possible. We can allow for trend stationarity however, suppose that $E[Y_t^d|t = \tau] = \mu(d) + f(\tau)'\delta$, where $f(\tau)$ is a vector of parametric functions of time. By including $f(\tau)$ in our model, we can identify $\mu(0)$ and $\mu(1)$ from pre- and post-treatment observations,

Figure A1: The Effect of a Food Scare (Carter and Smith, 2007)



Notes: Y_t is the logarithm of the price ratio of corn and sorghum. D_t is a dummy variable which equals 1 (0) for any period t after (before) the food scare occurs. The two horizontal red lines indicate the estimates of $E[Y_t|t \geq t^*]$ and $E[Y_t|t < t^*]$.

a 'shock'. It is hence plausibly independent of the potential outcomes, $D_t \perp (Y_t^0, Y_t^1)$, which is the definition of random assignment. This shows how exogenous events in time series are typically unpredictable; if they were predictable then markets may respond to the event before it occurs.

The StarLink example includes a discrete treatment, which matches nicely with the potential outcomes framework, but the treatment did not persist forever. By 2006, testing by the Environmental Protection Agency found that StarLink had been virtually eliminated from the U.S. food supply. Thus, the extent of contamination dissipated over time. The results of Carter and Smith (2007) imply that it had persistent price effects, but it would be incorrect to assume that observations in the year 2000 experienced the same magnitude of treatment as those in later years. This feature is common in time series settings, where a treatment applied to one observation is still present in later observations but at a lower intensity and its level decays to zero over time.

B.2 Multiple Discrete Treatment Events

In an example closer to that found in a typical time series setting, Angrist, Jorda, and Kuersteiner (2018) use the potential outcomes framework in a time-series setting with multiple discrete treatments. They estimate the effect of discrete changes in the Federal Funds Rate on macroeconomic outcomes. They employ propensity score methods to account for

respectively.

the non-random selection into treatment, which is necessary because the Federal Reserve changes interest rates in response to macroeconomic conditions.

Angrist, Jorda, and Kuersteiner (2018) define the treatment variable D_t as a vector of policy variables that can take values $d_0, \ldots, d_J$. They observe multiple realizations of each treatment value. By averaging over these realizations, they can estimate the treatment effect at various horizons. Define $Y_{t,h}(d)$ as the potential outcome in period $t+h$ if policy d is implemented at time t, and let z_t denote the vector of past data on the treatments, the outcome variables, and any covariates.

We can write the average policy effect of a change from d_0 to d_j conditional on z_t as

$$E[Y_{t,h}(d_j) - Y_{t,h}(d_0)|z_t] = E[Y_{t,h}|D_t = d_j, z_t] - E[Y_{t,h}|D_t = d_0, z_t].$$

This expression assumes that the potential outcomes are not confounded with the treatment assignment, specifically $Y_{t,h}(d) \perp D_t|z_t$ for all $h \geq 0$ and for all d. Angrist, Jorda, and Kuersteiner (2018) use propensity score methods to obtain the unconditional average policy effect

$$E[Y_{t,h}|D_t = d_j] - E[Y_{t,h}|D_t = d_0] = E\left[Y_{t,h}\left(\frac{1\{D_t = d_j\}}{P(D_t = d_j|z_t)} - \frac{1\{D_t = d_0\}}{P(D_t = d_0|z_t)}\right)\right]$$

The inverse probability weighting in the above equation has an important interpretation in the context of time series. When $P(D_t = d_j|z_t)$ is smaller, the occurrence of d_j is less predictable. Hence, it is more plausibly exogenous and is given a higher weight relative to observations with larger $P(D_t = d_j|z_t)$. Thus, as in the StarLink example, we observe a connection between unpredictability and exogeneity.

B.3 The General Case

In most time series applications, the variables, including the 'treatment variable', are not discrete. Non-discreteness does not create problems for causal inference as long as sufficient assumptions can be imposed. If a non-discrete treatment variable is conditionally independent of the potential outcomes and the linear model is correctly specified, then the average treatment effect can be consistently estimated by ordinary least squares. If the treatment variable is endogenous but a valid instrument exists, then an average treatment effect may be consistently estimated in a linear model by two stage least squares.[4]

Serial correlation, on the other hand, complicates causal inference because it implies that treatments and responses persist for multiple periods. If a serially correlated treatment

[4] In practice, linear models are used as approximations, but to make our discussion of causal effects in linear models precise, we emphasize the role of correct specification once we have continuous treatment variables.

variable jumps above its mean one period and remains above the mean for several periods, then we expect economic agents to respond as though they received a single treatment that lasted multiple periods rather than a sequence of independent treatments. Put differently, we expect them to respond to the *treatment path*. In addition to the treatment potentially lasting for multiple periods, the responses to treatment may also play out over multiple periods. For example, in response to a gasoline price increase (treatment), consumers may purchase a more fuel efficient vehicle if they expect prices to remain high for a long period, but they will not buy a new car if they expect the price increase to be shortlived.[5] Thus, the response of gasoline demand to price varies depending on the persistence of the price change. Moreover, for a price change of a given duration, the consumer responses will vary over time. Some consumers may respond to a persistent price change by buying a smaller car immediately; others will wait and buy a smaller car later. The SVAR provides a way to extract average treatment paths and dynamic responses from a set of variables.

C Impulse Response Functions as Causal Parameters

In a least squares regression, we only consider the slope coefficients as causal estimates when the regressors are exogenous and the linear model is correctly specified. Hence, a question about causality is a question about correct specification and exogeneity. To view the IRFs given in the static triangular system in (9) as causal parameters, we will assume that the triangular structure is correctly specified.

In our example, yield deviations are not determined by any other variable in the system, so $w_t = v_{wt}$. As a result, the first equation in (9) is redundant from a causal perspective.[6] Considering the price equation, if we assume that $E[v_{pt}|v_{wt}] = 0$, i.e. yield shocks are exogenous in the price equation, the resulting conditional expectation for the second equation is given by

$$E[p_t|v_{wt}] = E[\beta_{21}v_{wt} + v_{pt}|v_{wt}] = \beta_{21}v_{wt}.$$

In this case, β_{21}, the impulse response of p_t to v_{wt}, is the marginal effect of a yield shock on price $\partial E[p_t|v_{wt}]/\partial v_{wt}$. Intuitively, since yield shocks do not affect other price shocks, the change in price that coincides with a yield shock cannot be attributed – even partially – to other shocks that affect price.

[5] Bojinov and Shephard (2017) propose a model-free approach to identification, estimation and inference on causal effects of treatment paths in time series. Inspired by a large experiment by a quantitative hedge fund, they show how to extend the potential outcomes framework to define treatment paths and potential outcomes in order to achieve a completely model-free approach to causal inference solely relying on random assignment of treatment paths. Their approach is specific to the case of a large number of randomly assigned treatment paths.

[6] This is not the case when the model includes lags as in (7).

Similarly, for the quantity equation in (9), assuming $E[v_{qt}|v_{wt}, v_{pt}] = 0$, i.e. all price shocks are exogenous in the quantity equation, implies

$$E[q_t|v_{wt}, v_{pt}] = \underbrace{(\beta_{31} + \beta_{32}\beta_{21})}_{\partial E[q_t|v_{wt}, v_{pt}]/\partial v_{wt}} v_{wt} + \underbrace{\beta_{32}}_{\partial E[q_t|v_{wt}, v_{pt}]/\partial v_{pt}} v_{pt}.$$

It follows that lower off-diagonal elements of the coefficient matrix in (9) are causal effects.

An important byproduct of the mutual mean independence of the elements of v_t is

$$E[Y_t|v_{wt}, v_{pt}, v_{qt}] = E[Y_t|v_{wt}] + E[Y_t|v_{pt}] + E[Y_t|v_{qt}],$$

which implies that the marginal effect of conditional and unconditional expectations are equal. For instance,

$$\frac{\partial E[q_t|v_{wt}, v_{pt}]}{\partial v_{wt}} = \frac{\partial\{(\beta_{31} + \beta_{32}\beta_{21})v_{wt} + \beta_{32}v_{pt}\}}{\partial v_{wt}} = \beta_{31} + \beta_{32}\beta_{21},$$

$$\frac{\partial E[q_t|v_{wt}]}{\partial v_{wt}} = \frac{\partial\{(\beta_{31} + \beta_{32}\beta_{21})v_{wt} + \beta_{32}\overbrace{E[v_{pt}|v_{wt}]}^{=0}\}}{\partial v_{wt}} = \beta_{31} + \beta_{32}\beta_{21}.$$

Furthermore, mutual mean independence allows the SVAR to identify the impact of multiple contemporaneous changes, e.g.

$$\begin{aligned}
&E[p_t|v_{wt} = \bar{v}_w, v_{pt} = \bar{v}_p] - E[p_t|v_{wt} = 0, v_{pt} = 0] \\
=&E[p_t|v_{wt} = \bar{v}_w] - E[p_t|v_{wt} = 0] + (E[p_t|v_{pt} = \bar{v}_p] - E[p_t|v_{pt} = 0]) \\
=&\beta_{21}\bar{v}_w + \bar{v}_p.
\end{aligned}$$

This is an important feature of SVARs in some applications, where shocks to several variables in the system may occur at the same time, and a researcher aims to disentangle the effects of the different shocks. In such cases, it is not sufficient to identify the effect of a change in a single variable, but also the effect of multiple contemporaneous shocks.

Expressing causal effects as responses to shocks can seem abstract. To make them more tangible, we place economic labels on the shocks, which is a narrative component of SVAR analysis akin to the narrative about instrument validity that typically accompanies an IV identification strategy. We label v_{wt} as a weather shock, and we allow it to affect price and quantity. We label v_{pt} as non-weather supply shocks and v_{qt} as demand shocks. We assume that price does not respond to demand shocks, i.e., that supply is perfectly elastic. This assumption is imposed by the zero element in the second row and third column of the coefficient matrix in (9). We assume that observed weather does not respond to non-weather supply shocks or to demand shocks. The assumption of perfectly elastic supply is clearly false, and we relax it in our complete SVAR analysis.

By observing how price and quantity respond to weather shocks, we deduce how demand responds to a particular supply shock (weather). In particular, the elasticity of the demand response to weather is

$$\frac{\partial E[q_t|v_{wt}]/\partial v_{wt}}{\partial E[p_t|v_{wt}]/\partial v_{wt}} = \frac{\beta_{31} + \beta_{32}\beta_{21}}{\beta_{21}},$$

which is identified if $\beta_{21} \neq 0$. This ratio differs from the elasticity of the demand response to non-weather supply shocks, which is

$$\frac{\partial E[q_t|v_{pt}]/\partial v_{pt}}{\partial E[p_t|v_{pt}]/\partial v_{pt}} = \beta_{32}.$$

Hence, because there are two supply shocks in this model, there are two demand elasticities produced by the model. Next, we show how this analysis compares to the IV model in RS2013.

D Proof of Separable IRFs in Triangular Systems

The reduced-form VAR is

$$Y_t = \Pi_1 Y_{t-1} + \Pi_2 Y_{t-2} + \cdots + \Pi_\ell Y_{t-\ell} + g(t) + \varepsilon_t.$$

The structural shocks are $v_t = A_0\varepsilon_t$, where $E[v_t v_t'] = \Sigma$, where Σ is a diagonal matrix. The variance of the reduced-form errors is $E[\varepsilon_t\varepsilon_t'] = \Omega = A_0^{-1}\Sigma A_0'^{-1}$. Invert the reduced-form VAR to obtain the vector MA(∞) representation:

$$Y_t = m(t) + \Psi(L)v_t,$$

where $m(t) = (I - \Pi_1 L - ... - \Pi_\ell L^\ell)^{-1}g(t)$ and the MA lag polynomial is

$$\begin{aligned}\Psi(L) &= (I - \Pi_1 L - ... - \Pi_\ell L^\ell)^{-1}A_0^{-1} \\ &= (I + \Phi_1 L + \Phi_2 L^2 + ...)A_0^{-1} \\ &= \Psi_0 + \Psi_1 L + \Psi_2 L^2 + ...\end{aligned}$$

The coefficients $\Psi_j = \Phi_j A_0^{-1}$ are the impulse responses; the i^{th} column of Ψ_j equals the effect of shock i on each of the variables j periods in the future. Each matrix Φ_j is a function of $\Pi_1, ..., \Pi_\ell$. Thus, the first m_1 columns of Ψ_j depend on the first m_1 columns of A_0^{-1} and not on the remaining m_2 columns.

Write A_0^{-1} and Σ in block form as

$$A_0^{-1} = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \qquad \texttt{and} \qquad \Sigma = \begin{bmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} \end{bmatrix}$$

where B_{11} and B_{21} have m_1 columns. The impulse responses to the first m_1 shocks depend B_{11} and B_{21} and are independent of B_{22}. We need to show that B_{11} and B_{21} are identified independently of B_{22}.

Assume $B_{12} = 0$ and B_{11} is a lower-triangular matrix with ones along the diagonal. This means that the first m_1 shocks have a triangular structure and are exogenous to the remaining m_2 shocks.

The variance of the reduced form errors is identified by the data. It is

$$\begin{aligned} \Omega = \begin{bmatrix} \Omega_{11} & \Omega_{21}' \\ \Omega_{21} & \Omega_{22} \end{bmatrix} &= \begin{bmatrix} B_{11} & 0 \\ B_{21} & B_{22} \end{bmatrix} \begin{bmatrix} \Sigma_{11} & 0 \\ 0 & \Sigma_{22} \end{bmatrix} \begin{bmatrix} B_{11}' & B_{21}' \\ 0 & B_{22}' \end{bmatrix} \\ &= \begin{bmatrix} B_{11}\Sigma_{11}B_{11}' & B_{11}\Sigma_{11}B_{21}' \\ B_{21}\Sigma_{11}B_{11}' & B_{21}\Sigma_{11}B_{21}' + B_{22}'\Sigma_{22}B_{22}' \end{bmatrix} \end{aligned}$$

The $m_1 \times m_1$ matrix $B_{11}\Sigma_{11}B_{11}'$ is symmetric and has $m_1(m_1+1)/2$ elements. Because B_{11} is lower triangular with ones along the diagonal, it has $m_1(m_1-1)/2$ free elements. The diagonal matrix Σ_{11} has m_1 free elements. Thus, we can identify all the elements of B_{11} and Σ_{11} from Ω_{11}. Now, consider the $m_2 \times m_1$ matrix $B_{21}\Sigma_{11}B_{11}'$. There are $m_2 \times m_1$ free elements in B_{21}. Because we identify B_{11} and Σ_{11} from Ω_{11}, we can identify B_{21} using $B_{21} = \Omega_{21}B_{11}'^{-1}\Sigma_{11}^{-1}$.

Thus, we can identify impulse responses to the first m_1 shocks without specifying how the remaining m_2 shocks relate causally to each other, i.e., without specifying B_{22}.

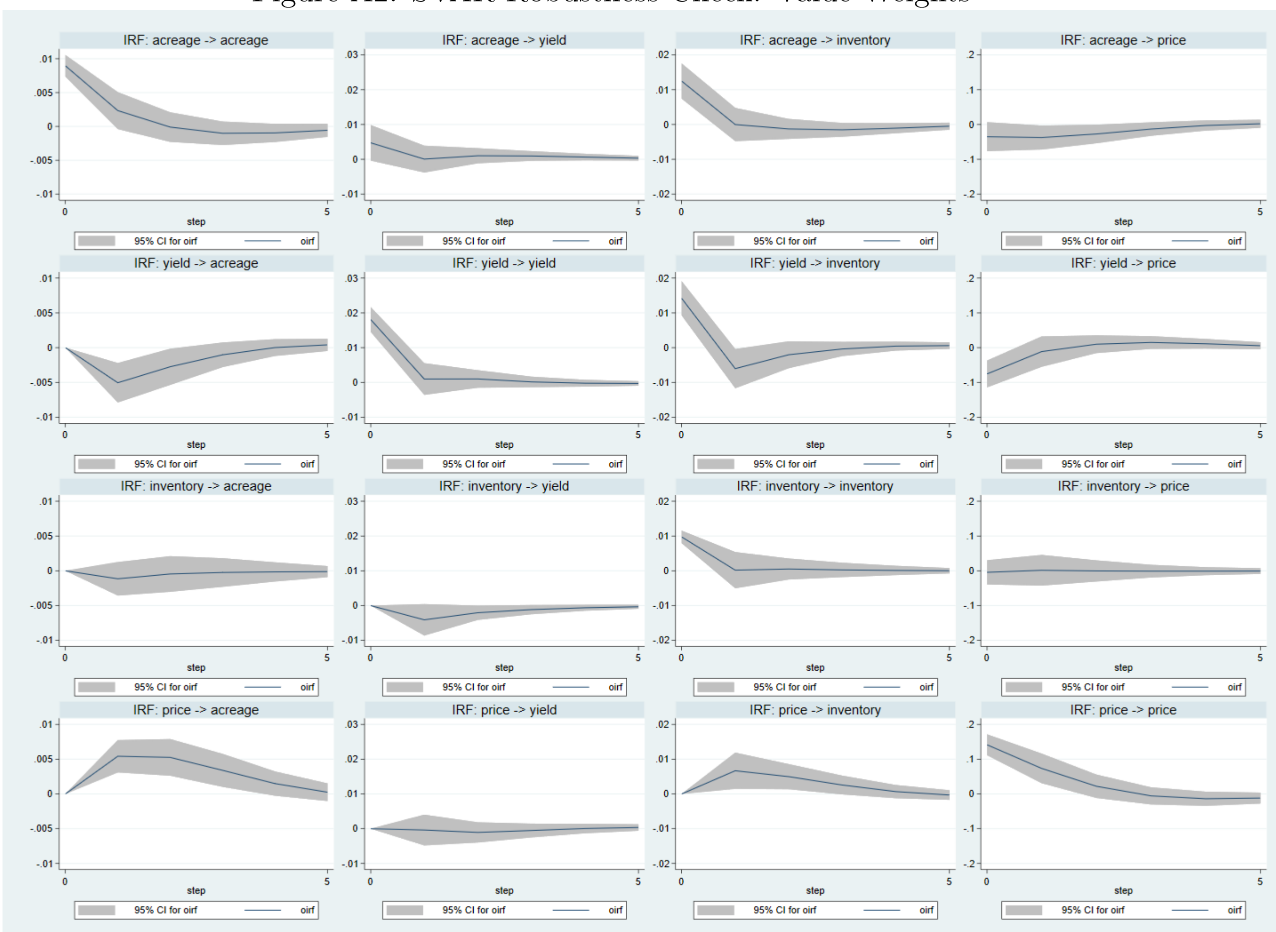
E Additional Robustness Checks

The baseline SVAR results rely on several specification choices in the baseline model in in the paper. We discuss the robustness of the results to deviations from the triangular SVAR assumption in the paper. This section presents robustness checks to additional specification choices, specifically the number of lags in the model and the type of time trend.

E.1 Order of the SVAR

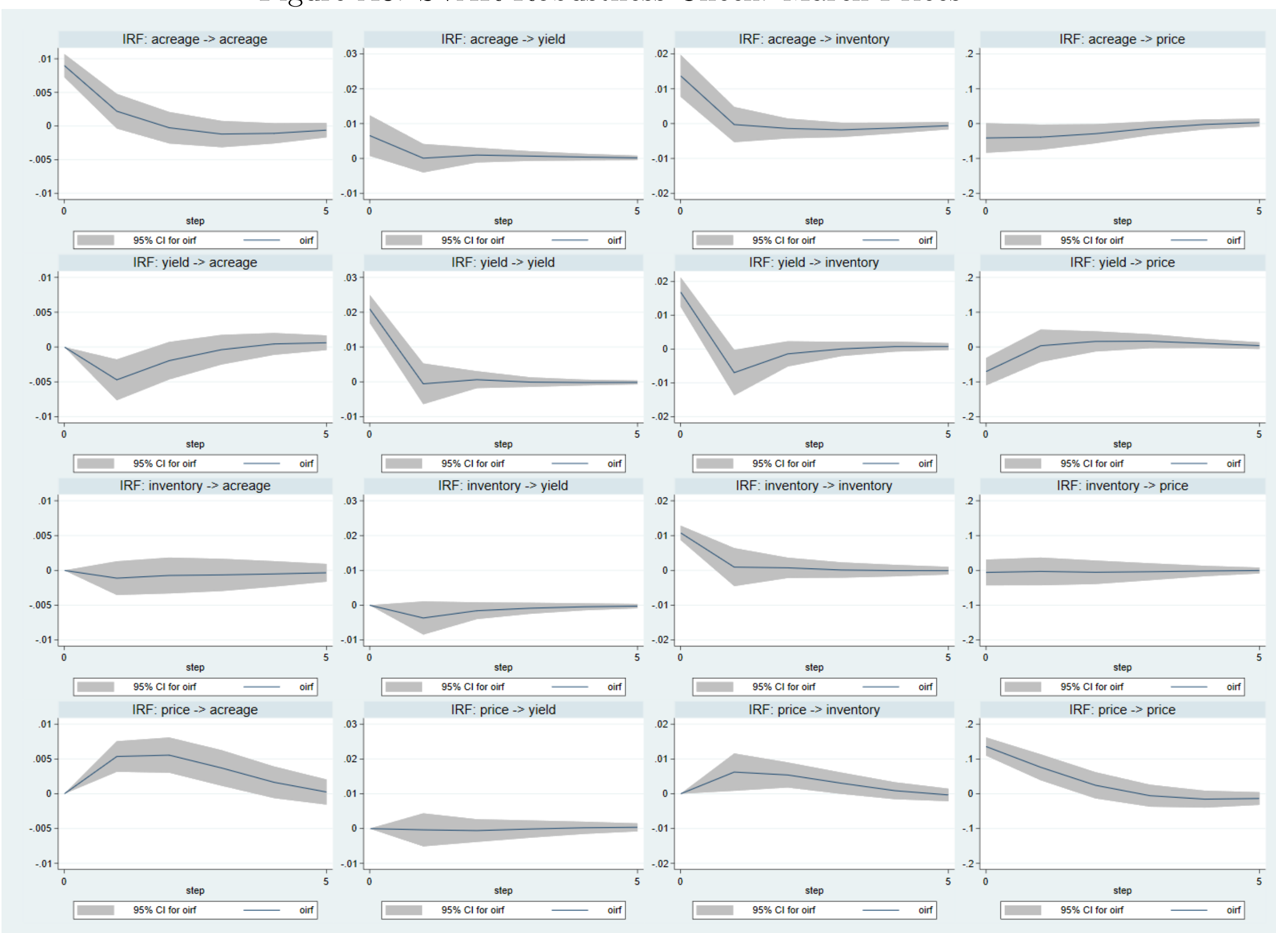
The purpose of including lags of all variables in the system in an SVAR is to decompose the variables into a series of uncorrelated shocks. However, the order of the lag is a model

Figure A2: SVAR Robustness Check: Value Weights



Notes: The above figure presents the impulse response functions over 5 years for the SVAR given in (18) using cubic spline trends but using value weights rather than calorie weights. The exact values of the impulse response functions are given in Tables A7-A8. In the first row, v_{at} is increased by its standard deviation and the response of all variables is presented. Similarly, in the second, third and fourth rows, v_{wt}, v_{it}, and v_{dt} are increased by their standard deviations, respectively. The plots in each column are presented on the same scale because they show the response of the same variable to different shocks. The impulse response functions (sirf) are plotted in solid lines and their 95% bootstrap confidence intervals are shaded in gray (1000 bootstrap replications).

Figure A3: SVAR Robustness Check: March Prices



Notes: The above figure presents the impulse response functions over 5 years for the SVAR given in (18) using cubic spline trends but using prices measured in March rather than the prior November/December. The exact values of the impulse response functions are given in Tables A7-A8. In the first row, v_{at} is increased by its standard deviation and the response of all variables is presented. Similarly, in the second, third and fourth rows, v_{wt}, v_{it}, and v_{dt} are increased by their standard deviations, respectively. The plots in each column are presented on the same scale because they show the response of the same variable to different shocks. The impulse response functions (sirf) are plotted in solid lines and their 95% bootstrap confidence intervals are shaded in gray (1000 bootstrap replications).

selection choice typically made by minimizing the Akaike or Schwarz information criteria (e.g., Hamilton (1994)). In our application, these criteria both choose a single lag. Nonetheless, we investigate robustness to the number of lags. Specifically, we consider second- and third-order SVARs.

Panels A and B of Figure A4 present the IRF graphs for the models with two and three lags of all variables, respectively.[7] Even though the resulting IRFs are more flexible, as we expect due to the additional lags, the results are qualitatively very similar to the SVAR(1) results. For an acreage shock, the signs of the IRFs and their statistical significance are unchanged for both the SVAR(2) and SVAR(3). The IRFs due to a yield shock for the SVAR(2) and SVAR(3) confirm that the nature of the yield shock is transitory as in the SVAR(1). However, some of the IRFs of other variables suggest a slightly longer horizon for the response of other variables to this shock. For instance, the two-step-ahead acreage and inventory responses to a yield shock are negative and statistically significant in the SVAR(2) and SVAR(3), whereas they are negative but statistically insignificant in the baseline SVAR(1) model. For the inventory demand shock, even though the IRFs have different shapes in the SVAR(2) and SVAR(3), they are statistically very similar to the SVAR(1) results. Finally, for the consumption-demand shock, the only key difference in the IRFs with different orders of the SVAR is that the one- and two-step ahead responses of inventory to a consumption-demand shock is no longer statistically significant for SVAR(2) and SVAR(3), even though the signs are the same.

Using the estimated IRFs provided in Table A4, we can compute the implied demand and supply elasticities from the SVAR(2) and SVAR(3). The implied demand elasticities identified by a yield shock are

$$\begin{aligned}\text{SVAR(2)}:\ & -(0.0206 - 0.0173)/0.0829 = -0.040\\ \text{SVAR(3)}:\ & -(0.0202 - 0.017)/0.0804 = -0.040\end{aligned}$$

which are somewhat smaller in magnitude than the corresponding SVAR(1) estimate of -0.051. The supply elasticity estimates implied by the yield shock are

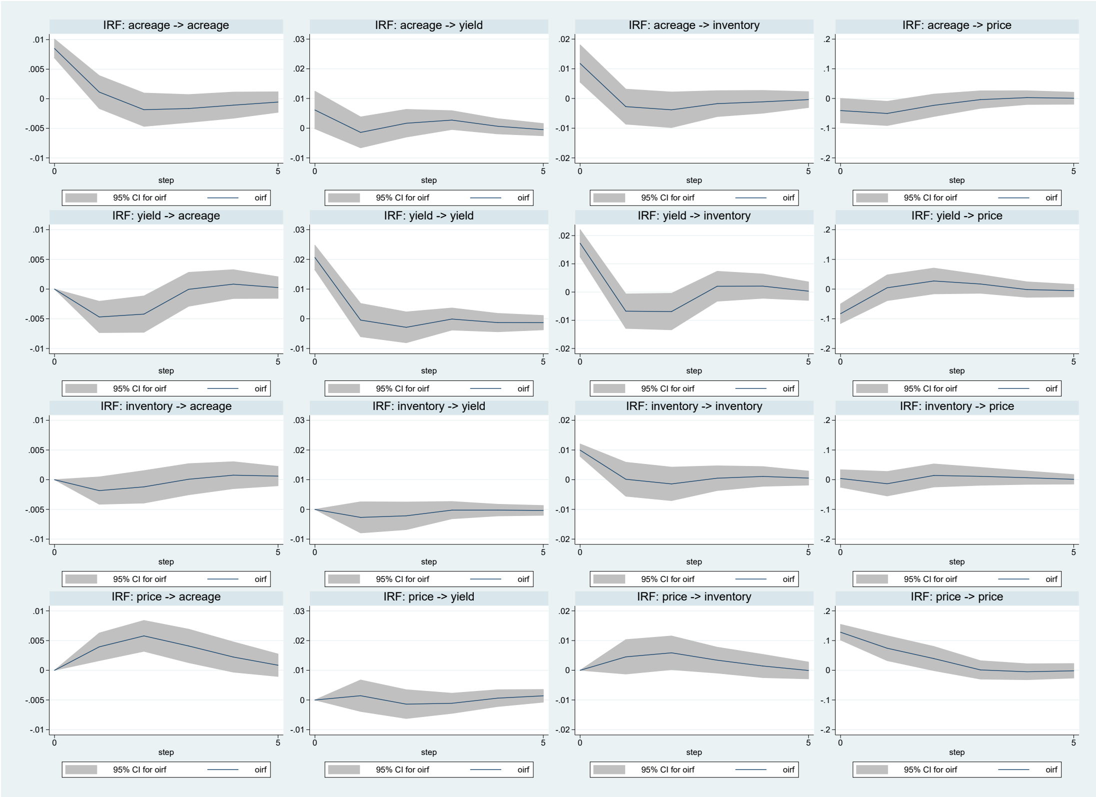
$$\begin{aligned}\text{SVAR(2)}:\ & -(-0.0047 - 0.0004)/0.0829 = 0.067\\ \text{SVAR(3)}:\ & -(-0.0051 - 0.0011)/0.0804 = 0.077\end{aligned}$$

which are close to the corresponding SVAR(1) estimate of 0.067. Similarly, the demand elasticity estimates identified by the acreage shock are -0.069 and -0.075 for the SVAR(2) and SVAR(3), compared to -0.051 in the SVAR(1). The implied supply elasticity due to a consumption-demand shock is 0.041 and 0.047 for the SVAR(2) and SVAR(3), which are slightly larger than the SVAR(1) estimate of 0.038.

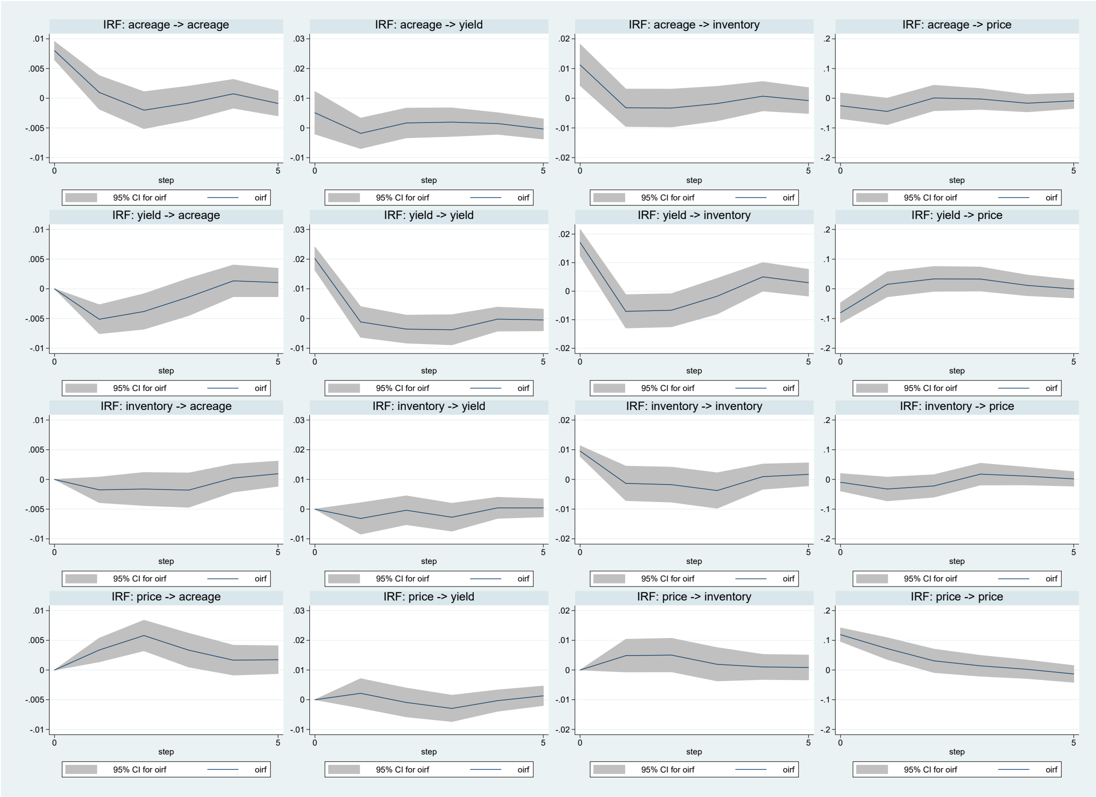
[7] We also present the estimated IRFs in response to an S.D. and unit change in Tables A4-A5.

Figure A4: SVAR Robustness Check: Order of Structural VAR

Panel A. Second-Order Structural VAR



Panel B. Third-Order Structural VAR



E.2 Alternative Trend Specifications

We have assumed throughout that the variables in the SVAR are trend stationary, which means that the series are stationary after de-trending. If we fail to control for deterministic trends, then these trends will dominate any statistical analysis of the data. Consider the acreage and yield series in Panels A.1 and A.2. of Figure 4 in the paper. Regressing acreage on yield produces a positive and apparently significant relationship merely because both series increased over time. Following RS2013, we use cubic spline trends in our baseline specification. The more standard choice in time series models however is to use linear trends rather than cubic splines.

Panel A of Figure A5 presents the time series plots of all the variables in our SVAR model after linear de-trending. This panel shows that with the exception of inventory, the de-trended variables mean-revert much less frequently than when we use the flexible trend function. As a result, the diagonal plots in Panel B of Figure A5 show that the yield and consumption-demand shocks in the SVAR with linear trends tend to have a longer duration than their counterparts in the baseline model, whereas acreage and inventory demand shocks are relatively transitory as in the baseline model.[8]

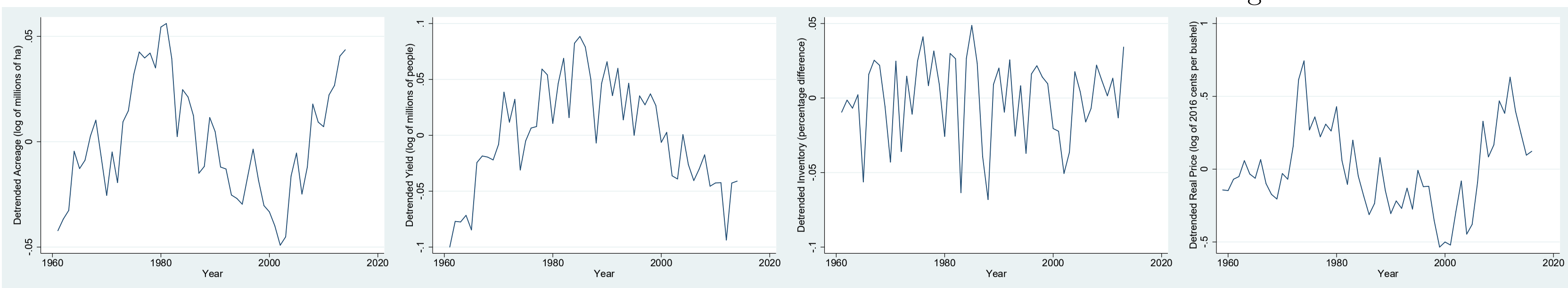
This difference in the nature of the yield and consumption-demand shocks implies different treatment paths, and hence their IRFs estimate different causal parameters. For acreage and inventory demand shocks, however, the IRFs should yield similar results to the baseline model. This is exactly what we find for the IRFs of acreage shocks in the first row. For inventory demand shocks, we similarly find that the IRFs of acreage and price due to that shock are similar to the baseline model. However, an inventory demand shock in the SVAR with linear trends produces a more persistent negative yield response in the future than in the baseline model. This difference stems from the fact that yield deviations from a linear trend are more persistent than yield deviations from a more flexible trend. It is difficult to construct an economic story under which inventory demand shocks would have very persistent negative yield effects without affecting acreage, which suggests that this result stems from insufficient de-trending of the yield series. The IRFs of the yield shock and the consumption-demand shock in Figure A5 are similar to, but more persistent than, those in the baseline model.

We next compute the implied supply and demand elasticities using the formulas in (19)–(22). The demand elasticity implied by the IRFs of an acreage shock in the model with linear trends is -0.084, which is larger than the baseline estimate of -0.053, whereas the demand elasticity implied by the IRFs of a yield shock, -0.046, is slightly smaller than the baseline model of -0.051. The supply elasticity implied by the yield shock is 0.0027 in the linear trend model, compared to 0.067 in the baseline. The supply elasticity implied by the

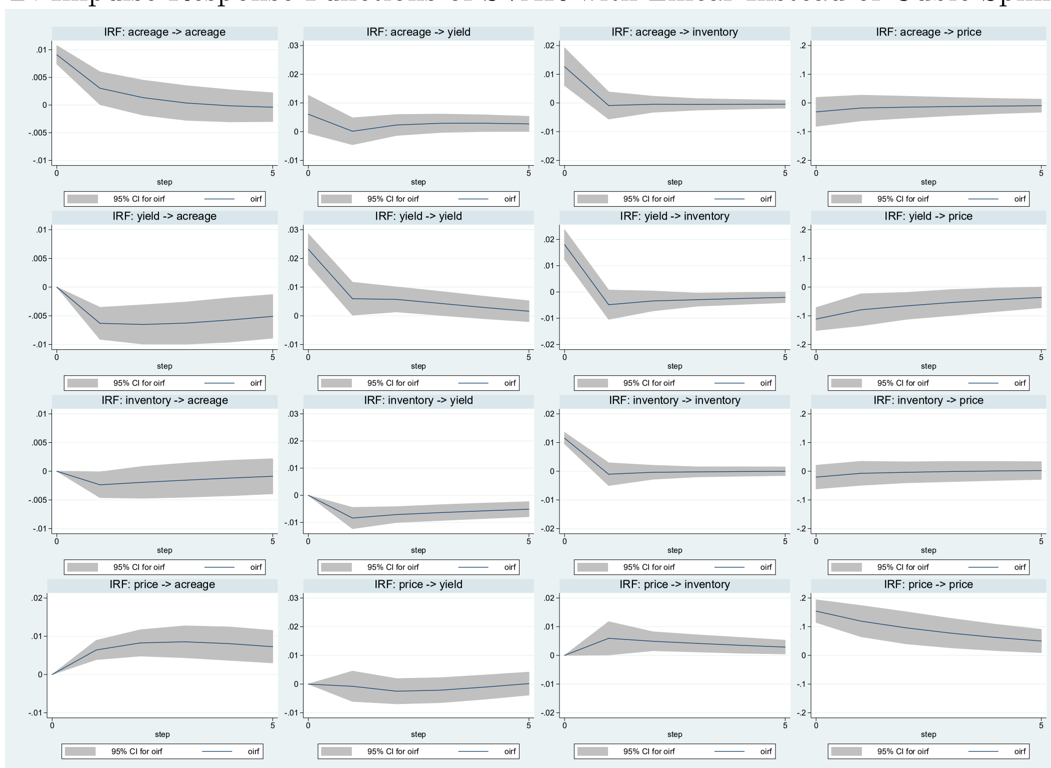
[8] For the exact estimated IRFs to an S.D. and unit change, see Table A6.

Figure A5: SVAR Robustness Check: Linear Time Trends

Panel A. Time Series Plots of all SVAR Variables after Linear Detrending



Panel B. Impulse Response Functions of SVAR with Linear Instead of Cubic Spline Trend



consumption-demand shock, 0.036, is very similar to the baseline model. Given the different treatment paths implied by the shocks, it is not surprising that the two models yield different elasticities.

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Table A1: IV Estimates of Supply Elasticities RS2013

Dependent Variable:	Quantity Supplied	
	(1)	(2)
Futures Price ($p_{t\|t-1}$)	0.104	
	(4.45)	
Lagged Spot Price (p_{t-1})		0.0755
		(3.78)
Yield Shock (w_t)	1.250	1.157
	(10.68)	(10.51)
N	52	52

Notes: (1) is estimated using 2SLS with w_{t-1} as the instrument for the futures (supply) price, $p_{t|t-1}$. (2) is estimated using 2SLS with w_{t-1} as the instrument for the lagged spot (demand) price, p_{t-1}. The t statistics in parentheses are computed using Newey-West standard errors to correct for heteroskedasticity and first-order autocorrelation. Sample: 1962-2013.

Table A2: IRF Tables for SVAR Robustness Check: Value Weights

		S.D. Change				*Unit Change*			
Impulse	h	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}
v_{at}	0	0.0090	0.0047	0.0125	-0.0349	1.0000	0.5286	1.3928	-3.8966
	1	0.0023	0.0001	0.0000	-0.0374	0.2610	0.0062	0.0003	-4.1760
	2	-0.0001	0.0010	-0.0013	-0.0272	-0.0110	0.1143	-0.1413	-3.0352
	3	-0.0010	0.0010	-0.0015	-0.0130	-0.1129	0.1063	-0.1704	-1.4515
	4	-0.0010	0.0006	-0.0011	-0.0028	-0.1072	0.0720	-0.1176	-0.3091
	5	-0.0006	0.0003	-0.0005	0.0022	-0.0642	0.0359	-0.0547	0.2426
v_{wt}	0	0.0000	0.0181	0.0142	-0.0757	0.0000	1.0000	0.7834	-4.1852
	1	-0.0050	0.0010	-0.0060	-0.0113	-0.2790	0.0542	-0.3338	-0.6242
	2	-0.0027	0.0010	-0.0020	0.0099	-0.1520	0.0551	-0.1125	0.5488
	3	-0.0010	0.0001	-0.0004	0.0148	-0.0567	0.0079	-0.0208	0.8190
	4	0.0000	-0.0002	0.0004	0.0112	0.0008	-0.0124	0.0242	0.6169
	5	0.0004	-0.0003	0.0006	0.0056	0.0221	-0.0162	0.0323	0.3117
v_{it}	0	0.0000	0.0000	0.0097	-0.0044	0.0000	0.0000	1.0000	-0.4549
	1	-0.0012	-0.0041	0.0002	0.0015	-0.1182	-0.4211	0.0187	0.1562
	2	-0.0005	-0.0021	0.0005	-0.0004	-0.0467	-0.2113	0.0532	-0.0373
	3	-0.0002	-0.0012	0.0003	-0.0010	-0.0251	-0.1193	0.0257	-0.1038
	4	-0.0002	-0.0006	0.0001	-0.0010	-0.0161	-0.0649	0.0107	-0.1076
	5	-0.0001	-0.0003	0.0000	-0.0008	-0.0119	-0.0347	0.0028	-0.0778
v_{dt}	0	0.0000	0.0000	0.0000	0.1414	0.0000	0.0000	0.0000	1.0000
	1	0.0054	-0.0004	0.0067	0.0734	0.0383	-0.0027	0.0471	0.5189
	2	0.0053	-0.0011	0.0050	0.0220	0.0371	-0.0075	0.0351	0.1558
	3	0.0034	-0.0005	0.0026	-0.0056	0.0240	-0.0037	0.0181	-0.0394
	4	0.0015	0.0000	0.0007	-0.0139	0.0105	0.0003	0.0047	-0.0984
	5	0.0002	0.0004	-0.0003	-0.0119	0.0018	0.0025	-0.0022	-0.0841

Notes: The above table presents the impulse responses to a s.d. and unit change in each shock on all variables in the system h-steps ahead for the baseline triangular SVAR using value weights instead of calorie weights. Sample: 1962-2013.

Table A3: IRF Tables for SVAR Robustness Check: March Prices

		S.D. Change				*Unit Change*			
Impulse	h	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}
v_{at}	0	0.0090	0.0066	0.0137	-0.0412	1.0000	0.7310	1.5282	-4.5853
	1	0.0022	0.0001	-0.0003	-0.0388	0.2456	0.0086	-0.0283	-4.3192
	2	-0.0003	0.0010	-0.0014	-0.0289	-0.0279	0.1082	-0.1529	-3.2131
	3	-0.0012	0.0007	-0.0018	-0.0134	-0.1329	0.0772	-0.1996	-1.4930
	4	-0.0011	0.0004	-0.0013	-0.0022	-0.1204	0.0450	-0.1392	-0.2483
	5	-0.0006	0.0002	-0.0006	0.0031	-0.0682	0.0176	-0.0640	0.3442
v_{wt}	0	0.0000	0.0210	0.0168	-0.0708	0.0000	1.0000	0.8021	-3.3782
	1	-0.0047	-0.0006	-0.0070	0.0037	-0.2250	-0.0270	-0.3336	0.1750
	2	-0.0020	0.0006	-0.0014	0.0162	-0.0935	0.0297	-0.0688	0.7724
	3	-0.0004	-0.0001	0.0000	0.0167	-0.0180	-0.0037	0.0004	0.7989
	4	0.0004	-0.0002	0.0007	0.0105	0.0212	-0.0094	0.0339	0.4995
	5	0.0006	-0.0002	0.0007	0.0040	0.0293	-0.0079	0.0336	0.1919
v_{it}	0	0.0000	0.0000	0.0108	-0.0059	0.0000	0.0000	1.0000	-0.5499
	1	-0.0011	-0.0037	0.0009	-0.0029	-0.1034	-0.3413	0.0878	-0.2711
	2	-0.0007	-0.0016	0.0007	-0.0054	-0.0678	-0.1466	0.0682	-0.5034
	3	-0.0006	-0.0009	0.0001	-0.0038	-0.0603	-0.0804	0.0101	-0.3547
	4	-0.0005	-0.0005	-0.0001	-0.0018	-0.0470	-0.0425	-0.0059	-0.1637
	5	-0.0003	-0.0003	-0.0001	-0.0003	-0.0317	-0.0240	-0.0064	-0.0236
v_{dt}	0	0.0000	0.0000	0.0000	0.1358	0.0000	0.0000	0.0000	1.0000
	1	0.0054	-0.0004	0.0062	0.0761	0.0394	-0.0027	0.0459	0.5602
	2	0.0056	-0.0006	0.0054	0.0245	0.0409	-0.0042	0.0397	0.1802
	3	0.0037	-0.0001	0.0030	-0.0056	0.0273	-0.0010	0.0223	-0.0410
	4	0.0017	0.0002	0.0009	-0.0155	0.0122	0.0016	0.0065	-0.1141
	5	0.0003	0.0004	-0.0003	-0.0136	0.0019	0.0027	-0.0024	-0.1004

Notes: The above table presents the impulse responses to a s.d. and unit change in each shock on all variables in the system h-steps ahead for the baseline triangular SVAR using March prices instead of November/December prices. Sample: 1962-2013.

Table A4: IRF Tables for Robustness Check: Different Orders of the VAR (*S.D. Change*)

		SVAR(1) (Baseline)				SVAR(2)				SVAR(3)			
Impulse	h	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}
v_{at}	0	0.0090	0.0061	0.0131	-0.0380	0.0085	0.0061	0.0118	-0.0407	0.0080	0.0051	0.0112	-0.0253
	1	0.0024	0.0001	-0.0003	-0.0395	0.0011	-0.0014	-0.0027	-0.0503	0.0010	-0.0018	-0.0032	-0.0444
	2	-0.0002	0.0009	-0.0016	-0.0288	-0.0019	0.0017	-0.0038	-0.0229	-0.0020	0.0017	-0.0033	0.0009
	3	-0.0011	0.0007	-0.0019	-0.0127	-0.0016	0.0027	-0.0017	-0.0037	-0.0008	0.0020	-0.0018	-0.0025
	4	-0.0010	0.0004	-0.0012	-0.0014	-0.0011	0.0007	-0.0011	0.0030	0.0007	0.0015	0.0007	-0.0167
	5	-0.0005	0.0002	-0.0005	0.0037	-0.0006	-0.0005	-0.0004	0.0009	-0.0009	-0.0004	-0.0008	-0.0088
v_{wt}	0	0	0.0211	0.0170	-0.0803	0	0.0206	0.0173	-0.0829	0	0.0202	0.0170	-0.0804
	1	-0.0049	-0.0006	-0.0072	-0.0026	-0.0047	-0.0004	-0.0068	0.0045	-0.0051	-0.0011	-0.0071	0.0151
	2	-0.0023	0.0007	-0.0017	0.0152	-0.0042	-0.0029	-0.0069	0.0273	-0.0038	-0.0036	-0.0067	0.0335
	3	-0.0005	0.0000	0.0000	0.0176	0.0000	-0.0001	0.0021	0.0172	-0.0014	-0.0038	-0.0018	0.0329
	4	0.0004	-0.0002	0.0008	0.0114	0.0008	-0.0013	0.0021	-0.0016	0.0013	-0.0002	0.0050	0.0117
	5	0.0006	-0.0002	0.0008	0.0045	0.0003	-0.0013	0.0003	-0.0052	0.0011	-0.0005	0.0030	-0.0004
v_{it}	0	0	0	0.0107	-0.0056	0	0	0.0099	0.0040	0	0	0.0095	-0.0095
	1	-0.0011	-0.0037	0.0009	-0.0085	-0.0018	-0.0027	0.0001	-0.0136	-0.0018	-0.0031	-0.0013	-0.0322
	2	-0.0010	-0.0016	0.0003	-0.0108	-0.0012	-0.0022	-0.0014	0.0142	-0.0016	-0.0004	-0.0018	-0.0219
	3	-0.0010	-0.0009	-0.0003	-0.0073	0.0001	-0.0003	0.0005	0.0113	-0.0018	-0.0027	-0.0037	0.0179
	4	-0.0008	-0.0004	-0.0004	-0.0032	0.0008	-0.0002	0.0011	0.0067	0.0002	0.0004	0.0009	0.0110
	5	-0.0005	-0.0003	-0.0002	-0.0004	0.0006	-0.0004	0.0005	0.0012	0.0010	0.0004	0.0017	0.0018
v_{dt}	0	0	0	0	0.1354	0	0	0	0.1282	0	0	0	0.1190
	1	0.0052	0.0001	0.0068	0.0758	0.0039	0.0014	0.0045	0.0743	0.0034	0.0022	0.0048	0.0722
	2	0.0053	-0.0005	0.0055	0.0241	0.0058	-0.0014	0.0059	0.0395	0.0058	-0.0009	0.0050	0.0310
	3	0.0035	-0.0002	0.0029	-0.0058	0.0041	-0.0011	0.0034	0.0012	0.0033	-0.0029	0.0019	0.0142
	4	0.0015	0.0001	0.0007	-0.0152	0.0022	0.0006	0.0014	-0.0050	0.0017	-0.0003	0.0010	0.0024
	5	0.0002	0.0003	-0.0004	-0.0129	0.0009	0.0014	-0.0001	-0.0018	0.0017	0.0013	0.0009	-0.0132

Notes: The above table presents the impulse responses to a standard deviation (S.D.) change in each shock on all variables in the system h-steps ahead for the baseline (first-order) SVAR as well as second- and third-order versions of it. Sample: 1962-2013.

Table A5: IRF Tables for Robustness Check: Different Orders of the VAR (*Unit Change*)

		SVAR(1) (Baseline)				SVAR(2)				SVAR(3)			
Impulse	h	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}
v_{at}	0	1	0.6702	1.4472	-4.2043	1	0.7223	1.3862	-4.7873	1	0.6368	1.3986	-3.1612
	1	0.2648	0.0073	-0.0288	-4.3723	0.1331	-0.1656	-0.3225	-5.9187	0.1232	-0.2284	-0.3995	-5.5354
	2	-0.0179	0.0966	-0.1764	-3.1852	-0.2178	0.1969	-0.4484	-2.6992	-0.2506	0.2095	-0.4118	0.1132
	3	-0.1202	0.0755	-0.2063	-1.4092	-0.1940	0.3208	-0.2039	-0.4300	-0.1027	0.2437	-0.2240	-0.3115
	4	-0.1060	0.0477	-0.1338	-0.1535	-0.1276	0.0771	-0.1318	0.3503	0.0932	0.1854	0.0860	-2.0851
	5	-0.0551	0.0220	-0.0533	0.4050	-0.0659	-0.0579	-0.0443	0.1063	-0.1089	-0.0439	-0.0972	-1.0928
v_{wt}	0	0	1	0.8032	-3.8036	0	1	0.8387	-4.0181	0	1	0.8439	-3.9837
	1	-0.2339	-0.0261	-0.3427	-0.1212	-0.2272	-0.0208	-0.3280	0.2173	-0.2533	-0.0562	-0.3499	0.7493
	2	-0.1067	0.0317	-0.0806	0.7220	-0.2041	-0.1389	-0.3352	1.3217	-0.1888	-0.1763	-0.3306	1.6575
	3	-0.0259	0.0004	0.0004	0.8316	-0.0017	-0.0038	0.0998	0.8313	-0.0683	-0.1873	-0.0869	1.6311
	4	0.0176	-0.0079	0.0371	0.5415	0.0406	-0.0615	0.1019	-0.0790	0.0667	-0.0096	0.2492	0.5774
	5	0.0279	-0.0082	0.0365	0.2144	0.0125	-0.0630	0.0155	-0.2532	0.0528	-0.0233	0.1472	-0.0187
v_{it}	0	0	0	1	-0.5230	0	0	1	0.4011	0	0	1	-0.9988
	1	-0.1050	-0.3439	0.0818	-0.7974	-0.1845	-0.2704	0.0149	-1.3658	-0.1836	-0.3289	-0.1389	-3.3700
	2	-0.0904	-0.1519	0.0307	-1.0127	-0.1214	-0.2178	-0.1425	1.4270	-0.1689	-0.0393	-0.1841	-2.2975
	3	-0.0898	-0.0809	-0.0286	-0.6863	0.0076	-0.0252	0.0506	1.1354	-0.1886	-0.2851	-0.3911	1.8712
	4	-0.0732	-0.0419	-0.0353	-0.3040	0.0764	-0.0238	0.1104	0.6771	0.0240	0.0459	0.0984	1.1566
	5	-0.0491	-0.0236	-0.0228	-0.0409	0.0608	-0.0353	0.0546	0.1243	0.1010	0.0434	0.1792	0.1933
v_{dt}	0	0	0	0	1	0	0	0	1	0	0	0	1
	1	0.0387	0.0011	0.0505	0.5599	0.0308	0.0112	0.0353	0.5799	0.0283	0.0182	0.0407	0.6069
	2	0.0391	-0.0034	0.0407	0.1782	0.0452	-0.0109	0.0459	0.3080	0.0488	-0.0077	0.0423	0.2607
	3	0.0255	-0.0014	0.0215	-0.0425	0.0320	-0.0087	0.0266	0.0097	0.0281	-0.0245	0.0162	0.1191
	4	0.0109	0.0009	0.0053	-0.1121	0.0174	0.0048	0.0112	-0.0390	0.0139	-0.0025	0.0087	0.0202
	5	0.0013	0.0020	-0.0033	-0.0950	0.0066	0.0109	-0.0005	-0.0138	0.0146	0.0110	0.0071	-0.1108

Notes: The above table presents the impulse responses to a unit change in each shock on all variables in the system h-steps ahead for the baseline (first-order) SVAR as well as second- and third-order versions of it. Sample: 1962-2013.

Table A6: IRF Tables for Robustness Check: Linear vs. Cubic Spline Trends

		Cubic Spline Trends (Baseline)				Linear Trends			
Impulse	h	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}
					S.D. Change				
v_{at}	0	0.0090	0.0061	0.0131	-0.0380	0.0091	0.0061	0.0126	-0.0311
	1	0.0024	0.0001	-0.0003	-0.0395	0.0030	0.0001	-0.0009	-0.0175
	2	-0.0002	0.0009	-0.0016	-0.0288	0.0013	0.0023	-0.0005	-0.0147
	3	-0.0011	0.0007	-0.0019	-0.0127	0.0004	0.0029	-0.0005	-0.0125
	4	-0.0010	0.0004	-0.0012	-0.0014	-0.0001	0.0030	-0.0005	-0.0108
	5	-0.0005	0.0002	-0.0005	0.0037	-0.0004	0.0027	-0.0004	-0.0095
v_{wt}	0	0	0.0211	0.0170	-0.0803	0	0.0232	0.0181	-0.1112
	1	-0.0049	-0.0006	-0.0072	-0.0026	-0.0063	0.0060	-0.0048	-0.0790
	2	-0.0023	0.0007	-0.0017	0.0152	-0.0065	0.0057	-0.0034	-0.0654
	3	-0.0005	0.0000	0.0000	0.0176	-0.0063	0.0043	-0.0029	-0.0538
	4	0.0004	-0.0002	0.0008	0.0114	-0.0057	0.0029	-0.0025	-0.0441
	5	0.0006	-0.0002	0.0008	0.0045	-0.0051	0.0016	-0.0021	-0.0360
v_{it}	0	0	0	0.0107	-0.0056	0	0	0.0115	-0.0203
	1	-0.0011	-0.0037	0.0009	-0.0085	-0.0024	-0.0084	-0.0010	-0.0072
	2	-0.0010	-0.0016	0.0003	-0.0108	-0.0019	-0.0071	-0.0004	-0.0037
	3	-0.0010	-0.0009	-0.0003	-0.0073	-0.0015	-0.0064	-0.0002	-0.0009
	4	-0.0008	-0.0004	-0.0004	-0.0032	-0.0012	-0.0057	-0.0001	0.0010
	5	-0.0005	-0.0003	-0.0002	-0.0004	-0.0009	-0.0051	0.0000	0.0024
v_{dt}	0	0	0	0	0.1354	0	0	0	0.1542
	1	0.0052	0.0001	0.0068	0.0758	0.0064	-0.0008	0.0060	0.1193
	2	0.0053	-0.0005	0.0055	0.0241	0.0083	-0.0025	0.0049	0.0960
	3	0.0035	-0.0002	0.0029	-0.0058	0.0086	-0.0021	0.0042	0.0774
	4	0.0015	0.0001	0.0007	-0.0152	0.0081	-0.0010	0.0035	0.0624
	5	0.0002	0.0003	-0.0004	-0.0129	0.0073	0.0002	0.0029	0.0501
					Unit Change				
v_{at}	0	1	0.6702	1.4472	-4.2043	1	0.6683	1.3896	-3.4141
	1	0.2648	0.0073	-0.0288	-4.3723	0.3350	0.0157	-0.0977	-1.9272
	2	-0.0179	0.0966	-0.1764	-3.1852	0.1475	0.2554	-0.0495	-1.6112
	3	-0.1202	0.0755	-0.2063	-1.4092	0.0414	0.3212	-0.0529	-1.3714
	4	-0.1060	0.0477	-0.1338	-0.1535	-0.0141	0.3245	-0.0512	-1.1923
	5	-0.0551	0.0220	-0.0533	0.4050	-0.0422	0.2984	-0.0482	-1.0463
v_{wt}	0	0	1	0.8032	-3.8036	0	1	0.7793	-4.7992
	1	-0.2339	-0.0261	-0.3427	-0.1212	-0.2723	0.2570	-0.2091	-3.4072
	2	-0.1067	0.0317	-0.0806	0.7220	-0.2808	0.2466	-0.1475	-2.8231
	3	-0.0259	0.0004	0.0004	0.8316	-0.2704	0.1859	-0.1268	-2.3220
	4	0.0176	-0.0079	0.0371	0.5415	-0.2473	0.1243	-0.1068	-1.9041
	5	0.0279	-0.0082	0.0365	0.2144	-0.2197	0.0690	-0.0890	-1.5524
v_{it}	0	0	0	1	-0.5230	0	0	1	-1.7587
	1	-0.1050	-0.3439	0.0818	-0.7974	-0.2046	-0.7266	-0.0894	-0.6211
	2	-0.0904	-0.1519	0.0307	-1.0127	-0.1666	-0.6156	-0.0310	-0.3217
	3	-0.0898	-0.0809	-0.0286	-0.6863	-0.1341	-0.5523	-0.0188	-0.0822
	4	-0.0732	-0.0419	-0.0353	-0.3040	-0.1031	-0.4957	-0.0081	0.0905
	5	-0.0491	-0.0236	-0.0228	-0.0409	-0.0759	-0.4439	0.0001	0.2125
v_{dt}	0	0	0	0	1	0	0	0	1
	1	0.0387	0.0011	0.0505	0.5599	0.0416	-0.0049	0.0386	0.7733
	2	0.0391	-0.0034	0.0407	0.1782	0.0535	-0.0161	0.0319	0.6224
	3	0.0255	-0.0014	0.0215	-0.0425	0.0555	-0.0137	0.0271	0.5021
	4	0.0109	0.0009	0.0053	-0.1121	0.0524	-0.0068	0.0227	0.4048
	5	0.0013	0.0020	-0.0033	-0.0950	0.0472	0.0011	0.0188	0.3247

Notes: The above table presents the impulse responses to a standard deviation (S.D.) as well as unit change in each shock on all variables in the system h-steps ahead for the baseline SVAR with cubic spline trends as well as with linear trend trends. Sample: 1962-2013.

Table A7: IRF Tables for Robustness Check: Non-zero α_{34} (*S.D. Change*)

		$\alpha_{34}=0$ (Baseline)				$\alpha_{34}=0.1$				$\alpha_{34}=0.25$				$\alpha_{34}=0.5$			
	h	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}
v_{at}	0	0.0090	0.0061	0.0131	-0.0380	0.0090	0.0061	0.0131	-0.0380	0.0090	0.0061	0.0131	-0.0380	0.0090	0.0061	0.0131	-0.0380
	1	0.0024	0.0001	-0.0003	-0.0395	0.0024	0.0001	-0.0003	-0.0395	0.0024	0.0001	-0.0003	-0.0395	0.0024	0.0001	-0.0003	-0.0395
	2	-0.0002	0.0009	-0.0016	-0.0288	-0.0002	0.0009	-0.0016	-0.0288	-0.0002	0.0009	-0.0016	-0.0288	-0.0002	0.0009	-0.0016	-0.0288
	3	-0.0011	0.0007	-0.0019	-0.0127	-0.0011	0.0007	-0.0019	-0.0127	-0.0011	0.0007	-0.0019	-0.0127	-0.0011	0.0007	-0.0019	-0.0127
	4	-0.0010	0.0004	-0.0012	-0.0014	-0.0010	0.0004	-0.0012	-0.0014	-0.0010	0.0004	-0.0012	-0.0014	-0.0010	0.0004	-0.0012	-0.0014
	5	-0.0005	0.0002	-0.0005	0.0037	-0.0005	0.0002	-0.0005	0.0037	-0.0005	0.0002	-0.0005	0.0037	-0.0005	0.0002	-0.0005	0.0037
v_{wt}	0	0	0.0211	0.0170	-0.0803	0	0.0211	0.0170	-0.0803	0	0.0211	0.0170	-0.0803	0	0.0211	0.0170	-0.0803
	1	-0.0049	-0.0006	-0.0072	-0.0026	-0.0049	-0.0006	-0.0072	-0.0026	-0.0049	-0.0006	-0.0072	-0.0026	-0.0049	-0.0006	-0.0072	-0.0026
	2	-0.0023	0.0007	-0.0017	0.0152	-0.0023	0.0007	-0.0017	0.0152	-0.0023	0.0007	-0.0017	0.0152	-0.0023	0.0007	-0.0017	0.0152
	3	-0.0005	0.0000	0.0000	0.0176	-0.0005	0.0000	0.0000	0.0176	-0.0005	0.0000	0.0000	0.0176	-0.0005	0.0000	0.0000	0.0176
	4	0.0004	-0.0002	0.0008	0.0114	0.0004	-0.0002	0.0008	0.0114	0.0004	-0.0002	0.0008	0.0114	0.0004	-0.0002	0.0008	0.0114
	5	0.0006	-0.0002	0.0008	0.0045	0.0006	-0.0002	0.0008	0.0045	0.0006	-0.0002	0.0008	0.0045	0.0006	-0.0002	0.0008	0.0045
v_{it}	0	0	0	0.0107	-0.0056	0	0	0.0064	0.1051	0	0	0.0028	0.1291	0	0	0.0012	0.1338
	1	-0.0011	-0.0037	0.0009	-0.0085	0.0035	-0.0021	0.0060	0.0556	0.0048	-0.0008	0.0068	0.0709	0.0051	-0.0003	0.0069	0.0743
	2	-0.0010	-0.0016	0.0003	-0.0108	0.0037	-0.0013	0.0046	0.0128	0.0049	-0.0009	0.0054	0.0204	0.0052	-0.0006	0.0055	0.0227
	3	-0.0010	-0.0009	-0.0003	-0.0073	0.0022	-0.0007	0.0021	-0.0090	0.0031	-0.0004	0.0027	-0.0075	0.0033	-0.0003	0.0029	-0.0066
	4	-0.0008	-0.0004	-0.0004	-0.0032	0.0007	-0.0002	0.0003	-0.0141	0.0012	0.0000	0.0006	-0.0155	0.0014	0.0001	0.0007	-0.0155
	5	-0.0005	-0.0003	-0.0002	-0.0004	-0.0002	0.0001	-0.0005	-0.0106	0.0000	0.0002	-0.0005	-0.0125	0.0001	0.0002	-0.0005	-0.0128
v_{dt}	0	0	0	0	0.1354	0	0	-0.0086	0.0856	0	0	-0.0103	0.0412	0	0	-0.0106	0.0212
	1	0.0052	0.0001	0.0068	0.0758	0.0040	0.0030	0.0034	0.0522	0.0025	0.0036	0.0010	0.0283	0.0017	0.0037	-0.0001	0.0172
	2	0.0053	-0.0005	0.0055	0.0241	0.0039	0.0010	0.0030	0.0231	0.0023	0.0014	0.0011	0.0168	0.0016	0.0016	0.0003	0.0135
	3	0.0035	-0.0002	0.0029	-0.0058	0.0028	0.0006	0.0020	0.0024	0.0018	0.0008	0.0011	0.0055	0.0014	0.0008	0.0006	0.0066
	4	0.0015	0.0001	0.0007	-0.0152	0.0015	0.0004	0.0007	-0.0065	0.0011	0.0005	0.0006	-0.0009	0.0009	0.0005	0.0005	0.0015
	5	0.0002	0.0003	-0.0004	-0.0129	0.0005	0.0004	-0.0001	-0.0074	0.0006	0.0003	0.0001	-0.0030	0.0005	0.0003	0.0002	-0.0011

Notes: The above table presents the impulse responses to a standard deviation (S.D.) change in each shock on all variables in the system h-steps ahead for the baseline triangular SVAR ($\alpha_{34}=0$) as well as SVARs with $\alpha_{34}=0.1, 0.25, 0.5$. Sample: 1962-2013.

Table A8: IRF Tables for Robustness Check: Non-zero α_{34} (*Unit Change*)

		$\alpha_{34} = 0$ (Baseline)				$\alpha_{34} = 0.1$				$\alpha_{34} = 0.25$				$\alpha_{34} = 0.5$			
	h	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}	a_{t+h}	y_{t+h}	i_{t+h}	p_{t+h}
v_{at}	0	1	0.6702	1.4472	-4.2043	1	0.6702	1.4472	-4.2043	1	0.6702	1.4472	-4.2043	1	0.6702	1.4472	-4.2043
	1	0.2648	0.0073	-0.0288	-4.3723	0.2648	0.0073	-0.0288	-4.3723	0.2648	0.0073	-0.0288	-4.3723	0.2648	0.0073	-0.0288	-4.3723
	2	-0.0179	0.0966	-0.1764	-3.1852	-0.0179	0.0966	-0.1764	-3.1852	-0.0179	0.0966	-0.1764	-3.1852	-0.0179	0.0966	-0.1764	-3.1852
	3	-0.1202	0.0755	-0.2063	-1.4092	-0.1202	0.0755	-0.2063	-1.4092	-0.1202	0.0755	-0.2063	-1.4092	-0.1202	0.0755	-0.2063	-1.4092
	4	-0.1060	0.0477	-0.1338	-0.1535	-0.1060	0.0477	-0.1338	-0.1535	-0.1060	0.0477	-0.1338	-0.1535	-0.1060	0.0477	-0.1338	-0.1535
	5	-0.0551	0.0220	-0.0533	0.4050	-0.0551	0.0220	-0.0533	0.4050	-0.0551	0.0220	-0.0533	0.4050	-0.0551	0.0220	-0.0533	0.4050
v_{wt}	0	0	1	0.8032	-3.8036	0	1	0.8032	-3.8036	0	1	0.8032	-3.8036	0	1	0.8032	-3.8036
	1	-0.2339	-0.0261	-0.3427	-0.1212	-0.2339	-0.0261	-0.3427	-0.1212	-0.2339	-0.0261	-0.3427	-0.1212	-0.2339	-0.0261	-0.3427	-0.1212
	2	-0.1067	0.0317	-0.0806	0.7220	-0.1067	0.0317	-0.0806	0.7220	-0.1067	0.0317	-0.0806	0.7220	-0.1067	0.0317	-0.0806	0.7220
	3	-0.0259	0.0004	0.0004	0.8316	-0.0259	0.0004	0.0004	0.8316	-0.0259	0.0004	0.0004	0.8316	-0.0259	0.0004	0.0004	0.8316
	4	0.0176	-0.0079	0.0371	0.5415	0.0176	-0.0079	0.0371	0.5415	0.0176	-0.0079	0.0371	0.5415	0.0176	-0.0079	0.0371	0.5415
	5	0.0279	-0.0082	0.0365	0.2144	0.0279	-0.0082	0.0365	0.2144	0.0279	-0.0082	0.0365	0.2144	0.0279	-0.0082	0.0365	0.2144
v_{it}	0	0	0	1	-0.5230	0	0	1	16.4197	0	0	1	45.6499	0	0	1	108.2021
	1	-0.1050	-0.3439	0.0818	-0.7974	0.5505	-0.3253	0.9377	8.6888	1.6814	-0.2931	2.4144	25.0545	4.1011	-0.2239	5.5740	60.0768
	2	-0.0904	-0.1519	0.0307	-1.0127	0.5723	-0.2086	0.7200	2.0072	1.7161	-0.3066	1.9095	7.2171	4.1633	-0.5158	4.4543	18.3662
	3	-0.0898	-0.0809	-0.0286	-0.6863	0.3425	-0.1042	0.3353	-1.4063	1.0884	-0.1446	0.9632	-2.6482	2.6847	-0.2304	2.3072	-5.3064
	4	-0.0732	-0.0419	-0.0353	-0.3040	0.1117	-0.0272	0.0538	-2.2033	0.4307	-0.0019	0.2072	-5.4802	1.1140	0.0525	0.5360	-12.4923
	5	-0.0491	-0.0236	-0.0228	-0.0409	-0.0264	0.0100	-0.0783	-1.6511	0.0127	0.0682	-0.1736	-4.4293	0.0970	0.1924	-0.3783	-10.3743
v_{dt}	0	0	0	0	1	0	0	-0.1000	1	0	0	-0.2500	1	0	0	-0.5000	1
	1	0.0387	0.0011	0.0505	0.5599	0.0472	0.0354	0.0397	0.6104	0.0599	0.0870	0.0235	0.6860	0.0811	0.1728	-0.0036	0.8122
	2	0.0391	-0.0034	0.0407	0.1782	0.0461	0.0120	0.0355	0.2702	0.0566	0.0351	0.0277	0.4081	0.0741	0.0734	0.0147	0.6380
	3	0.0255	-0.0014	0.0215	-0.0425	0.0332	0.0068	0.0232	0.0284	0.0446	0.0190	0.0258	0.1346	0.0637	0.0394	0.0302	0.3118
	4	0.0109	0.0009	0.0053	-0.1121	0.0177	0.0050	0.0085	-0.0758	0.0278	0.0112	0.0134	-0.0215	0.0447	0.0216	0.0215	0.0692
	5	0.0013	0.0020	-0.0033	-0.0950	0.0062	0.0042	-0.0008	-0.0860	0.0134	0.0076	0.0029	-0.0724	0.0256	0.0133	0.0090	-0.0497

Notes: The above table presents the impulse responses to a unit change in each shock on all variables in the system h-steps ahead for the baseline triangular SVAR ($\alpha_{34} = 0$) as well as SVARs with $\alpha_{34} = 0.1, 0.25, 0.5$. Sample: 1962-2013.