Impacts of the Drug Trade on Latin American Food Production.

Marco A. Palma[1], Luis Ribera[2] , and David Bessler[3],

[1]Corresponding author. Associate Professor and Extension Economist, Department of

Agricultural Economics. Texas A&M University. 2124 TAMU, College Station, Texas, 77843.

(979) 845-5284. E-mail: mapalma@tamu.edu

[2]Associate Professor and Extension Economist, Department of Agricultural Economics, TAMU.

[3]Professor, Department of Agricultural Economics, TAMU.

**Selected Paper prepared for presentation at the Agricultural & Applied Economics
Association's 2014 AAEA Annual Meeting, Minneapolis, MN, July 27-29, 2014.**

Impacts of the Drug Trade on Latin American Food Production.

Abstract

This article compiles several sources of drug data to provide an analysis of supply and demand factor influencing the drug trade, including potential effects to agricultural production. All effects were found to be contemporaneously independent with the exception of coca production causing arrests in the U.S. Significant lagged effects were found linking agricultural production and coca production. Seizures and arrests were found to have a lagged deterrent effect on coca production. Seizures and arrests had lagged effects in explaining the variance of each other. It is likely that arrests increase intelligence information, resulting in more seizures and eventually more arrests.

Key Words: coca, cocaine, directed acyclic graphs, drug production, drug trafficking, forecast error variance decomposition.

JEL Classifications: K42, Q15.

Drugs have been part of the human culture throughout history with uses ranging from religious to medicinal and recreational purposes. Coca leaf chewing has been reported as far back as 3,000 years ago by South American habitants (Rivera et al. 2005). Spanish conquistadors found that the Incas used coca leaves for ritual, social and physiological reasons as stimulant, a local anesthetic, an agent to suppress appetite, fatigue, altitude effects, and to combat many illnesses (Allen 1988). Cocaine was first extracted from coca leaves around 1860 and used in several drinks, such as Coca Cola and Vin Mariani until its use in beverages was prohibited in the early 1900s (Smart, Liban, and Brown 1981). In the 1970s cocaine was viewed as a benign drug; in fact the relative high prices of the drug contributed to its status as a glamour drug (Agar 2003). Miech (2008) points out that a white paper of the Ford White House in 1975 states that "Cocaine is not physically addictive. Cocaine as currently used, usually does not result in serious consequences, such as crime, hospital emergency room admissions, or death" (Domestic Council Drug Abuse Task Force 1975). However, the glamorous reputation of cocaine did not last long, and by the late 1980s, its name became immediately associated with crime and violence (Agar 2003). Miech, Chilcoat, and Harder (2005) found that the distribution of adult cocaine-use prevalence changed around 1990 from upper socioeconomic strata to lower socioeconomic strata. They argue that perhaps the main reason for this change and the consequent surge in demand for lower income users was the availability of crack cocaine at substantially lower prices.

Today, drug trafficking is considered a serious crime and it is severely punished. In 2012, there were over 30,000 drug related arrests in the U.S. alone (U.S. Department of Justice 2014). Recently, there have been increased efforts in the U.S. to legalize and decriminalize the use and possession of marijuana for medical and recreational purposes. Today there are 20 states, plus the District of Columbia, that allow the use of marijuana for medical purposes. In addition,

Colorado and Washington, allow the use of marijuana for medical and recreational purposes by adults. The increased support for the legalization of marijuana has been debated and it has sparked the attention of policymakers and also the scientific community to study the potential social effects of marijuana legalization (Morris et al. 2014). Svrakic et al. (2012) found significant adverse effects that outweigh the benefits of medical marijuana use. The significance of the marijuana legislation is the argument that its use may result in a broader social acceptance of drug use; and that marijuana serves as a gateway drug to other more dangerous drugs such as cocaine and heroin (Morris et al. 2014). As Musto (1991) points out, the results of these trends remain uncertain, and it is likely that this issue will generate more attention and research among the scientific community.

The cultivation of illicit crops is concentrated in certain regions of the world. Coca is grown almost exclusively in South America, with Colombia, Peru and Bolivia accounting for more than 98 percent of total production (UNIDC 1998). The coca plant is used to extract a cocaine paste that is then chemically converted into cocaine hydrochloride. It takes between 100 to 200 pounds of coca leaves to produce one pound of coca paste; and about 2.5 pounds of coca paste to produce one pound of cocaine (Weiss, Mirin, and Bartel 1994). In 1985, Peru was by far the largest supplier of coca with almost 60 percent, while Bolivia had 33 percent and Colombia a modest 7 percent (National Drug Control Strategy 2011; United Sates Department of State Bureau for International Narcotics and Law Enforcement Affairs 2013). Bagley (2012) provides an informative perspective of policy interventions that changed the coca production environment in the last three decades. He argues that the United States led "war on drugs" intervention in Bolivia and Peru in the 1980s and 1990s shifted production to Colombia. In fact, by the year 2000, Colombia supplied more than 81 percent of the coca, while Peru and Bolivia accounted for

14 and 4 percent respectively (National Drug Control Strategy 2011; United Sates Department of State Bureau for International Narcotics and Law Enforcement Affairs 2013). The U.S. implementation of the "Plan Colombia" in 2002 which provided over $8 billion in aid to combat illicit drugs over a decade was effective in reducing Colombia's coca production (Bagley 2012). Coca production in Colombia was reduced 76 percent over the 2002-2011 period (National Drug Control Strategy 2011; United Sates Department of State Bureau for International Narcotics and Law Enforcement Affairs 2013). As a consequence of the successful anti-drug efforts in South America, drug related violence and criminality shifted to Mexico and Central America (Bagley 2012). Today, it is estimated that as much as 95% of all the cocaine entering into the U.S. flows through Mexico, with about 60% of it stopping first in Central America (Seelke et al. 2011).

Another important consideration for illicit drug trafficking is consumption, with several Latin American political leaders stating that if high demand for illicit drugs in the U.S. did not exist, then Latin American countries would not produce them (Bagley 2012). This statement has been the cause of heated debates among political leaders in the Americas about causal effects of illicit drug production, trafficking and consumption. While the U.S. is still the number one consumer of illicit drugs, cocaine use has been declining since the 1990s (Bagley 2012). Other regions of the world, including the European Union and Latin America are becoming important markets for cocaine use (Bagley 2012).

Drug production, trade, and the drug culture are known to have substantial economic destabilization, social unrest, and cultural, political, work force and violence effects in Latin American countries. Columbia, Peru, Bolivia, Mexico, and a number of Central American countries appear to have been the most adversely affected. However, aside from anecdotal indications of farmers and ranchers temporarily abandoning their operations; moving their

families to countries such as the United States; and reduced availability of farm workers; the impacts of drugs on the agricultural economies go largely ignored. The objective of this article is to analyze the impacts of drug production, trade, and the drug culture on agricultural production for Latin American countries. In order to accomplish the overall objective, several sub-objectives will be accomplished, including: (1) Compile data sets of fragmented and sometimes divergent sources for relevant variables of drug production and trafficking; (2) to evaluate causal patterns of agricultural and drug trade innovations for agricultural production, drug production, prices, consumption, and trade; and (3) to assess the contemporaneous and lagged effects of the drug production, prices, consumption, trafficking, and agricultural production series.

Data and Methods

Due to the illicit nature of the drug culture with clandestine growing and trafficking operations, obtaining uniform and reliable data is a huge challenge. In order to create a uniform data set for relevant variables, several sources were used. The data consists of yearly observations from 1985-2012 of agricultural production in Colombia, coca production in Colombia, cocaine retail prices in the U.S., number of cocaine users in the U.S., number of drug-related domestic arrests by the Drug Enforcement Administration (DEA), and DEA domestic cocaine seizures. Colombia was selected since it is the number one supplier of cocaine and due to data availability issues. Agricultural production includes crop and livestock quantity in metric tons (MT) obtained from the Food and Agriculture Organization (FAO 2014); coca production in (MT) are estimates from the United States General Accounting Office and the United Nations Office for Drugs and Crime (USGAO 1988; UNODC 2012); cocaine retail prices in the U.S. are in dollars per 0.1-2 grams obtained from the Institute from Defense Analysis, National Drug Control Strategy, and United Nations Office for Drugs and Crime (IDA 2008; NDCS 2011a; UNODC 2014); the number of

cocaine users in the U.S. was obtained from UNODC and NDCS (UNODC 2002; NDCS 2011b);

the number of domestic DEA arrests and DEA domestic cocaine seizures in kilograms were

obtained from the U.S. Department of Justice (USDOJ 2012);

A vector autoregression (VAR) model in which directed acyclical graphs (DAG) are used

to sort out causal flows of information is applied following Palma et al. (2010) and Palma et al.

(2013). The model explores how information is communicated across the six variables,

agricultural production (AgQ), coca production (cQ), price (p), users (u), arrests (a) and DEA

seizures (s). Let X_t denote a vector that includes yearly observations for each series:

$$(1) \qquad X_t = \begin{pmatrix} AgQ_t \\ cQ_t \\ p_t \\ u_t \\ a_t \\ s_t \end{pmatrix}$$

where t is an index of time observed. Under fairly general conditions the dynamic correlation

structure between these variables can be summarized as a structural vector autoregression. The

structural VAR representing a $N \times 1$ vector of variables X_t can be written as:

$$(2) \qquad \Phi_0 X_t - \sum_{k=1}^{K} \Phi_i X_{t-k} = \varepsilon_t$$

Here contemporaneous and lagged values of observational measures on X at periods t-k, $k = 0$,

1, …, K are mapped into the white noise innovation term ε_t, where $Cov(\varepsilon_t) = \Omega$ and M_i, i=0, 1,

…, K are square autoregressive matrices of order 6. The innovations ε_t represent new

information arising in each element of the X vector at time t. Equation (2) can be written in an equivalent form as:

(3) $\quad X_t - \Phi_0^{-1}\Phi_1 X_{t-1} - \cdots - \Phi_0^{-1}\Phi_k X_{t-k} = \Phi_0^{-1}\varepsilon_t.$

The reduced form (non-structural) VAR is written in similar form as:

(4) $\quad X_t - \Pi_1 X_{t-1} + \cdots + \Pi_k X_{t-k} = u_t;$

where $\Pi_h = \Phi_0^{-1}\Phi_h$ for k = 1, …, K and $u_t = \Phi_0^{-1}\varepsilon_t$. The reduced form innovations (u_t) are "mongrel" or mixtures of structural innovations ε_t. It follows thus that

$$Cov(u_t) = \Sigma = \Phi_0^{-1}\Omega\left(\Phi_0^{-1}\right).$$

The key to modeling equation (4) is proper identification of the matrix M_0. Bernanke (1986) and Sims (1986) used prior theory to achieve such identification. Swanson and Granger (1997) used the causal pattern exhibited by observed innovations $\hat{u}_t$ to identify M_0. This article uses the machine learning algorithms of Spirtes, Glymour and Scheines (2000) to achieve structural identification.

The dynamic response patterns summarized by a VAR are difficult to interpret (Sims, 1980; Swanson and Granger, 1997). They can be best summarized through the moving average representation (MAR) solved for equation 4 where the vector X_t is written as a function of the infinite sum of past innovations:

(5) $\quad X_t = \sum_{i=0}^{\infty}\Theta_i u_{t-i}$

where Θ_i is a 6x6 matrix of moving average parameters, which map historical innovations at lag i into the current position of the vector X. Notice Θ_0 is generally not the identity matrix, as we use directed graph structures on the observed innovations from equation (4) to translate nonstructural innovations to structural innovations (Swanson and Granger 1997).

A directed graph is a graphic representing the causal patterns among a set of variables. Lines with arrowheads represent such flows. For instance, $X_1 \rightarrow X_2$ indicates that variable X_1 causes variable X_2. Observed innovations from an estimated form of equation (4) are modeled as a directed acyclic graph for each series. An acyclic graph has no path (sequence of connected variables) that returns to a variable. The direction of causal flow among a set of variables is caused by the screening-off phenomena and the more formal representation as d-separation (Pearl, 2000). For three variables X_1, X_2, and X_3, if variable X_1 is a common cause of X_2 and X_3 such that $X_2 \leftarrow X_1 \rightarrow X_3$, then the unconditional association between X_2 and X_3 will be non-zero, as both have a common cause in X_1 (this pattern is labeled a causal fork (Pearl 2000)). If correlation is measured by association, then X_2 and X_3 will have a correlation not equal to zero However, if we condition on X_1, the partial correlation between X_2 and X_3 will be zero. A common cause (X_1) screens off association between its effects (X_2 and X_3). A causal inverted fork exists if the causal patters exhibit the form $X_1 \rightarrow X_2 \leftarrow X_3$, where X_2 is a common effect of X_1 and X_3, and X_2 screens off association between its causes. If the pattern is as follows, $X_1 \rightarrow X_2 \rightarrow X_3$, then a causal chain exists, and X_2 screens off communication between X_1 and X_3.

An algorithm embedded in TETRAD IV was used for the analysis. In order for the methods to converge to correct decisions, the significance level used in making decisions should decrease as the sample size increases and the use of higher significance levels (e.g., .2 at sample sizes less than 100, and .1 at sample sizes between 100 and 300) may improve performance at

small sample sizes." (Spirtes, Glymour and Scheines, 2000). This is particularly important for this article, given the low number of data points for each series.

The directed acyclic graph VAR results are used to decompose the variance of ε_t in equation 2 and generate impulse responses and forecast error variance decompositions (FEVD) over extended forecast horizons. FEVD show the contributions of each of the variables in X_t to its own shocks and to shocks of the other series. Hence, FEVD provides a useful way to measure the degree of endogeneity (or exogeneity) of each series in contemporaneous time and also over extended forecast periods. If shocks to a variable are mostly explained by its own series in the forecast error variance, then that variable may be considered highly exogenous to the other variables in the system (McKenzie, Goodwin, and Carreira 2009); Alternatively, if one or more series have large FEVD contributions to the shocks of that variable, then it is considered endogenous.

Results and Discussion

The data series plots for each variable X_t are presented in Figure 1. A VAR was fit with one lag for each variable X_t in the series. Coca is a perennial plant that can only be harvested 6 months to three years after planting; however, once it is mature its leaves can be harvested several times a year for up to twenty years or more (Weiss, Mirin, and Bartel 1994). Due to the perennial nature of the coca plant, a two-lag VAR was also estimated, but given the very small size of the sample the pattern on causal flows in contemporaneous time resulted in unstable responses. An analysis of a first difference VAR was also conducted with very similar results to the one lag VAR. Since there are no prior theoretical assumptions (such as the law of one price) cointegration was not pursued, although the results of such model would be expected to yield very similar results. Causal patterns on innovations from the one-lag VAR model were fit to

annual observations of agricultural production (AgQ), coca production (cQ), retail price of

cocaine (p), number of users (u), number of arrests (a) and DEA seizures (s). The causal patterns

on innovations for X_t are presented in Figure 2. There are not many causal patterns on

innovations for the series in contemporaneous time. In fact innovations for Colombia agricultural

production, U.S. cocaine retail prices, Number of users, and DEA seizures are

contemporaneously independent. Information flows of Colombia coca production and DEA

arrests are connected but it is not clear which variable causes which. Therefore, impulse

responses from the VAR fit to each variable X_t are presented in Figure 3. The undirected edge

between arrests and Colombia coca quantity presented in Figure 2 is directed as cQ→a

(Colombia coca production causes arrests) as the estimated coefficient on this edge is positive. In

contemporaneous time, the production and supply of coca in Colombia causes arrests in the U.S.

Seizures are contemporaneously independent with coca production in Colombia. The

independence of seizures and coca production in Colombia seems to point out that coca

production is not affected by losses due to confiscated cocaine seizures in the U.S. Perhaps

cocaine seizures are viewed as a cost of doing business at least in contemporaneous time.

Forecast error variance decompositions (FEVD) at Horizons of 0, 1, 2, and 7 years ahead

on each series are presented in Table 1. The standard error for each series increases at a

decreasing rate, providing some evidence of valid regression non-stationary errors terms (Sims

1980). The uncertainty in each series, at horizons 0 (contemporaneous time), 1, 2, and 7 years

ahead (column a), is measured and presented as the standard errors (column b). This measure is

accounted for by variations in information arising from each series. Each series contributions are

headed by the label "Due to." Each row then adds up to 100% (except for rounding errors). In

contemporaneous time (horizon 0), 100% of the uncertainty in cocaine retail prices in the U.S. is

accounted for by variation in the cocaine retail prices series itself. As the time horizon increases to 1, 2, and 7 years ahead, the uncertainty in cocaine retail prices is explained by variations in the number of users in the U.S., the number of arrests in the U.S., agricultural production in Colombia, and to a lesser degree by the number of DEA seizures and coca production in Colombia. In looking seven years ahead in the time horizon (last row of the first panel), cocaine retail prices are still highly exogenous, with 82.85% of the uncertainty in the retail prices of cocaine explained by retail prices itself; however, cocaine retail prices are also explained, although in a small way, by variations in the number of users (5.17%), number of arrests (4.78%), agricultural production in Colombia (4.62%), DEA seizures (1.80%), and coca production in Colombia (0.78%). Both supply and demand factors affect the retail price of cocaine with agricultural production explaining part of the variance, suggesting a potential lagged effect of non-drug agricultural production in Colombia and cocaine prices in the U.S.

Recall from Figure 2, that agricultural production and coca production in Colombia were contemporaneously independent. This result is reinforced in table 2 where 100% of the uncertainty for agricultural production in Colombia, and 100% of the coca production in Colombia are explained by innovations in their own series. Moving beyond the time horizon results in increasing contributions of the other series to explain both agricultural and coca production in Colombia. In a seven year horizon the variation on agricultural production is explained by changes in the agricultural production series itself (66.24%), cocaine seizures in the U.S. (9.75%), coca production in Colombia (9.42%), arrests (9.36%), and a small contribution of users (2.78%) and cocaine prices (2.46%). Coca production in Colombia at the horizon of seven years ahead is accounted for variations in its own coca production series (23.69%), DEA seizures

(27.17%), arrests (21.28%), Colombia agricultural production (23.26%), and in a smaller way by cocaine retail prices (4.12%) and the number of users (0.48%).

Agricultural and coca production FEVD show some interesting results. First, the findings reinforce the results of the price series, where there seems to be a lagged influence, perhaps in the form of a land trade-off, between agricultural production and coca production. As the time horizon is increased, coca production significantly influenced agricultural production. A possible explanation is that as coca production increases, which mainly takes place in rural areas, those communities flourish economically bringing more agricultural development to the area. Angrist and Kugler (2007) found that rural communities in Colombia engaged in coca leaf production and harvesting generated modest economic gains and increased self-employment income. They define self-employment income as that generated from short-term contracts, from the sale of domestically produced goods and from commercial or family based agricultural production. Consequently, in addition to competing for land, coca production may also be directly influencing agricultural production through is revenue generating stream. Secondly, in contemporaneous time, coca production in Colombia is fully explained by variations in its own series, but as the time horizon is expanded, in a short-term of one to two years, agricultural production accounts for a major variation of coca production. Arrests and retail prices seem to have modest effects in accounting for the variance of coca production. Note that expanding beyond the two year horizon to a seven year horizon notably increases the variation in coca production explained by seizures (27.17%); in fact seizures in a seven year horizon explain a larger portion of the variance of coca production than its own series (23.69%). So while in the very short-term seizures do not seem to impact coca production, they do have a significant role when looking at seven years ahead in the horizon. This would suggest that the decision to expand

the production of coca is affected by the amount of cocaine seizures. Finally, the role of arrests in explaining uncertainty in coca production is large (21.28%). This seems to indicate that over time arrests may be a deterrent to coca production. Although modest, the role of cocaine retail prices in explaining coca production seems to increase as the time horizon is increased from 2.18% in a one year horizon to 4.12% in a seven year horizon.

Seizures are exogenous in contemporaneous time. Interestingly, as the time horizon is increased, arrests seem to have an increasing role in explaining uncertainty in seizures. The variation of seizures explained by arrests goes from 0% in year 0, to 6.55% in year 7. The logical explanation for this is that as arrests are increased, more information is obtained about the drug trafficking network, practices, and traffickers, resulting in increased seizures. Uncertainty in arrests is explained by variation in itself (66.17%), and coca production (33.83%). Coca production leads to arrests as noted previously (Figures 2 and 3). Seizures do play a bigger role in explaining arrests as the time horizon is expanded. Again, the reason is that more seizures lead to more arrests, which in turn leads to intelligence gains about drug activities and hence more arrests. The number of users is exogenously determined in contemporaneous time. The role of price in accounting for the variation in the number of users increases as the time horizon is expanded.

Summary and Conclusions

Drug production, trade, money laundering, and the drug culture are known to have substantial economic destabilizing, social unrest, and cultural, political, work force and violence effects on Latin American countries. Columbia, Peru, Bolivia, Mexico, and a number of Central American countries appear to have been the most adversely affected. Aside from anecdotal indications of farmers and ranchers temporarily abandoning their operations; moving their families to countries

such as the United States; and reduced availability of farm workers; the impacts of drugs on the agricultural economies go largely ignored.

Due to the illicit nature of drug trade, obtaining reliable and uniform data about production and trade of coca was extremely difficult. Several sources were used to gather yearly information from 1985-2012 of agricultural production in Colombia, coca production in Colombia, cocaine retail prices in the U.S., number of cocaine users in the U.S., number of drug-related domestic arrests by the Drug Enforcement Administration (DEA), and DEA domestic cocaine seizures. Several other variables were also collected, but given the low number of observations the analysis was limited. This article provides an analysis of supply and demand factor influencing the drug trade, including potential effects to agricultural production.

Most effects were found to be contemporaneously independent. Coca production causes arrests in the U.S. Lagged effects existed linking agricultural production and coca production. As the time horizon is increased, coca production significantly influenced agricultural production. A possible explanation is that as coca production increases, which mainly takes place in rural areas, those communities flourish economically bringing more agricultural development to the area. These results would support the findings of Angrist and Kugler (2007) who found that rural communities in Colombia who engaged in coca leaf production and harvesting generated modest economic gains and increased income in commercial and family based agriculture. Seizures and arrests were found to have a lagged deterrent effect on coca production. Seizures and arrests were also found to have lagged effects in explaining the variance of each other. It is likely that as arrests are made, more intelligence information is gathered about practices, routes, and people involved which results in more seizures and eventually more arrests.

This exploratory analysis about cocaine trafficking and its impacts to Latin American agriculture was restricted by the availability of a uniform data set. The number of variables that could be used in the analysis was a limiting factor; however the article provides some quantitative answers to questions that had only been answered by anecdotal information. The whole area of drug trade and its associated economic, social, and political effects merits more attention. It is the prerogative of this article to start this discussion and to motivate further research in the area.

References

Agar, Michael. 2003. "The story of crack: Towards a theory of illicit drug trends." *Addiction Research & Theory* 11 (1):3-29.

Allen, Catherine J. 1988. *The hold life has: coca and cultural identity in an Andean community*. Vol. 35: Smithsonian Institution Press Washington, DC.

Bagley, Bruce Michael. 2012. *Drug Trafficking and Organized Crime in the Americas: Major Trends in the Twenty-First Century*: Woodrow Wilson International Center for Scholars, Latin American Program.

Bernanke, B. S. 1986. "Alternative explanations of the money-income correlation." *Carnegie-Rochester conference series on public policy* 25 (C):49-99.

Bureau of International Narcotics and Law Enforcement Affairs. 2013. "Bureau of International Narcotics and Law Enforcement Affairs Fact Sheets." Accessed June 5, 2014. http://www.state.gov/j/inl/rls/fs/.

Drug Abuse Task Force, Domestic Council. 1975. *White paper on drug abuse, September 1975: a report to the President from the Domestic Council Drug Abuse Task Force*: For sale by the Supt. of Docs., U.S. Govt. Print. Off.

FAO, Food and Agriculture Organization of the United Nations. 2014. Accessed June 5, 2014.

    http://faostat3.fao.org/faostat-gateway/go/to/download/Q/QP/E.

Institute for Defense Analyses. 2008. Accessed June 5, 2014.

    http://www.whitehouse.gov/sites/default/files/ondcp/policy-and-research/bullet_1.pdf.

McKenzie, Andrew A, Harold L. Goodwin, and Rita I Carreira. 2009. "Alternative Model

    Selection Using Forecast Error Variance Decompositions in Wholesale Chicken

    Markets." Journal of Agricultural and Applied Economic 41 (1): 227-240.

Miech, Richard. 2008. "The formation of a socioeconomic health disparity: the case of cocaine

    use during the 1980s and 1990s." *Journal of health and social behavior* 49 (3):352-366.

Miech, Richard A, Howard Chilcoat, and Valerie S Harder. 2005. "The increase in the

    association of education and cocaine use over the 1980s and 1990s: evidence for a

    'historical period'effect." *Drug and alcohol dependence* 79 (3):311-320.

Morris, Robert G, Michael TenEyck, JC Barnes, and Tomislav V Kovandzic. 2014. "The effect

    of medical marijuana laws on crime: evidence from state panel data, 1990-2006." *PloS*

    one 9 (3):e92816.

Musto, David F. 1989. "History of American Drug Control, The." *Update on L. Related Educ.*

    13:3.

Pearl, Judea. 2000. *Causality : models, reasoning, and inference*. Cambridge, U.K. New York:

    Cambridge, U.K. New York : Cambridge University Press.

Rivera, Mario A, Arthur C Aufderheide, Larry W Cartmell, Constantino M Torres, and Odin

    Langsjoen. 2005. "Antiquity of coca-leaf chewing in the south central Andes: a 3,000

    year archaeological record of coca-leaf chewing from northern Chile." *Journal of*

    psychoactive drugs 37 (4):455-458.

Seelke, Clare Ribando;, Liana; Beittel Sun Wyler, June S.;, and Mark P. Sullivan. 2010. "Latin America and the Caribbean: Illicit Drug Trafficking and US Counterdrug Programs." *Congressional Reearch Service*.

Sims, Christopher A. 1980. "Macroeconomics and Reality." *Econometrica* 48 (1):1-48. doi: 10.2307/1912017.

Smart, RG, C Liban, and G Brown. 1980. "Cocaine use among adults and students." *Canadian journal of public health= Revue canadienne de sante publique* 72 (6):433-438.

Spirtes, Peter, Clark N Glymour, and Richard Scheines. 2000. *Causation, prediction, and search*. Vol. 81: MIT press.

Svrakic, DM, PJ Lustman, A Mallya, TA Lynn, R Finney, and NM Svrakic. 2011. "Legalization, decriminalization & medicinal use of cannabis: a scientific and public health perspective." *Missouri medicine* 109 (2):90-98.

Swanson, N. R., and C. W. J. Granger. 1997. "Impulse response functions based on a causal approach to residual orthogonalization in vector autoregressions." *J. Am. Stat. Assoc.* 92 (437):357-367.

The White House. 2011. "National Drug Control Strategy." The White House Accessed June 5, 2014. http://www.whitehouse.gov/sites/default/files/ondcp/ndcs2011.pdf.

U.S. Department of Justice. 2014. "DEA.gov/ Statistics & Facts." Accessed June 5, 2014. http://www.justice.gov/dea/resource-center/statistics.shtml#arrests.

United Nations International Drug Control Programme, UNODC. 2014. "UNODC.org." Accessed June 5, 2014. www.unodc.org/pdf/technical_series_1998-01-01_1.pdf.

USGAO, United States General Accounting Office. 2014. "General Accounting Office

    Publications on Drugs and Drug Policy." Accessed June 5, 2014.

    http://druglibrary.net/schaffer/GovPubs/gao/gaomen1.htm.

Weiss, Roger D., Steven M. Mirin, and Roxanne L. Bartel. 1994. *Cocaine*. Edited by Steven M.

    Mirin and Roxanne L. Bartel. Washington, DC: Washington, DC : American Psychiatric
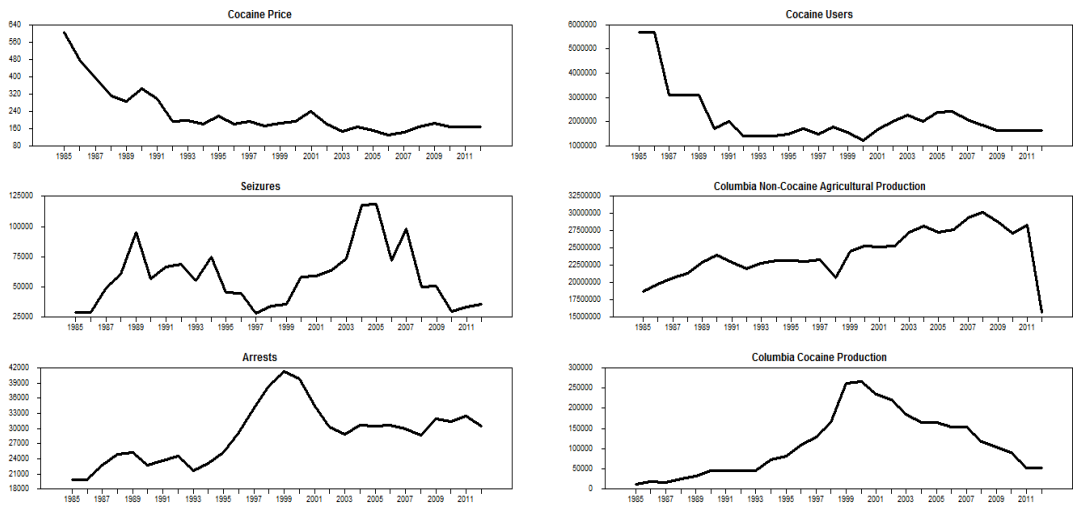
    Press.

Figure 1. Data on agricultural production in Colombia (AgQ), coca production in Colombia (cQ), retail price of cocaine in the U.S. (p), number of users in the U.S. (u), number of arrests in the U.S. (a), and DEA seizures in the U.S.

Units are as follows: Agricultural Production in Colombia is in MT; Coca Production in Colombia is in MT; Retail Price of Cocaine is in $ per 0.1-2 grams; number of users and arrests are the actual number; DEA seizures are in Kg.
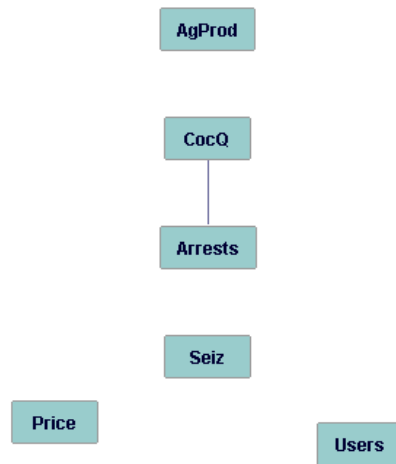
Figure 2. Causal Patterns on Innovations from a Vector Autoregression fit to 1985 – 2012 data on innovations in Colombia Agricultural Production, Columbia Cocaine Quantity, Cocaine Price in the US , Cocaine Users in the US, US Cocaine Arrests, and USDEA Cocaine Seizures.
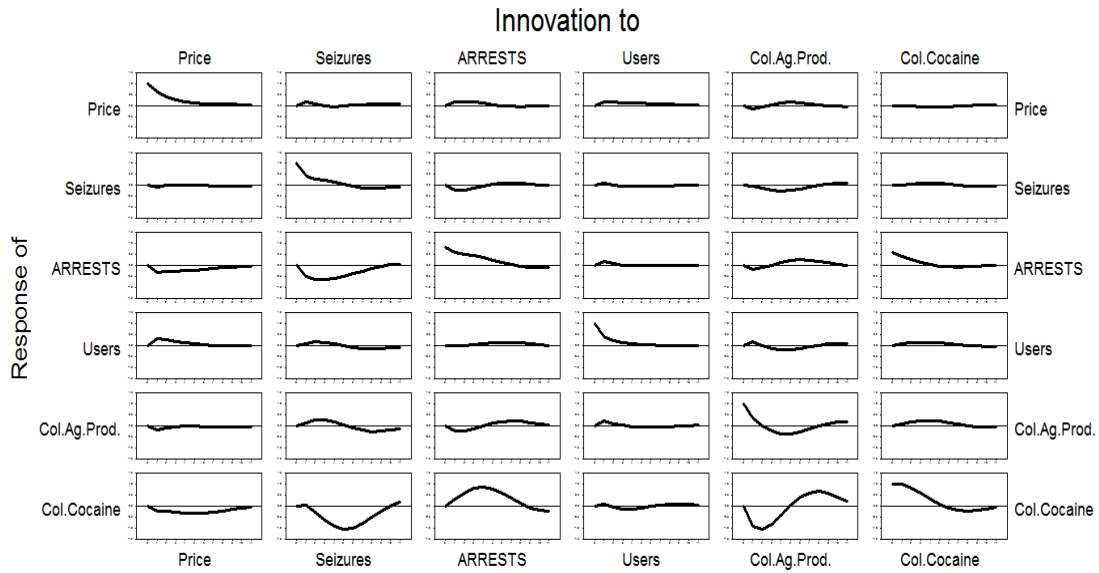
Figure 3. Impulse responses from a Vector Autoregression fit to 1985 – 2012 data on Colombia Agricultural Production, Columbia Cocaine Quantity, Cocaine Price in the US, Cocaine Users in the US, US Cocaine Arrests, and USDEA Cocaine Seizures.

Note: The undirected edge between Arrests and Cocaine Quantity presented in Figure 2 is directed as Cocaine Quantity → Arrests as the estimated coefficient on this edge is positive.

Table 1. Forecast Error Variance Decomposition at Horizons of 0, 1, 2, and 7 years Ahead on agricultural production in Colombia (AgQ), coca production in Colombia (cQ), retail price of cocaine in the U.S. (p), number of users in the U.S. (u), number of arrests in the U.S. (a), and DEA seizures in the U.S., Yearly Data 1985-2012.

Horizon (a)	Standard Error (b)	Due To: Price (c)	Due To: Seizures (d)	Due To: Arrests (e)	Due To: Users (f)	Due To: Agricultural Production (g)	Due To: Coca Production (h)
Price
0	28.23	100.00	0.00	0.00	0.00	0.00	0.00
1	34.09	93.04	1.84	1.75	1.46	1.91	0.00
2	36.56	90.05	1.81	3.50	2.65	1.94	0.05
7	39.69	82.85	1.80	4.78	5.17	4.62	0.78
Seizures
0	18152.33	100.00	0.00	0.00	0.00	0.00	0.00
1	20197.74	0.43	95.33	3.40	0.59	0.17	0.07
2	21386.60	0.39	91.66	5.61	0.55	1.27	0.51
7	23975.67	0.40	78.23	6.55	0.81	11.43	2.58
Arrests
0	1958.30	0.00	0.00	66.17	0.00	0.00	33.83
1	2725.40	5.10	12.55	52.30	1.76	1.81	26.47
2	3259.95	6.47	22.88	46.34	1.45	1.53	21.32
7	4320.03	8.13	37.66	35.26	.089	5.20	12.86
Users
0	417170.77	0.00	0.00	0.00	100.00	0.00	0.00
1	477263.71	7.94	0.97	0.02	88.03	2.65	0.41
2	508555.68	11.48	3.08	0.02	81.72	2.33	1.38
7	568612.91	12.62	5.39	3.61	67.42	6.55	4.41
Agricultural Production
0	1972185.66	0.00	0.00	0.00	0.00	100.00	0.00
1	2228178.07	2.95	1.46	4.01	3.26	87.64	0.69
2	2370589.799	3.37	5.41	7.27	3.57	77.42	2.96
7	3013380.21	2.46	9.75	9.36	2.78	66.24	9.42
Coca Production
0	16842.18	0.00	0.00	0.00	0.00	0.00	100.00
1	29058.50	2.18	0.06	2.69	0.17	29.43	65.47
2	38591.46	2.49	1.54	8.05	0.21	37.94	49.77
7	60464.19	4.12	27.17	21.28	0.48	23.26	23.69

Note: The uncertainty in each series, at horizons 0, 1, 2 and 7 years ahead, is measured as the column labeled "Standard Error." This measure is accounted for by variations in information arising from each series. We label each series' contribution under the columns headed by the label "Due To:". For example 100% of the uncertainty in Coca Production in Colombia at the seven year ahead horizon (last row of the last panel (60464.19)) is accounted for by variation in Cocaine Price (4.12%), Seizures (27.17%), Arrests (21.28%), Users (0.48%), Agricultural Production (23.26%) and Coca Production (23.69%).