Han and Ng'ombe
Agricultural and Food Economics (2023) 11:1
https://doi.org/10.1186/s40100-023-00242-1

Agricultural and Food Economics

RESEARCH

Open Access

The relation between wheat, soybean, and hemp acreage: a Bayesian time series analysis

Joohun Han[1*] and John N. Ng'ombe[2]

*Correspondence: gomted3@gmail.com

[1] Department of Agricultural Economics and Agribusiness, University of Arkansas, Fayetteville, AR 72701, USA
[2] Department of Agribusiness, Applied Economics and Agriscience Education, North Carolina A&T State University, Greensboro, NC 27411, USA

Abstract

The 2018 United States Farm Bill has opened the possibility for farmers to increase their profits through hemp cultivation. The literature suggests hemp has the potential to replace soybeans in soybean–wheat double-cropping because hemp shares key attributes of soybeans as a rotation crop (profitability, potential as an energy crop, and maintenance of soil fertility). Nonetheless, due to a short history of hemp cultivation in the USA, it is difficult to predict a time series relationship between hemp, soybean, and wheat through conventional approaches. In this article, we use Bayesian time series models and data from Statistics Canada and the Alberta Agricultural and Rural Development Department to examine a time series relationship between hemp, wheat, and soybean acreage and therefore predict farmers' decision when hemp is a legal alternative agricultural commodity. Our results show evidence of complementary and substitution relationships for hemp–wheat and hemp–soybean, respectively. In addition, the results indicate a potential of hemp monoculture as a positive response to self-positive shock on hemp acreage that lasts for years.

Keywords: Industrial hemp, Wheat, Double-cropping, Bayesian vector autoregressive model, Impulse response analysis

Introduction

Since the full legalization of hemp production and consumption in the USA by the 2018 Farm Bill, industrial hemp (i.e., hemp) farming has been growing in North America (Kraszkiewicz et al. 2019). Recent studies show that hemp has an economic potential to become a viable alternative crop for farmers (Cherney and Small 2016). Farmers can choose hemp over other agricultural commodities, especially for the crops that share farming conditions with hemp, such as wheat and the corresponding rotation crops (e.g., soybean and corn) (Adesina et al. 2020).

The wheat–soybean rotation is one of the most conventional double-cropping methods (53% among all double-cropped acres) in the US agriculture (Borchers et al. 2014). This is supported by previous studies that suggest double-cropping has lower production costs and higher yields, residues, and glucose than single-variety cultivation (Caviglia et al. 2011). Also, soybean is one of the most common energy crops that is profitable for farmers (Hitaj and Suttles 2016). On the other hand, there is an argument for agronomic and economic potential of hemp. For example, Fortenbery and Bennett (2004) suggest hemp could be a more profitable crop than other row crops in the USA because of the country's favorable agronomic and economic conditions. Also, some experiment studies contend that a wheat–hemp rotation could increase wheat yield by enhancing soil conditions (Struik et al. 2000; Gorchs et al. 2017; Adesina et al. 2020). Moreover, Cherney and Small (2016), Kraszkiewicz et al. (2019) and Parvez et al. (2021) show that hemp could be a sustainable bioenergy crop for biofuel and biochar. These findings suggest that hemp shares the role of soybean in a wheat–soybean double-cropping rotation. Thus, if hemp production was legalized in the USA, the farmers would have to replace soybean with hemp in the wheat–soybean double-cropping rotation order to increase their yield and profit. This implies that a potentially significant correlation over time between wheat, soybean, and hemp acreage is plausible. However, to the best of our knowledge, only a few studies consider the correlation between hemp and other crops (e.g., wheat) in terms of cultivation (e.g., Lambert and Hagerman 2022), and there is no study that examines the relationship between hemp, wheat, and soybean using time series analysis (i.e., cointegration). The cointegration between hemp and corresponding crops could affect farmers' decisions on which crop to cultivate in the long-run (Mushtaq and Dawson 2002). Our study is therefore the first to attempt to close this important research gap.

The purpose of this study is to examine the time series relationship of hemp, wheat, and soybean acreage to predict farmers' decision when hemp is a legal alternative agricultural commodity. Based on previous research findings that hemp is a potentially profitable substitute for conventional double-cropping crops for wheat, this study demonstrates the choices that wheat and corresponding crop farmers would make in an environment where hemp is legal. Therefore, the results will provide policy implications for farmers and local governments considering hemp farming in areas where hemp has been legalized in recent years. To achieve our objective, we employ a Bayesian vector autoregressive (BVAR) model and Bayesian impulse response analysis (BIRA) with a Minnesota prior[1] to resolve the limited data and subjective prior issues.

While the USA has considered hemp as an agricultural commodity since 2018, unlike other agricultural commodities, there is neither a stable hemp market nor a sure way to predict farmers' behavior to choose hemp (Mark et al. 2020). A Bayesian approach could remedy the insufficient sample size problem and could provide a more reliable and consistent estimation result than the frequentist estimation approach in time series analysis (Price 2012; Gelman et al. 2013; Wanless et al. 2015; McNeish 2016). Indeed, results from a Bayesian estimation could be manipulative if the results over-rely on a prior, i.e., subjective prior. Thus, we apply the Minnesota prior (i.e., Litterman prior) to address the subjective prior issue (Litterman 1979).

We find partial complementary relationships between wheat and soybean acreage and a partial substitution relationship between hemp and wheat acreage. Moreover, our

[1] The Minnesota prior was originally developed by Litterman (1980) and other researchers at the University of Minnesota. While there are so many variants of the Minnesota prior, the one used here requires all the endogenous variables in the model to follow a random walk process. Such models are known to perform well for time series and agricultural data and provide more accurate estimation results (Bessler and Hopkins 1986; Bessler and Kling 1986; Mushtaq and Dawson 2002). Generally, Minnesota priors belong to the family of Gaussian-inverse-Wishart priors (Kopytin et al. 2021; Kuschnig and Vashold 2021).

Table 1 Descriptive statistics of soybean, wheat, and hemp acreage in Canada, 1998–2011. *Source*: Alberta Agriculture and Rural Development (2012) and Statistics Canada (2021)

Variables	Soybean	Wheat	Hemp
Mean	2,947,424.00	17,844,235.00	17,987.00
Median	2,900,900.00	17,844,235.00	13,837.00
Standard deviation	426,406.47	1,590,192.14	13,371.33

results show that hemp acreage responds to a positive shock with a significant increase on hemp acreage over years.

Data and methods

Our study uses time series data collected by Statistics Canada (2022) and the Alberta Agricultural and Rural Development Department (Laate 2012). Each data source provides the national level spring wheat and soybean acreage from 1999 to 2011 and hemp acreage from 1999 to 2011 in Canada, respectively. The data from Canada provide us with a suitable environment for this research due to the following reasons: First, Canada started the pilot program for hemp cultivation at the federal level since 1998, which explains a more stable hemp market and farmers' higher awareness of hemp than the USA (Johnson 2014). Second, the Canadian economic conditions and potentials of hemp cultivation are similar to those of the USA (Johnson 2014; Cherney and Small 2016). Third, Canada and the US hemp industries may be positively correlated especially since Canada is one of the largest exporters of hemp products to the USA (Mark et al. 2020). Thus, the Canadian data and its estimation results can be useful to picture what will happen in the US agriculture in terms of hemp cultivation.

Table 1 shows the descriptive statistics of soybean, wheat, and hemp acreage in Canada from 1998 to 2011. As mentioned before, we use Canadian data since the USA does not have similar data especially due to regulatory limitations on hemp production. While these data are not sufficiently large for conventional statistical analyses, Bayesian analysis is an alternative suitable approach as mentioned previously. The mean and median show that hemp cultivation is smaller than wheat and soybean on average. Also, the standard deviation shows that hemp acreage is more volatile than soybean and wheat over time. It implies that hemp acreage may rapidly change, possibly increasing over time on average.

Figure 1 shows the time pattern of hemp, wheat, and soybean acreage and their correlation coefficients from 1998 to 2011. With regard to a comparison between soybean and hemp, both soybean and hemp variables show an increasing trend over time. On the other hand, in contrast between wheat and hemp, we observe these variables may have reacted to the same shock: the spike in 2006 and downfall afterward. Therefore, we could suggest that the hemp, wheat, and soybean acreage are cointegrated.

Table 2 shows the augmented Dickey–Fuller (ADF) test and Johansen cointegration test to validate the stationarity of each first-differenced variable and cointegration between variables, respectively. The third row in Table 2 refers to the rank of the parameter matrix for cointegration test. For instance, if the test rejects the null in Rank $=1$ and failed to reject the null hypothesis in Rank $=2$, it means there is a cointegrating relationship between two or more variables but not more than three

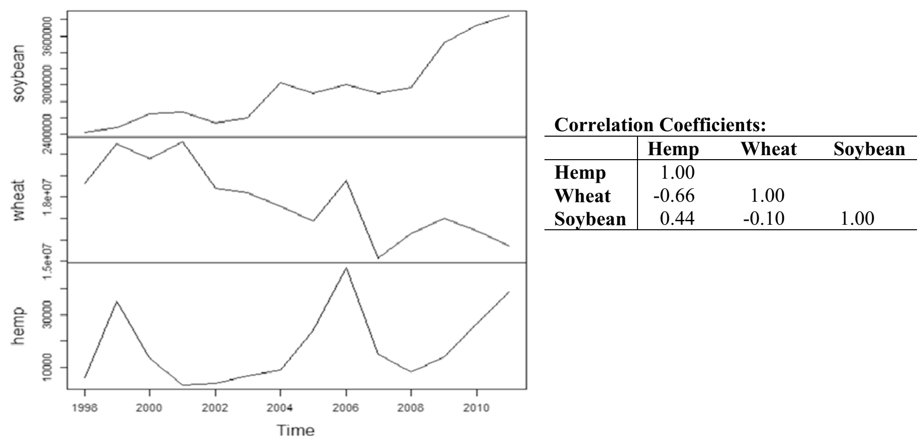

Fig. 1 Acreages of hemp, wheat, and soybean in Canada, 1998–2011, and their correlation coefficients

Table 2 Unit-root test and cointegration test of selected first-differenced time series variables

	Soybean	Wheat	Hemp
Augmented Dickey–Fuller test	− 2.41	− 3.17**	− 2.16
	Rank = 0	**Rank = 1**	**Rank = 2**
Johansen cointegration test	46.31**	16.89*	6.81*

A single asterisk indicate significance at a 10% level. A double asterisk indicate significance at a 5% level

variables. The significant test result for Rank = 2 implies there is no cointegrating relationship between the three variables. Therefore, the test result supports the need for a vector autoregressive regression (VAR) model is suitable for our study. The ADF test was conducted on differenced data for the VAR model. This framework is consistent with Papana et al. (2014)'s suggestion that in case of non-stationary data, a first-differenced variable should be used for VAR model to ensure accurate forecast (Seaks and Vines 1990). The ADF test result indicated failure to reject the null hypothesis of presence of a unit root for soybean and hemp acres. Therefore, we concluded that there is a unit root, which confirms non-stationarity.

While our data are non-stationary, multivariate VAR models can still be estimated with non-stationary data in many applications (Sims 1980, 1989; Fanchon and Wendel 1992). Examples of studies that have estimated VAR models on non-stationary data include Fanchon and Wendel (1992), Christiano et al. (1999), Uhlig (2005), Carriero et al. (2015), Lueger (2018), Binatli and Sohrabji (2019), Çelik and Binatli (2022), among others. For instance, Sims (1988, 1989) argued that Bayesian analysis is optimal for estimating VAR models for non-stationary data because parameter estimates are unaffected by non-stationarity as non-Bayesian estimates are. Besides, Bayesian analysis produces reliable estimation results regardless of the sample size (Gelman et al. 2013; Ng'ombe and Boyer 2019; McElreath 2020). Therefore, motivated by these arguments and in addition to data limitations raised previously, we use a Bayesian framework in the present study.

We use a Bayesian VAR (BVAR) model to capture the relationship between wheat, soybean, and hemp acreage over time. A Bayesian approach is employed due to the following reasons: (a) to overcome the problem of short time series data by using prior statistical information and due to non-stationarity of our data and (b) impose the random walk prior for better estimation results (Sims 1989; Ma et al. 2021).

Consider the first-difference VAR(1) model:

$$\begin{bmatrix} \Delta Y_{S,t} \\ \Delta Y_{W,t} \\ \Delta Y_{H,t} \end{bmatrix} = \begin{bmatrix} \alpha_{S,0} \\ \alpha_{W,0} \\ \alpha_{H,0} \end{bmatrix} + \begin{bmatrix} \beta_{S,S} & \beta_{S,W} & \beta_{S,H} \\ \beta_{W,S} & \beta_{W,W} & \beta_{W,H} \\ \beta_{H,S} & \beta_{H,W} & \beta_{H,H} \end{bmatrix} * \begin{bmatrix} \Delta Y_{S,t-1} \\ \Delta Y_{W,t-1} \\ \Delta Y_{H,t-1} \end{bmatrix} + \begin{bmatrix} \Delta e_{S,t} \\ \Delta e_{W,t} \\ \Delta e_{H,t} \end{bmatrix} \quad (1)$$
$$e_t \sim N(0, \Sigma),$$

where ΔY_t is a vector of first-differenced agricultural commodities' acreage (soybean, wheat, and hemp) in year t, α is a drift vector corresponding to each commodity, β is a coefficient matrix, ΔY_{t-1} is first-differenced agricultural commodities' acreage in year $t-1$, $\Delta\ e$ is a first-differenced error term vector, and Σ is an error covariance matrix. Each element in a coefficient matrix represents the relationship between commodities' acreage over time. For instance, $\beta_{W,S}$ shows how the acreage of soybean in $t-1$ year would affect the wheat acreage in year t.

Consider the multivariate normal population for time series variable. In this case, the conjugate priors of coefficient and corresponding error covariance matrix are

$$\begin{aligned} (\beta|\boldsymbol{\Sigma}) &\sim N(\boldsymbol{b}, \boldsymbol{\Sigma} \otimes \boldsymbol{\Omega}) \\ \boldsymbol{\Sigma} &\sim IW(\boldsymbol{\psi}, d), \end{aligned} \quad (2)$$

where b is a mean vector of conditional multivariate normal distribution, $\boldsymbol{\Sigma} \otimes \boldsymbol{\Omega}$ is a parameter covariance matrix, and $\boldsymbol{\psi}$ and d, scale matrix and degree of freedom, are inverse-Wishart distribution parameters of the error covariance matrix (Murphy 2007). Following Kuschnig and Vashold (2021) and Giannone et al. (2015), we consider prior parameters $\boldsymbol{b}, \boldsymbol{\Omega}, \boldsymbol{\psi}$, and d as functions of a lower-dimensional vector of hyper-parameters γ.

We use a Minnesota prior to impose objectivity as it provides non-subjective prior information (Litterman 1980). The Minnesota prior is a shrinkage prior that prevents overfitting issue and provides high prediction accuracy for BVAR models (Van Erp et al. 2019). The BVAR framework with Minnesota prior has several empirical advantages. These include higher efficiency in impulse response analysis, reduction in potential estimation error, and lower dependence of sample size for estimation than conventional VAR models (Litterman 1986; Giannone et al. 2015; Jarocinski and Marcet 2010).

Other motivations for the use of the Minnesota prior in this study are as follows. Numerous studies have shown that Bayesian VARs with a Minnesota prior produce superior estimates to those many that have used traditional multivariate simultaneous equations (Robertson and Tallman 1999). Additionally, the Minnesota prior can deal with the so-called curse of dimensionality which in a non-Bayesian estimation sense is dealt with a simple t test or similar procedures to remove unnecessary lags (Favero 2001). This type of analysis is claimed to impose strong restrictions on what variables and which lags should be in the VAR model (Canova 2007). On the other hand, the Minnesota prior is capable to introduce restrictions in a flexible way. For instance, Canova (2007) suggests that the Minnesota prior imposes probability distributions on the coefficients of the VAR which remedy the dimensionality problem without imposing restrictions on particular variables or lags. This study therefore favors a Minnesota prior.

The Minnesota prior framework hypothesizes that each variable follows a random walk process. This specification is somehow unfounded, yet it explains the approximated economic behavior in time series variables (Litterman 1979; Kuschnig and Vashold 2021). This assumption and corresponding prior setting allows a faster computational process and better forecasting results (Kuschnig and Vashold 2021). By following Litterman (1980)'s derivation, the first and second moments (Eqs. (3) and (4), respectively) represent a relationship between Minnesota prior parameters.

$$E\left((\beta_s)_{ij}|\boldsymbol{\Sigma}\right) = \begin{cases} 1 \text{ if } \quad i=j \quad \text{and} \quad s=1, \\ 0 \text{ otherwise.} \end{cases} \tag{3}$$

$$\mathrm{cov}\left((\beta_s)_{ij},(\beta_r)_{kl}|\boldsymbol{\Sigma}\right) = \begin{cases} \lambda^2 \frac{1}{s^\alpha} \frac{\boldsymbol{\Sigma}_{ik}}{\psi_j/(d-M-1)}, & \text{if} \quad l=j \quad \text{and} \quad r=s, \\ 0 & \text{otherwise,} \end{cases} \tag{4}$$

where λ is a hyper-parameter that determines the scale of a variance–covariance matrix and tightness (i.e., influence) of prior, s and r are lag lengths of associated coefficient, M is a number of variables, and α is a scale that controls the shrinkage level for more distant lag observations. A larger λ ensures a bigger influence of sample information, e.g., variance Σ_{ik}, on the posterior. The smaller λ increases the prior's influence, e.g., scale parameter ψ_j, on the posterior distribution. Therefore, the choice of λ determines how informative this prior is and furthers prior influence on posterior estimates. Giannone et al. (2015) present a hierarchical approach to choosing the non-subjective Minnesota prior's hyper-parameter λ in a BVAR process. Consider the following posterior density of a hyper-parameter based on Bayes' Theorem:

$$P\left(\gamma|y\right) \propto P\left(y|\gamma\right) * P(\gamma), \tag{5}$$

where $P(\gamma)$ is a hyper-prior, y is data, and $P\left(y|\gamma\right)$ is a marginal likelihood of data with respect to the hyper-prior. The likelihood function in Eq. (5) corresponds to

$$P\left(y|\gamma\right) = \int P\left(y|\theta,\gamma\right)P(\theta|\gamma)d\theta, \tag{6}$$

where θ is a BVAR parameter vector. Therefore, we can choose the hyper-parameters that maximize the likelihood of obtained data with this framework. This method helps to choose the hyper-parameters solely based on the given data, not on any subjective information. Therefore, the Minnesota prior ensures informative prior with less subjectivity issue in parameter choice (Kilian and Lütkepohl 2017; Kuschnig and Vashold 2021).

In general, a VAR coefficient is difficult to interpret because there is no independent variable in VAR framework to obtain a marginal effect (Johansen 2005). Thus, we employ the Bayesian impulse response analysis (BIRA) to analyze the positive shock response of each variable over time (i.e., dynamic marginal effect of shock on each variable) (Johansen 1995). This procedure aims to predict the response of a particular variable to a given shock (i.e., a one standard deviation of target variable) in another variable (Nazlioglu et al. 2013). For instance, BIRA could show how hemp acreage would change if soybean acreage is increased for a certain amount.

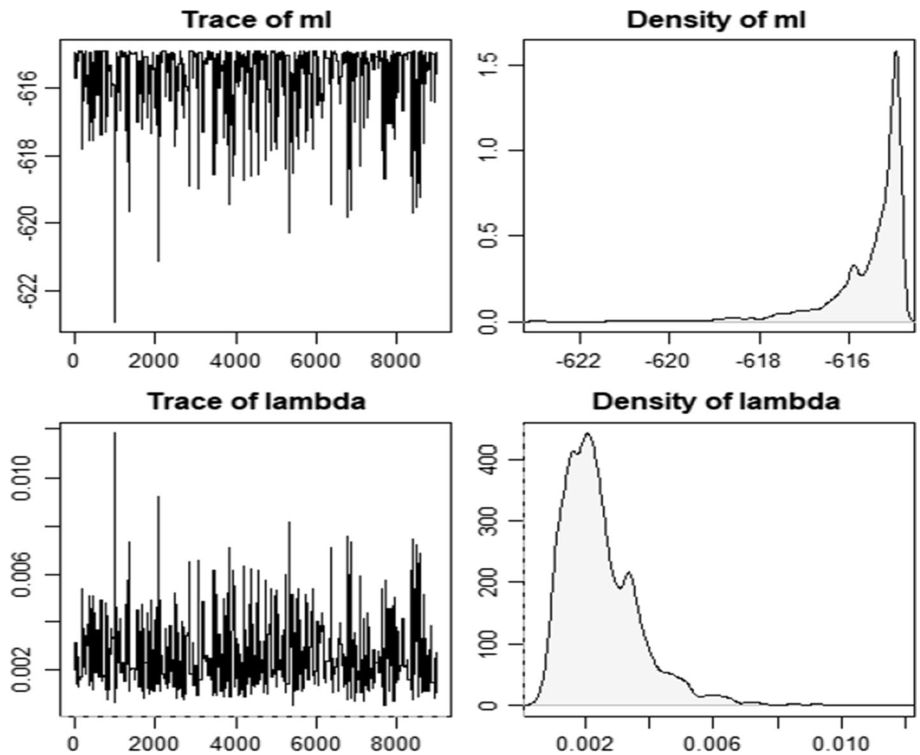

Fig. 2 Trace of hyper-parameter γ and corresponding marginal likelihood

As for estimation of the BVAR and BIRA model, we used the R package *BVAR* relying on Metropolis–Hastings algorithms (R Core Team 2013; Kuschnig and Vashold 2021). The Markov chain Monte Carlo (MCMC) techniques that we employed involved 3 chains with a burn-in phase of 1000 to enable the Markov chains discard their starting regions. The total number of iterations per chain was 200,000.

Results

Figure 2 shows the trace and density plots of the hyper-parameter γ and corresponding marginal likelihood $P(y|\gamma)$ (indicated as *ml* in Fig. 2). The trace plots indicate adequate mixing for MCMC procedure, which suggests successful convergence of MCMC chains for the parameters (Gelman et al. 2013; Ng'ombe and Boyer 2019; Kiwanuka-Lubinda et al. 2021).

In addition, Table 3 shows the convergence diagnostic test results for BVAR parameters. As shown, all autoregressive parameters and the hyper-parameter γ have their Gelman–Rubin statistic, $\widehat{R}$, less than 1.10, which suggests adequate mixing of the Markov chains and their successful convergence (Gelman and Rubin 1992). The effective sample size (the third column of Table 3) also supports that the convergence was successful for all parameters (Vehtari et al. 2021).

Figure 3 shows the BIRA plot for all possible shock (a positive one standard deviation) response cases between soybean, wheat, and hemp. Since we use Canadian data, the BIRA results could be interpreted under the conditions that (a) hemp is considered as an alternative crop for farmers and (b) the farmers are experienced or informed to

Table 3 Convergence diagnostic tests for BVAR parameters

Variables	$\widehat{R}$	Effective sample size
$\beta_{S,S}$	1.01	29,910.25
$\beta_{S,W}$	1.01	68,620.42
$\beta_{S,H}$	0.99	72,826.14
$\beta_{W,S}$	1.01	99,800.34
$\beta_{W,W}$	1.00	97,039.37
$\beta_{W,H}$	1.00	88,090.56
$\beta_{H,S}$	1.00	82,998.06
$\beta_{H,W}$	0.99	36,380.07
$\beta_{H,H}$	1.00	10,932.95
γ	1.00	4178.17

These tests are based on 200,000 MCMC samples with 1000 burn-in per chain

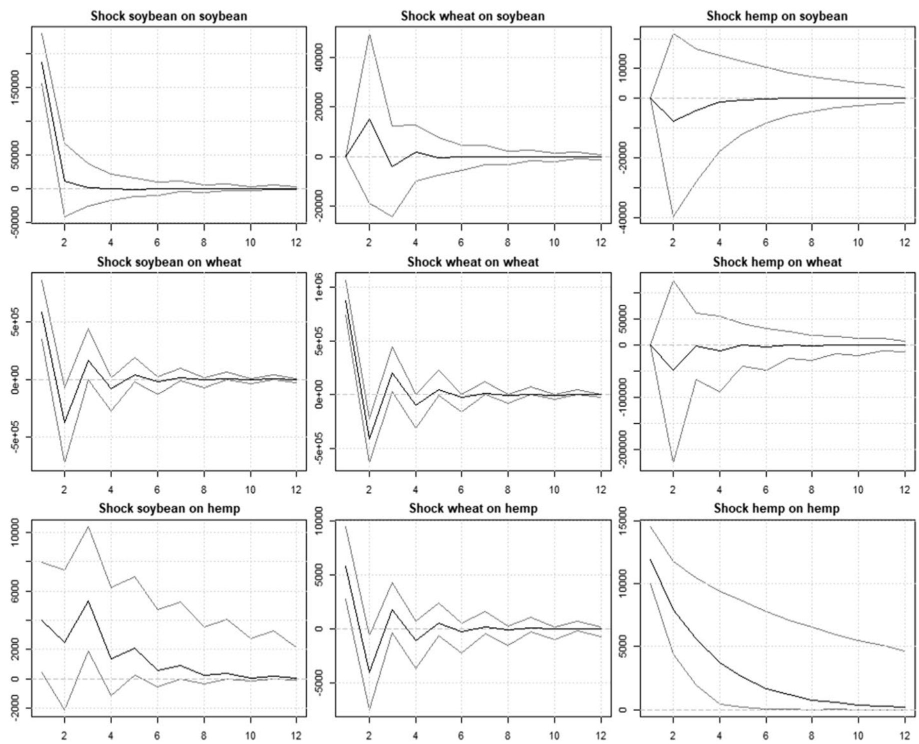

Fig. 3 Impulse response from soybean, wheat, and hemp with 90% confidence band

acknowledge the potential on hemp (Dingha et al. 2019; Parvez et al. 2021). For instance, if hemp acreage responds positively/negatively to a one standard deviation shock of wheat acreage (i.e., shock wheat on hemp), it implies that the farmers would cultivate more/less hemp to maximize their profit through the complementary/substitution effect between wheat and hemp.

Overall, (a) BIRA results show an initial positive response for all cases except for the shock of hemp on the wheat case. (b) Shock of wheat on soybean, hemp on soybean, hemp on wheat, soybean on hemp, and hemp on hemp show fat credible bounds, especially for the short-run shock. It suggests the shock response for these cases is highly volatile, mostly in the early stages. The self-positive shock cases (e.g., shock wheat on wheat) indicate a reasonable response. For example, wheat shock on wheat case shows a positive response in odd years and negative response in even years and converges to zero over time. It implies that in wheat cultivation case, wheat farmers would increase acreage in the first year and fallow or rotate with other crop for the next year to keep the soil in good condition and repeat this process biennially (Gan et al. 2012; Ghimire et al. 2019; Hansen et al. 2019). On the contrary, we can find no fallow or rotation behavior with self-positive shock cases on soybean and hemp, and hemp case's positive response lasting for eight years. These outcomes imply that farmers could prefer monoculture of profitable crops (i.e., soybean and hemp), and hemp could be more sustainable under monoculture than other crops (Gorchs et al. 2017; Poniatowska et al. 2019; Schnitkey et al. 2022). This suggests that when the hemp cultivation is encouraged (i.e., positive initial shock) by its potential, farmers would choose hemp monoculture over substituting soybean in double-cropping rotation (Adesina et al. 2020; Farinon et al. 2020; Mark et al. 2020).

The possible rotation combinations (soybean–wheat and hemp–wheat) show partial evidence of complementary and substitute relationship for each combination. Shock soybean on wheat and vice versa show a positive response, but the effect decays after 3 years. On the other hand, shock hemp on wheat shows insignificant response yet wheat on hemp shows a significant positive response. These findings partially support the previous studies' finding that wheat and hemp yield can complement each other, and farmers could choose hemp over soybean based on this complementary relation (Gorchs et al. 2017). As for hemp and soybean, which we hypothesize to be substitutes, results confirm the weakness of our assumption. The shock hemp on soybean shows the initial negative response for 4 years. Nonetheless, the fat credible band of shock hemp on soybean (the third graph from the first row in Fig. 3) denotes less credibility in this result. Interestingly, the shock soybean on hemp shows a positive response, and the shock remains for 8 years. It suggests that just as hemp–wheat and soybean–wheat complement each other, soybean–hemp could be a possible double-crop choice for farmers.

Concluding remarks

The hemp market is rapidly growing in the USA since the 2018 Farm Bill's legalization of hemp cultivation. Previous studies suggest hemp could substitute for soybean in the wheat–soybean double-cropping rotation, which is the most common double-cropping method in the USA. Despite that, only a few studies examine the relationship between wheat, soybean, and hemp in terms of cultivation. One of the main reasons for the few applicable studies in the USA is that access to data is limited due to the short history of hemp as an agricultural commodity. This study applies the Bayesian vector autoregressive (BVAR) model with Canadian data to remedy the limited data issue and provide a proxy for hemp study in the countries with a short history of hemp, such as the USA. We use the Minnesota prior to mitigate the subjective prior effects on our estimations.

While the literature on production, politics, and registration of hemp and similar controversial crops in North America (e.g., marijuana) continues to grow (e.g., Baxter and Scheifele 2000; Robbins et al. 2013; Small 2015; Vonapartis et al. 2015; Caulkins et al. 2016; Small and Naraine 2016; Cherney and Small 2016; Cash et al. 2020; Health Canada 2016; Adesina et al. 2020; Han and Ng'ombe 2022), this study adds to the literature by providing insights on a time series relationship between hemp, wheat, and soybean acreage. This provides a picture of how acreage for hemp, wheat, and soybean would change when hemp becomes a legal alternative agricultural commodity for agricultural producers in the USA.

Results from a BIRA model provide evidence of complementarity between wheat and soybean, hemp, and wheat, and between hemp and soybean. The results also show that hemp and soybean can substitute for each other. In addition, the self-positive shock on hemp denotes the longest-lasting positive response. Thus, given that the demand for hemp and the corresponding profits are acknowledged by farmers and increasing over time (Dingha et al. 2019; Parvez et al. 2021), these results have the following implications. First, hemp indicates potential to replace soybean in a farming system such as soybean–wheat rotation. Second, famers with sufficient experience with hemp as a crop choice could choose hemp over wheat instead of applying it as a part of double-cropping rotation. Moreover, farmers could even choose hemp monoculture over wheat or soybean due to hemp's profitability and sustainability in monoculture condition (Poniatowska et al. 2019; Adesina et al. 2020). Due to this potential to replace crops in the rotation portfolios among farmers, hemp has the potential to become one of the profitable crops in the USA. However, that possibility is subject to the US hemp industry becoming immune to marijuana politics like Canada (Cherney and Small 2016; Mark et al. 2020; Lambert and Hagerman 2022). Cherney and Small (2016) discuss that the aggressive movement against industrial hemp crowds out the genuine potential of hemp as a field crop in the USA especially due to numerous marijuana advocates promoting declassification of hemp. If such aggressive attempts to declassify hemp production are mitigated through hemp legalization, hemp might as well become one of the prized crops in the USA. Our study indicates that hemp has the potential to replace soybean in double-cropping system, and farmers could choose hemp over both wheat and soybean. Such scenarios could arise based on robust hemp markets via legalization in the USA and other countries (Cherney and Small 2016; Adesina et al. 2020).

Author contributions

JH contributed to conceptualization, methodology, data curation, analysis, and draft writing and provided software. JNN was involved in methodology, supervision, and editing the manuscript. Both authors read and approved the final manuscript.

Funding

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Availability of data and materials

The datasets used for current study are available from the corresponding author on request.

Declarations

Ethics approval and consent to participate

This manuscript does not report any experimental research or research on humans.

Competing interests

The authors declare no competing interest.

Received: 6 June 2022 Revised: 22 December 2022 Accepted: 4 January 2023
Published online: 19 January 2023

References

Adesina I, Bhowmik A, Sharma H, Shahbazi A (2020) A Review on the current state of knowledge of growing conditions, agronomic soil health practices and utilities of hemp in the United States. Agriculture 10(4):129. https://doi.org/10.3390/agriculture10040129

Baxter BJ, Scheifele G (2000) Growing industrial hemp in ontario: ministry of agriculture. Food and Rural Affairs. Accessed October 2022

Bessler DA, Hopkins JC (1986) Forecasting an agricultural system with random walk priors. Agric Syst 21(1):59–67

Bessler DA, Kling JL (1986) Forecasting vector autoregressions with Bayesian priors. Am J Agric Econ 68(1):144–151

Binatli AO, Sohrabji N (2019) Monetary policy transmission in the euro zone. Athens J Bus Econ 5(1):79–92

Borchers A, Truex-Powell E, Wallander S, Nickerson C (2014) Multi-cropping practices: recent trends in double-cropping. United States Department of Agriculture. https://www.ers.usda.gov/publications/pub-details/?pubid=43865

Canova F (2007) Methods for applied macroeconomic research, vol 13. Princeton University Press, Princeton

Carriero A, Clark TE, Marcellino M (2015) Bayesian VARs: specification choices and forecast accuracy. J Appl Economet 30(1):46–73

Cash MC, Cunnane K, Fan C, Romero-Sandoval EA (2020) Mapping cannabis potency in medical and recreational programs in the United States. PLoS ONE 15(3):e0230167

Caulkins JP, Kilmer B, Kleiman MA (2016) Marijuana legalization: what everyone needs to know. Oxford University Press, New Work, NY

Caviglia OP, Sadras VO, Andrade FH (2011) Yield and quality of wheat and soybean in sole-and double-cropping. Agron J 103(4):1081–1089. https://doi.org/10.2134/agronj2011.0019

Çelik M, Oğuş Binatlı A (2022) How effective are macroprudential policy instruments? Evidence from Turkey. Economies 10(4):76

Cherney JH, Small E (2016) Industrial hemp in North America: production, politics and potential. Agronomy 6(4):58. https://doi.org/10.3390/agronomy6040058

Christiano LJ, Eichenbaum M, Evans CL (1999) Monetary policy shocks: What have we learned and to what end? Handb Macroecon 1:65–148

Dingha B, Sandler L, Bhowmik A, Akotsen-Mensah C, Jackai L, Gibson K, Turco R (2019) Industrial hemp knowledge and interest among North Carolina organic farmers in the United States. Sustainability 11(9):2691

Fanchon P, Wendel J (1992) Estimating VAR models under non-stationarity and cointegration: alternative approaches for forecasting cattle prices. Appl Econ 24(2):207–217

Farinon B, Molinari R, Costantini L, Merendino N (2020) The seed of industrial hemp (*Cannabis sativa* L.): nutritional quality and potential functionality for human health and nutrition. Nutrients 12(7):1935

Favero CA (2001) Applied macroeconometrics. Oxford University Press, Oxford

Fortenbery TR, Bennett M (2004) Opportunities for commercial hemp production. Appl Econ Perspect Policy 26(1):97–117

Gan Y, Liang C, Campbell CA, Zentner RP, Lemke RL, Wang H, Yang C (2012) Carbon footprint of spring wheat in response to fallow frequency and soil carbon changes over 25 years on the semiarid Canadian prairie. Eur J Agron 43:175–184

Gelman A, Carlin JB, Stern HS, Rubin DB (2013) Bayesian data analysis, 3rd edn. Chapman and Hall/CRC, London

Gelman A, Rubin DB (1992) Inference from iterative simulation using multiple sequences. Stat Sci 7(4):457–472. https://doi.org/10.1214/ss/1177011136

Ghimire R, Ghimire B, Mesbah AO, Sainju UM, Idowu OJ (2019) Soil health response of cover crops in winter wheat–fallow system. Agron J 111(4):2108–2115

Giannone D, Lenza M, Primiceri GE (2015) Prior selection for vector autoregressions. Rev Econ Stat 97(2):436–451. https://doi.org/10.1162/REST_a_00483

Gorchs G, Lloveras J, Serrano L, Cela S (2017) Hemp yields and its rotation effects on wheat under rainfed mediterranean conditions. Agron J 109(4):1551–1560. https://doi.org/10.2134/agronj2016.11.0676

Han J, Ngombe JN (2022) The supply-side effects of cannabis legalization. J Cannabis Res 4(1):1–16

Hansen JC, Schillinger WF, Sullivan TS, Paulitz TC (2019) Soil microbial biomass and fungi reduced with canola introduced into long-term monoculture wheat rotations. Front Microbiol 10:1488. https://doi.org/10.3389/fmicb.2019.01488

Health Canada (2016) Government of Canada. www.hc-sc.gc.ca

Hitaj C, Suttles S (2016) Trends in US agriculture's consumption and production of energy: renewable power, shale energy, and cellulosic biomass. United States Department of Agriculture. https://www.ers.usda.gov/publications/pub-details/?pubid=74661

Jarocinski M, Marcet A (2010) Autoregressions in small samples, priors about observables and initial conditions. European Central Bank, Frankfurt

Johansen S (1995) Likelihood-based inference in cointegrated vector autoregressive models. OUP, Oxford

Johansen S (2005) Interpretation of cointegrating coefficients in the cointegrated vector autoregressive model. Oxford Bull Econ Stat 67(1):93–104. https://doi.org/10.1111/j.1468-0084.2005.00111.x

Johnson R (2014) Hemp as an agricultural commodity. Library of Congress Washington DC Congressional Research Service. https://apps.dtic.mil/sti/citations/ADA599368

Kilian L, Lütkepohl H (2017) Structural vector autoregressive analysis. Cambridge University Press, Cambridge

Kiwanuka-Lubinda RN, Ng'ombe JN, Machethe C (2021) Impacts of interlocked contractual arrangements on dairy farmers' welfare in Zambia: a robust Bayesian instrumental variable analysis. Agrekon 60(1):10–30

Kopytin IA, Pilnik NP, Stankevich IP (2021) Modelling five variables BVAR for economic policies and growth in Azerbaijan, Kazakhstan and Russia: 2005–2020. Int J Energy Econ Policy 11(5):510–518. https://doi.org/10.32479/ijeep.11324

Kraszkiewicz A, Kachel M, Parafiniuk S, Zając G, Niedziółka I, Sprawka M (2019) Assessment of the possibility of using hemp biomass (*Cannabis sativa* L.) for energy purposes: a case study. Appl Sci 9(20):4437. https://doi.org/10.3390/app9204437

Kuschnig N, Vashold L (2021) BVAR: Bayesian vector autoregressions with hierarchical prior selection in R. J Stat Softw 100:1–27. https://doi.org/10.18637/jss.v100.i14

Laate EA (2012) Industrial hemp production in Canada. Alberta Agriculture and Rural Development. https://open.alberta.ca/publications/industrial-hemp-production-in-canada

Lambert LH, Hagerman AD (2022) Industrial hemp production and market risk analysis in Oklahoma. J Appl Farm Econ 5(1):1

Litterman RB (1979) Techniques of forecasting using vector autoregressions. Federal Reserve Bank of Minneapolis, Minneapolis
Litterman RB (1980) Bayesian procedure for forecasting with vector autoregressions. Massachusetts Institute of Technology, Cambridge
Litterman RB (1986) Forecasting with Bayesian vector autoregressions—five years of experience. J Bus Econ Stat 4(1):25–38
Lueger T (2018) A VAR evaluation of classical growth theory. In: Darmstadt discussion papers in economics. Technische Universität Darmstadt, Germany
Ma J, Shang Y, Zhang H (2021) Application of Bayesian vector autoregressive model in regional economic forecast. Complexity 2021
Mark T, Shepherd J, Olson D, Snell W, Proper S, Thornsbury S (2020) Economic viability of industrial hemp in the United States: a review of state pilot programs. United States Department of Agriculture. https://www.ers.usda.gov/publications/pub-details/?pubid=95929
McElreath R (2020) Statistical rethinking: A Bayesian course with examples in R and Stan. Chapman and Hall/CRC
McNeish D (2016) On using Bayesian methods to address small sample problems. Struct Equ Model A Multidiscip J 23(5):750–773. https://doi.org/10.1080/10705511.2016.1186549
Murphy KP (2007) Conjugate Bayesian Analysis of the Gaussian Distribution. Def 1(2σ2):16
Mushtaq K, Dawson P (2002) Acreage response in Pakistan: a co-integration approach. Agric Econ 27(2):111–121
Nazlioglu S, Erdem C, Soytas U (2013) Volatility spillover between oil and agricultural commodity markets. Energy Econ 36:658–665
Ng'ombe JN, Boyer TA (2019) Determinants of earthquake damage liability assignment in Oklahoma: A Bayesian Tobit censored approach. Energy Policy 131:422–433
Papana A, Kyrtsou K, Kugiumtzis D, Diks CGH (2014) Identifying causal relationships in case of non-stationary time series. In: Universiteit van Amsterdam, Center for Nonlinear Dynamics in Economics and Finance
Parvez AM, Lewis JD, Afzal MT (2021) Potential of industrial hemp (*Cannabis sativa* L.) for bioenergy production in Canada: status, challenges and outlook. Renew Sustain Energy Rev 141:110784
Poniatowska J, Wielgus K, Szalata M, Ozarowski M, Panasiewicz K (2019) Contribution of polish agrotechnical studies on *Cannabis sativa* L. to the global industrial hemp cultivation and processing economy. Herba Polonica 65(2)
Price LR (2012) Small sample properties of Bayesian multivariate autoregressive time series models. Struct Equ Model A Multidiscip J 19(1):51–64. https://doi.org/10.1080/10705511.2012.634712
R Core Team (2013) R: A language and environment for statistical computing. Vienna, Austria. https://www.R-project.org/
Robbins L, Snell W, Halich G, Maynard L, Dillon C, Spalding D (2013) Economic considerations for growing industrial hemp: implications for Kentucky's farmers and agricultural economy. University of Kentucky, Lexington, KY
Robertson JC, Tallman EW (1999) Vector autoregressions: forecasting and reality. Econ Rev Fed Reserv Bank Atlanta 84(1):4
Schnitkey G, Swanson K, Zulauf C, Coppess J, Paulson N, Baltz J (2022) Production from double-crop soybean rotations. Farmdoc Daily 12(71)
Seaks TG, Vines DP (1990) A Monte Carlo evaluation of the box–cox difference transformation. Rev Econ Stat 506–510
Sims CA (1988) Bayesian skepticism on unit root econometrics. J Econ Dyn Control 12(2–3):463–474
Sims CA (1989) Models and their uses. Am J Agric Econ 71(2):489–494
Sims CA (1980) Macroeconomics and reality. Econom J Econom Soc 1–48
Small E (2015) Evolution and classification of *Cannabis sativa* (marijuana, hemp) in relation to human utilization. Bot Rev 81(3):189–294
Small E, Naraine SG (2016) Size matters: evolution of large drug-secreting resin glands in elite pharmaceutical strains of *Cannabis sativa* (marijuana). Genet Resour Crop Evol 63(2):349–359
Statistics Canada (2021) Estimated areas, yield, production, average farm price and total farm value of principal field crops. In: Metric and imperial units. Statistics Canada
Statistics Canada (2022) Estimated areas, yield, production, average farm price and total farm value of principal field crops. In: Metric and imperial units. Last Modified February 11, 2022. Accessed December 20, 2021. https://www150.statcan.gc.ca/t1/tbl1/en/tv.action?pid=3210035901
Struik P, Amaducci S, Bullard M, Stutterheim N, Venturi G, Cromack H (2000) Agronomy of fibre hemp (*Cannabis sativa* L.) in Europe. Ind Crops Prod 11(2–3):107–118. https://doi.org/10.1016/S0926-6690(99)00048-5
Uhlig H (2005) What are the effects of monetary policy on output? Results from an agnostic identification procedure. J Monet Econ 52(2):381–419
Van Erp S, Oberski DL, Mulder J (2019) Shrinkage priors for bayesian penalized regression. J Math Psychol 89:31–50. https://doi.org/10.1016/j.jmp.2018.12.004
Vehtari A, Gelman A, Simpson D, Carpenter B, Bürkner P-C (2021) Rank-normalization, folding, and localization: an improved R for assessing convergence of MCMC (with discussion). Bayesian Anal 16(2):667–718
Vonapartis E, Aubin M-P, Seguin P, Mustafa AF, Charron J-B (2015) Seed composition of ten industrial hemp cultivars approved for production in Canada. J Food Compos Anal 39:8–12
Wanless SB, Rimm-Kaufman SE, Abry T, Larsen RA, Patton CL (2015) Engagement in training as a mechanism to understanding fidelity of implementation of the responsive classroom approach. Prevent Sci 16(8):1107–1116. https://doi.org/10.1007/s11121-014-0519-6

Publisher's Note