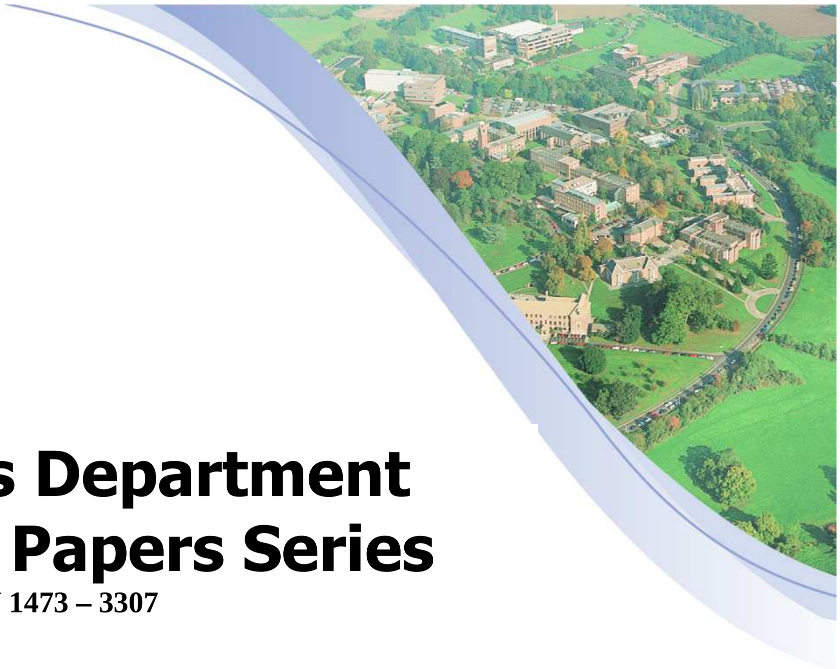
UNIVERSITY OF EXETER



Economics Department Discussion Papers Series

ISSN 1473 – 3307

Weather, Prices and Spillovers

Annalisa Marini and Steve McCorriston

Paper number 19/05

Weather, Prices and Spillovers

Annalisa Marini and Steve McCorriston*

This Version: 4th June, 2019

Abstract

Changes in weather patterns associated with climate change can be an important determinant of commodity price volatility. In this paper, we provide new insights into this issue from two perspectives. First, by using detailed country-level precipitation data for a specific commodity (bananas), and employing a panel VAR model, we show that untypical rainfall patterns are an important influence on export prices and that the impact on export prices varies across exporters given the largely uncorrelated experience of anomalous levels of precipitation. Second, we show that source-specific rainfall patterns generate spillovers across competing exporters and these spillover effects can dominate the own-country precipitation anomaly effect. Accounting for these spillover effects is important for several reasons: (i) the aggregate impact of weather fluctuations on importers depends on the magnitude of these effects which we show to be quantitatively strong; (ii) for some exporters, the spillover effect on export prices can be a more important source of price volatility than their own experience of untypical weather; (iii) given the frequency of precipitation anomalies across all export countries, untypical variations in weather is an important source of commodity price volatility for all exporters and importers. In sum, the impact of climate-related weather events on prices is more nuanced than recent research has suggested.

Keywords: Weather, Spillovers, Export Prices, Panel Vector Autoregression (PVAR)

*Marini, Department of Economics, University of Exeter Business School, Exeter, England, UK, a.marini@exeter.ac.uk; McCorriston, Department of Economics, University of Exeter Business School, Exeter, England, UK, s.mccorriston@exeter.ac.uk. This research was funded by the UK Global Food Security Programme (grant number BB/N020847/1). We are grateful for interactions with Dan Bebber and Varun Varma on this project and particular thanks to Varun Varma for technical support in the collection of weather data.

Weather, Prices and Spillovers

Introduction

In this paper, we contribute to recent research on the international dimensions of climate change. Fitting between two recent strands of this avenue, as with Dell and Olken (2014), we focus on the potential impact of climate change on a specific importing country; as with Brunner (2002) and Cashin *et al.* (2017), we consider price effects given fluctuations in weather in exporting countries. Given that for many primary commodities, importing countries will be potentially exposed to extreme climate events in exporting countries, the extent to which importing countries are susceptible is an issue which has been largely absent from the literature (see Dell *et al*., 2014). The exposure of importing countries to climate events has only been captured at an aggregate level to date. In Dell and Olken (2014), they aggregate across all imports into the US where the climate data relates to annual variations in weather as determinants of imports into the US. In terms of recent research on the impact on prices, the focus has been on world commodity prices employing ENSO anomaly data that is non-specific to the commodity sectors and exporting countries. While the Dell and Olken (2014) approach uses annual data and therefore can be used to address long-run aspects of weather fluctuations, Brunner (2002) and Cashin *et al.* (2017) employ quarterly data which allows for a more short-to medium term focus. However, while Brunner (2002) and Cashin *et al*. (2017) employ ENSO anomaly data to capture climate events on world commodity prices, we take a more granular approach: we focus on monthly export prices from the main exporters of a specific commodity to a given destination importer using country and commodity-specific weather data. In that context, our approach measures the short-to-medium run impact on price volatility that arises from untypical-but more accurately recorded-fluctuations in weather experienced in specific countries.

This more granular approach is premised on accounting for a number of factors that we argue are relevant in addressing the price impacts of climate-related events. First, weather fluctuations are often country or region-specific. This spatial diversity (even across countries that are geographically close) in weather fluctuations is not captured with more aggregate ENSO data. This measure of climate variability may not accurately account for the weather variations that impact on specific crops in given locations. To this end, we use commodity and country-specific variations in rainfall. There has been a long-standing linkage between ENSO variability and fluctuations in precipitation but, as Ropelewski and Halpbert (1987) point out, the experience across different geographic regions is not necessarily uniform.

Second, by accounting for all exporters to a specific destination, the aggregate price effect that will impact on the import market will depend not only on the direct effect due to weather fluctuations arising in one country but also the spillover effects resulting from the impact of prices from other exporting countries, even if they did not experience the same weather fluctuation. By combining data that relates to the spatial diversity of weather coupled with employing a methodology that captures the direct and spillover effects on prices across the range of exporters, we provide a more nuanced approach to assessing the price effects arising from short-to medium run climate-related weather fluctuations than more aggregate approaches.

Specifically, we apply a panel vector auto-regression (VAR) model as set out by Canova and Ciccarelli (2009). We apply this panel VAR approach to exports of a single agricultural commodity (bananas) to a specific destination (the UK) from its main suppliers (Belize, Costa Rica, Ecuador, Colombia, the Dominican Republic, the Côte d'Ivoire and Cameroon); we carefully detail weather fluctuations as they relate specifically to the banana growing regions of each of these export countries. While recent research on the long-run climate impacts indicate that some countries will gain from changes in climate and others lose, even in countries that may reap productivity improvements in the long-run may be subject to extreme weather events in the short-run. For example, various banana exporting countries are also impacted by short-run climate extremes though the frequency and timing of these extremes will likely vary across the main exporting countries and they are also likely to increase in frequency. Recent media reports provide some context to the effects of anomalous rainfall on banana sectors across various countries. Examples of heavy rainfall in banana exporting countries include: in 2012, a substantial reduction in banana exports from Ecuador due to flooding; in 2015, banana producing regions in Costa Rica experienced an increase in rainfall 50 per cent above average; in 2016, heavy rain associated with El Niño was seen as a major threat to banana production in Ecuador; the UK media reported the potential threat to prices in the UK in 2018 following heavy rain in Costa Rica (and Guatemala not in our sample) and followed heavy rain and flooding in the previous year in Costa Rica and the Dominican Republic. In sum, the aim of this paper is to combine detailed measures of fluctuations in weather in each of the main banana exporting countries to the UK, while accounting for other determinants of export prices from each of these countries, to identify the short-run impact of weather on export prices to the UK.

Our approach offers a number of new insights into the potential impact of climate change across countries. First, we show that 'untypical' monthly variations in precipitation have significant effects on commodity prices to the UK. Second, following from the observation that the spatial dispersion in 'untypical' weather variation is not highly correlated, we isolate the weather effect arising from specific countries but also the impact on prices from other exporters. Importantly, the effect of a source-specific weather anomaly on the import market is therefore a combination of the direct export price effect from weather-impacted country plus the spillover effect across all other exporters. These potentially significant spillover effects are therefore important determinants of commodity price volatility across exporters: our results show the spillover effects originating from competing exporters can even dominate the direct impact of weather fluctuations in individual exporting countries.

In sum, untypical precipitation fluctuations across banana exporting countries increase export prices where the magnitude of the overall effect depends on the direct and spillover effects. These weather fluctuations are therefore an important source of commodity price volatility for both importing countries and for competing exporters even when the weather event is geographically localised. The paper is organised as follows. In Section 2, we relate our approach to recent literature on the international dimensions of climate change. Details of the weather data as it relates to export countries are presented in Section 3. The econometric methodology is outlined in Section 4 together with details of the additional data involved in estimating the model. The results are presented in Section 5. We summarise and conclude in Section 6.

2. Related Literature

There has been a burgeoning literature on the economic and wider social impacts of climate change which have been summarised in recent reviews by, *inter alia*, Dell *et al.* (2014) and Carleton and Hsiang (2016). As these reviews highlight, differentiating between climate and variations in weather is an important dimension of this research. Dell *et al*. (2014) review primarily panel methodologies employed to identify the impact of weather variations while Carleton and Hsiang (2016) take a broader view of the impact of climate including coverage of extreme events. As noted by both reviews, the impact of climate extends across economic outcomes, health and mortality, crime and conflict, among other issues.

One dimension of the economic outcomes that has received relatively little attention to date is the potential impact of climate change across borders and the potential for spillover effects (see Dell *et al*., 2014). There are two aspects to this. First, climate change and variation in weather can have a spatial dimension such that variations in weather may be relatively uncorrelated across different countries; just as the longer term trends in climate change will have a differential impact across countries, so will short-run variations in weather as untypical weather patterns that will impact on prices will not (necessarily) be common across all countries. But even uncorrelated anomalous weather patterns will have impacts across borders. This extends to a second aspect of the cross-border dimension of climate change which relates to the trade and commodity market implications. A recent FAO report (FAO, 2018) has highlighted the trade implications of climate change, an issue which has been also addressed by Golin and Laborde (2018).

More pertinent to the focus of his paper is recent research on the links between climate and commodity prices. Brunner (2012) and Cashin *et al.* (2017) address the impact of El Niño on a several macroeconomic aggregates including world commodity prices; Cashin *et al*. (2017) report a significant positive impact on world commodity prices with El Niño-related anomalies leading to a cumulative impact (after 4 quarters) on world commodity prices by approximately 4 per cent. Ubilinov (2017) focuses on the quantifying the link between El Niño and the world prices for a number of agricultural commodities. There are two common features to this recent line of research on climate events on commodity prices. First is the use of ENSO anomaly data to identify the climate event: however, the weather-related implications of ENSO anomalies may not be common across commodity exporting countries. Second is the focus on 'world' commodity prices rather than export prices from specific countries that were the source of the weather fluctuations. Observing that the 'world' price for any given commodity is an indicator price recorded in a given market, these indicator prices may not be wholly representative of the specific prices paid by importers given the role of contracts, the designation of standards and quality, and other aspects of vertical coordination that are common features of trade and the distribution of banana exports across countries. For example, in the UK market, imports are sourced from a relatively small number of countries, where multinational firms play a key role in the distribution of bananas but where the highly-concentrated retail sector is an important determinant of pricing throughout the value chain. For some retailers, direct negotiation with banana producers in exporting countries is also a feature of procurement in the UK banana market.

Our approach is closest in methodological approach to Cashin *et al*. (2017) insofar as we use a panel VAR approach. As Dell *et al.* (2014) note, one potential downside to the use of standard panel approaches is that other time-varying determinants within each cross-section unit of the variable of interest are likely to be omitted, the panel VAR approach permitting a route to dealing with this downside. We apply the panel VAR approach to specific commodity (bananas) from 7 exporting countries to a specific destination which allows us to address spillover effects. Spatial spillovers relate not only to the (lack of) correlation in weather variations across countries but also allow us to accommodate and isolate the economic impact insofar as country-level weather variations will have an effect on other exporters, in our case on export prices of competing exporters. The aggregate impact of weather variation in exporting countries on the destination market therefore relates to both the direct effect of weather variation in one country and the spillover effects on prices from competing exporters. The methodological approach is outlined following the discussion of the weather data.

3. Climate and Weather in Banana Exporting Countries

Bananas are the 4th most important commodity trade (by value) on world markets; most developed countries are largely dependent on imports for consumption and, for exporting countries located mainly in developing and emerging economies of Central and Latin America and some African and Asian countries, banana exports are significant contributors to export earnings. For the countries covered in the econometric model below, export earnings from bananas as a proportion of total exports earnings can be significant, particularly for some Central and Latin American countries: export earnings from bananas as a proportion of total exports for Belize are 15 per cent; for Costa Rica, 9 per cent; the Dominican Republic, 7 per cent; and for Ecuador, 15 per cent[1]. For the other countries exporting to the UK (Colombia, Côte d'Ivoire and Cameroon), banana exports as a share of

[1] Data relates to 2015.

total exports are considerably lower. These seven countries account for 90 per cent of banana imports into the UK. As such, climate change and untypical variations in weather have potentially significant impacts on both exporting and importing countries.

Bananas are largely grown around the central latitude with the main production areas located in Central and Latin America, the Philippines and some regions of Africa. Ideal conditions correspond to temperatures within the range of 26-28 degrees. Weather variation around the central latitude is associated with El Niño and some areas of banana production (particularly the Caribbean and the Philippines) are prone to tropical storms and hurricanes. Despite the importance of banana exports as a traded commodity and in the export earnings for the main producers, there has been only limited consideration of the potential impact of climate change on banana production. Two exceptions to this are the studies by Ramirez *et al.* (2011) and Van der Bergh *et al*. (2010): using the IPCC climate forecasts, they confirm that climate change will alter the production of bananas globally over the long-run. Machiveno and Feeley (2013) explore the potential impact of climate change across banana exporting regions more directly. Climate change and the costs associated with mitigation will also be associated with increasing disease risk. Gasparotto and Pereira (2008) relate changing weather patterns to Panama disease.

Whatever the long-run implications of climate change on the distribution of banana production, climate change will also be related to the increasing frequency of extreme events and more volatile weather patterns. For banana exporting countries, the most common occurrence of extreme events relate to excessive rainfall, hurricanes and storms and, associated with this, flooding. Excessive rainfall is related to El Niño patterns where rising sea temperatures has been associated with the increased incidence of excessive rainfall in the western Pacific which impacts on banana exporting countries in Latin and Central America. While storms and hurricanes can cause obvious destruction of banana plantations, flooding and heavy rain can also impact on banana exports and prices in the short-run. With respect to variations in temperature, for many exporting countries, cooler temperatures are as much of source for negatively impacting on yields as rising temperatures. These short-run weather fluctuations are the focus of the analysis below.

Specifically, the focus is on the transmission of weather variations on prices from these (seven) major exporters to the UK, data on precipitation were acquired for these countries. The weather data is sourced from the Climate Research Unit at the University of East Anglia which provides both weather and precipitation data available at high resolution grid level (0.5x0.5 degrees) on a daily basis. Given the topography of banana production, the weather data detail banana growing regions in each of these countries excluding the mountainous regions that are not compatible with banana production. This data is aggregated across space and time to provide an average monthly frequency for precipitation for each exporting country.

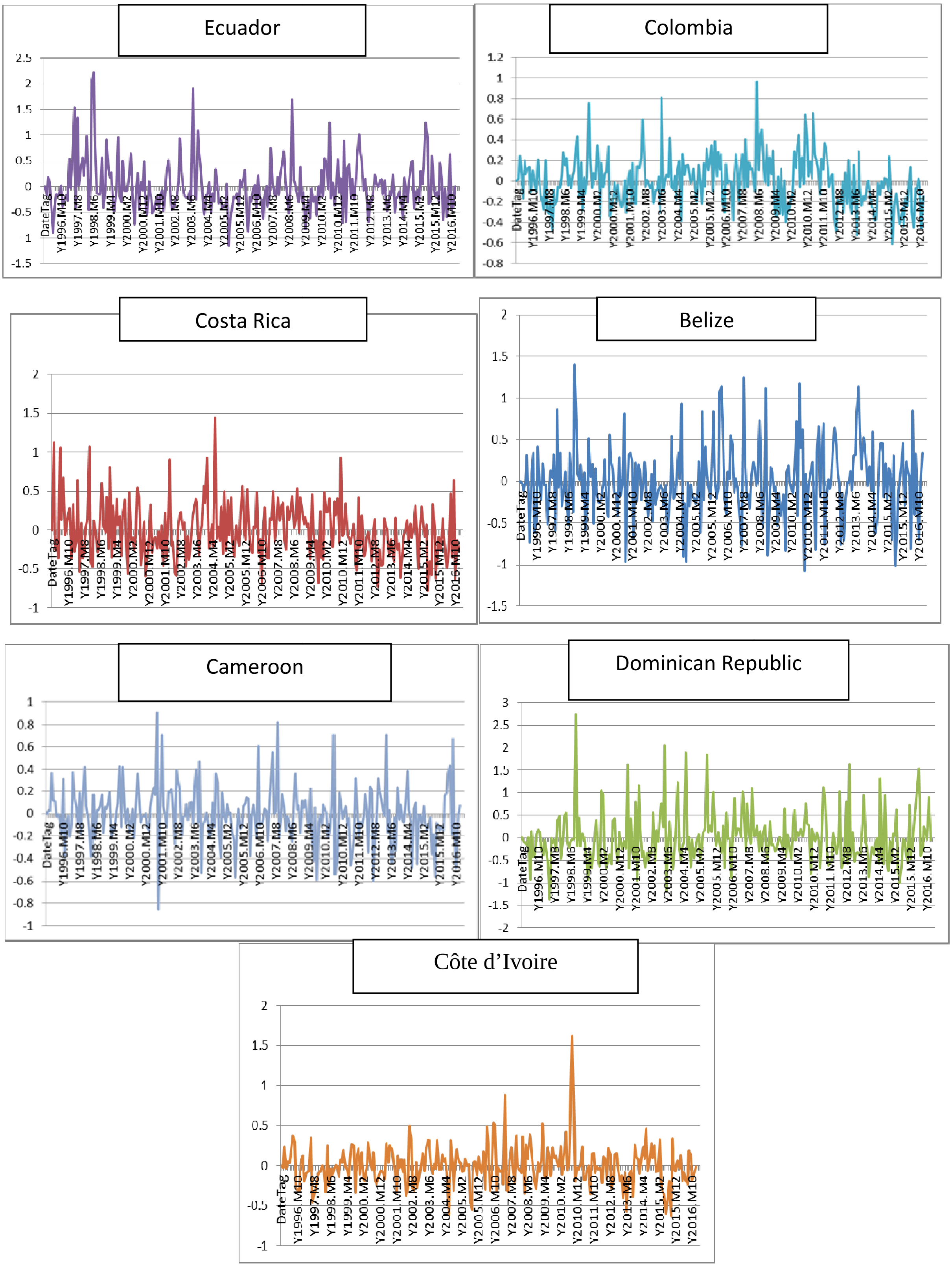
Precipitation fluctuations have an obvious seasonal dimension. To identify 'untypical' variation in monthly precipitation, we derive a seasonal moving average precipitation for each country. From this, we calculated a 'typical' monthly average for precipitation for each month. The 'untypical' variation in weather is then defined as the recorded measure of precipitation compared to what we may have expected for that specific month from the underlying seasonally-adjusted trend.

In Figure 1, we present the 'untypical' weather variations for precipitation for each of the 7 main exporting countries to the UK. As is evident from Figure 1, 'untypical' variations in weather precipitation are common with the data indicating that untypical wetter than normal months are more common than drier months. In terms of addressing the impact of weather variations originating in exporting countries on importers, the spatial correlation of weather fluctuations is also pertinent to assessing the overall effect. This is important: since we can isolate the impact of weather variations on export prices across countries, exporting countries will also be impacted by spatial correlation in weather patterns i.e. even if a specific exporting country experienced a typical seasonal temperature or precipitation, export prices will still be influenced by weather variations in competing exporters. We report the correlation in 'untypical' variations in monthly weather for precipitation in Table 1. Comparing the correlation coefficients across exporting countries, correlation in 'untypical' monthly precipitation is not that common.

Table 1: Correlation Coefficients for 'Untypical' Variations in Precipitation across Main Exporting Countries

	Belize	Costa Rica	Dom. Rep	Ecuador	Colombia	Iv. Coast	Cameroon
Belize	1						
Costa Rica	0.13	1					
Dom. Rep	0.17	0.11	1				
Ecuador	0.02	0.06	-0.02	1			
Colombia	0.08	0.31	0.14	0.20	1		
Côte d'Ivoire	0.12	0.10	-0.03	-0.043	0.19	1	
Cameroon	-0.03	0.01	0.001	0.07	0.05	0.07	1

Figure 1: 'Untypical' Variations in Monthly Precipitation for Main Exporting Countries, 1996-2016



4. Econometric Methodology

Specification

Following recent advances of the panel VAR literature, we apply a multi-country VAR approach to investigate the impact of weather anomalies on commodity price transmission across exporting countries; this methodology allows us to address cross-country interdependencies following shocks originating in one (or more than one) source country. The idea that spatial dependence should be taken into account in economics and geography is not new (e.g., Anselin, 1988). Recent advances in the VAR literature (e.g., Canova and Ciccarelli, 2004, 2009; Pesaran, Schuermann and Weiner, 2004; Chudik and Pesaran, 2014; Koop and Korobilis, 2016) stress the importance of accounting in time series studies the effects of events in one country on outcomes in other (not necessarily nearby) countries.□ Multi-country approaches should be considered overall better than bilateral approaches because the latter should only be used when assessing bilateral relations that are really independent on any other party (see e.g., Georgiadis, 2017; Chudik and Pesaran, 2011, for a discussion on the suitability of bilateral approaches). In our context, a bilateral approach would not be consistent with the characteristics of commodity exporters to a specific market where the implications of shocks originating in one supplying country would clearly spillover to other countries via commodity export prices. We have time series of moderate length (given the constraints on deriving export price data), we adopt the methodology associated with Canova and Ciccarelli (2009) which, for this reason, is more appropriate than other methodologies, such as the one developed by Koop and Korobilis (2016) for long time series.

In detail, the methodology allows for the presence of a common effect (such as an international factor that may affect all countries), a variable effect (that is, effects that are specific to the variables across all countries covered in the model), as well as the presence of country effects (which account for country-specific dynamics). The framework also allows for the presence of time-varying coefficients as well as lagged interdependences, that is, the possibility that a variable in country *i* at time *t-1* may affect a variable of another country at time *t*.

Formally, we estimate the following model:

$$y_{it} = D_{it} (L)\, Y_{t-1} + C_{it} (L) W_{t-1} + e_{it} \tag{1}$$

where $i = 1..N$ represents the units (countries) and $t = 1\dots T$ represent time, y_{it} is a vector of dimension $Gx1$ (G is the number of variables, in our case equal to 4) for each country i; $Y_t = (y'_{1t} \dots, y'_{Nt})$, W_t is a $qx1$ vector that may include common variables, time-invariant variables or unit-specific variables, e_{it} is a $Gx1$ vector representing the error terms; D_{itj} are $GxGN$ matrices and $C_{it,j}$ are $G\ x\ q$ matrices for each j. Interdependences across countries exist if D_{it} is not a block diagonal matrix for at least one j. However, allowing for the presence of interdependences and time varying coefficients increases the number of coefficients to estimate and causes an over-parametrization problem. As such, we adopt the factor structure used by Canova and Ciccarelli (2009) and impose restrictions so that the number of coefficients to estimate is reduced.

Specifically, define δ_{it}^{g} as a $kx1$vector containing the stacked G rows of the matrices C_{it} and D_{it}; then, $\delta_{it} = (\delta_{it}^{1'}, \dots \delta_{it}^{G'})'$ and $\delta_t = (\delta'_{it}, \dots \delta'_{Nt})$ is a $NGkx1$ vector. The vector is factorized as:

$$\delta_t = \textstyle\sum_f^F \Xi_f \theta_{ft} + u_t \tag{2}$$

where the number of factors is lower than NGk and θ_{ft} is a low dimensional vector, $\Xi_f$are matrices that can vary depending on the application and u_t is a vector of disturbances.

Assume $X'_t = (Y'_{t-1}, \dots Y'_{t-p}, W'_t, \dots W'_{t-1})'$ and $X_t = I_{NG} \otimes X'_t$. Setting $\Xi = [\Xi_{t,\dots,}\Xi_f]$ and $\chi_t \equiv X_t \Xi$ and $\zeta_t \equiv X_t u_t + E_t$, we can re-write equation (1) as follows:

$$Y_t = X_t \delta_t + E_t$$

$$= X_t(\Xi\theta_t + u_t) + E_t \qquad (3)$$
$$\equiv \chi_t\theta_t + \zeta_t$$

This reduces the number of coefficients to estimate.

The choice of the factors depends on the application. In our benchmark model, we include three factors: a common effect, a country-specific effect, and a variable-specific effect. As noted above, the framework includes also the presence of lagged interdependences as well as time-varying coefficients. The factor structure transforms the multi-country VAR into a seemingly-unrelated regression (SUR) model. We are in presence of time-varying coefficients so, given the likelihood of the SUR model, we estimate the model using Markov Chain Monte Carlo (MCMC) methods to obtain posterior distributions.

The benchmark model can be formalized as follows:

$$y_{it} = \chi_{1t}\theta_{1t} + \chi_{2t}\theta_{2t} + \chi_{3t}\theta_{3t} + \varsigma_t \qquad (4)$$

where $\Xi_{11t} = \Sigma_{LA}\Sigma_g\Sigma_j y_{igt-j}$, $\Xi_{12t} = \Sigma_{NotLA}\Sigma_g\Sigma_j y_{igt-j}$ and θ_{1t} is a $2x1$ vector of common factors; this factor distinguishes between common factors across groupings of countries, in this case, Latin American countries and non-Latin American countries. $\Xi_{2it} = \Sigma_g\Sigma_j y_{igt-j}$ and θ_{2t} is an $nx1$vector of country-specific factors; $\theta_{3t}$is a $gx1$ vector of variable-specific factors where $\Xi_{3gt} = \Sigma_i\Sigma_j y_{igt-j}$; where $i = 1 \dots n$ and $g = 1, \dots g$. Following Canova and Ciccarelli (2009), factors are assumed to evolve according to the law of motion:

$$\theta_t = \theta_{t-1} + \eta_t$$

where $\eta_t \sim (0, B)$ and $B = diag(\bar{B}_1, \bar{B}_2, \bar{B}_3)$ and $\theta_t = (\theta'_{1t}, \theta'_{2t}, \theta'_{3t})'$.

This econometric methodology is particularly suitable to evaluate the impact of weather variations on export prices since the specification takes into account the presence of fixed effects for spatial areas (e.g., countries), controls for variable-specific characteristics, and the presence of the common effect ensures that the effect of the shock is the consequence of idiosyncratic shocks, so identification is reached. In this context, to the extent that our weather variable is tied with other country-specific differences (e.g. temperature, topography, mitigation), these factors are effectively controlled for in the panel VAR specification. A variety of specification tests can be applied to this framework to determine whether the three factor structure of the model (i.e. the inclusion of the common effect, the variable-specific effect and the common factor) is appropriate (i.e. against the alternative of a lower order factor structures) and they are reported below.

Additional Data

The data collected relate to the main banana exporters to the UK namely: Belize, Colombia, Costa Rica, Dominican Republic, and Ecuador, all from Central and Latin America, and Côte d'Ivoire and Cameroon from Africa. These countries account for approximately a 90 percent of the UK banana imports, so they alone cover almost the entire network of exports towards the UK. The share of the UK market accounted for these exporters over the time series of our trade data is reported above. Details on untypical fluctuations in monthly precipitation for each of these exporting countries are reported above (Figure 1 and Table 1). We collected data for four endogenous variables in the following order: precipitation anomalies, exchange rate, quantities exported and unit export prices. The variable common to all countries but taken as a driver of commodity prices more generally and exogenous to country exports is taken as the world oil price.

Given the constraints on accessing trade data to the UK and therefore export prices, the data coverage relates to 2011-2016. Data frequency is monthly so the focus is on short-to medium term impacts arising from weather fluctuations. Data are seasonally adjusted and annualized and the variables are scaled for their standard deviation. Data is sourced from COMTRADE for the export quantity and price data, the data for the monthly exchange rate come from the International Monetary Fund (IMF) for the monthly exchange rate data and the monthly real world oil prices are sourced from the World Bank. Since the data coverage relates to 2011-2016, we use a sub-set of the time period of the measures of untypical precipitation levels relative to the data presented in Figure 1.

Specification Results

In the context of the panel VAR methodology, there are a number of tests that can be applied to assess the overall specification of the econometric model. These tests involve testing the benchmark model against alternative specifications; namely, Chib's maximum likelihood method (Chib, 1995), the Schwartz approximation and the harmonic mean estimator (Newton and Raftery,1994) and compare the models using the Bayes factor. We compare four different models, that is, our benchmark model, Model 1, where we allow for the presence of a common effect, country fixed effects, variable-specific effects, lagged interdependences and time varying parameters, to other three models. Model 2 differs from Model 1 in that we do not allow for the presence of lagged interdependences, Model 3 does not have country fixed effects and Model 4 does not include variable-specific factors. We compare the models using the Chib test, the harmonic mean criteria and the Schwartz approach. Since Model 1 is not always discarded in favour of any of the other three models, we conclude that Model 1 is the most suitable to provide econometric evidence about the impact of climate on commodity prices. Details on the statistical results from these specification tests are presented in Appendix 1.

5. Results

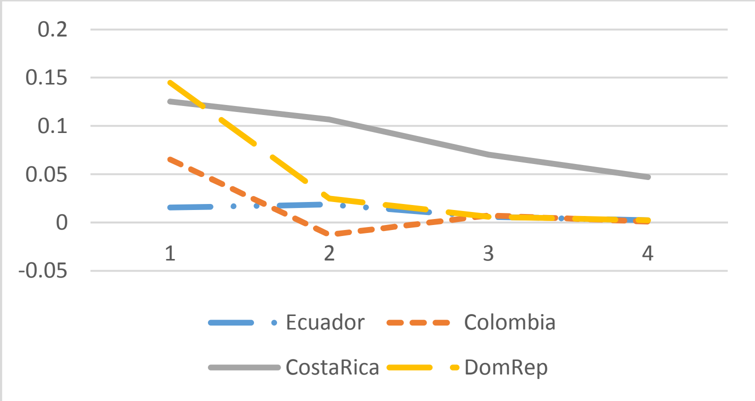
Precipitation Shocks and Export Prices

We use the estimates from the panel VAR model outlined above to assess the impact of changes in untypical rainfall on export prices to the UK. Since there is a low correlation in untypical changes in precipitation across exporting countries (see Table 1), we simulate the impact for each country individually[2]. In Figure 2, we report the central point estimates from the impulse responses for the main exporters to the UK; we do not report all the point estimates but only the central ones, because overall the shocks become significant only after a few periods (as expected, since the reaction of prices to climate shocks is likely to be perceived a few periods after the shock occurs) and negligible towards the eighth period. Since the impulse responses tend towards zero after around 6 months after the shock, we highlight the short-run effects.

The main insight from Figure 2 is that the short-run impact on export prices varies by exporting country. The country whose precipitation anomalies generates the strongest and most persistent price effect is Costa Rica; the Dominican Republic also generates a relatively strong impact on export prices though this effect is more short-lived. The effect from two other main exporters, Ecuador (the world's leading banana exporting country) and Colombia (the main exporter to the UK) are relatively weak. Note however that given the frequency of precipitation anomalies reported in Figure 1, these short-lived price impacts are therefore an important source of commodity price volatility. Although further investigation is needed to understand the reasons behind such cross-country differences, it could be that Ecuador and Colombia, who are the two largest exporters from Latin America to the UK, are more equipped to face weather anomalies and to be resilient to weather shocks.

[2] This is not a restriction of the framework we employ. For example, we could allow for weather shocks occurring simultaneously across more than one country.

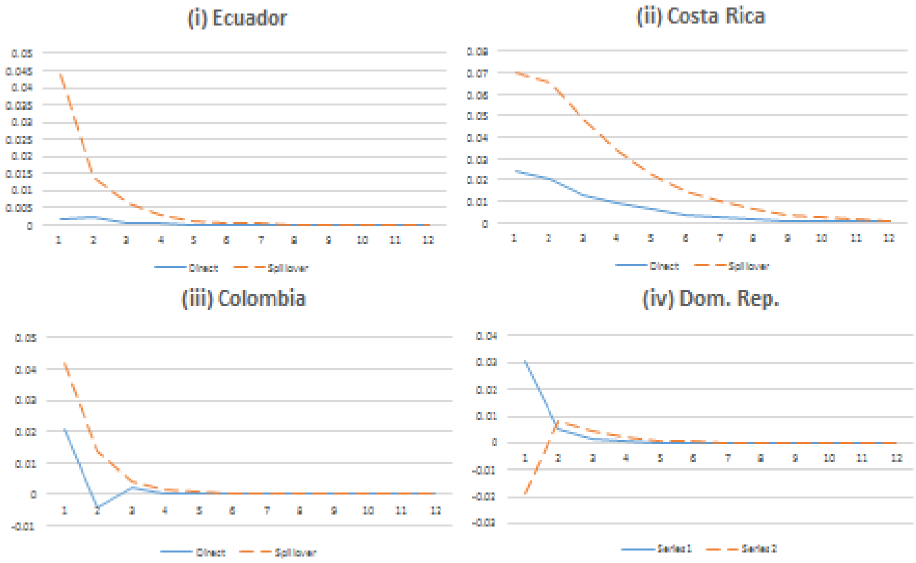
Figure 2: Short-Run Direct Impact of Country-Specific Precipitation Anomalies



Even when the direct effects differ and need not be necessarily strong as in the case of Ecuador and Colombia, this does not give the full picture of the impact on the importing country. As discussed above, changes in weather patterns that are reflected in export prices will impact on other exporting countries. To highlight the direct and spillover effects, we take the impulse response effects following a precipitation anomaly arising in a specific country and identify the direct impact (the own-price effect) and the spillover effects (i.e. the impact on all other exporters). In this case, to gauge the relative importance of these effects, we weight the impulse response effects on competing exporters by market shares to the UK. We do this for the 4 main exporters reported in Figure 2, again reporting the central values for the impulse response estimates. These results are reported in Figure 3.

There are two main observations from Figure 3. First, the relative importance of spillover effects depends on the source of the precipitation anomaly. For some exporters, the spillover effects can be relatively weak; the case of the Dominican Republic is notable here. Spillover effects are however strong for the other exporting countries reported in Figure 3. Second, the market-weighted spillover effects-with the exception of the Dominican Republic-dominate the direct effects. For Costa Rica, the spillover effects are strong and persistent; for Ecuador and Colombia, the spillover effects are stronger than the direct effects though the impact on prices is more short-lived compared to the Costa Rica case.

Figure 3: Market Share Weighted Impulse Responses: Direct and Spillover Effects following Precipitation Anomalies in Specific Exporters



The existence of spillover effects reported in Figure 3 suggests that anomalous weather patterns arising in one country can be an important determinant of price instability in other exporters. In Table 2, we report the cumulative (12 month) effects on export prices countries. The entries in the table relate to the source of the precipitation increase. The entries on the main diagonal represent the direct effects for each country (they are in bold); the off-diagonal entries represent the spillover effects, so for instance the cells in each column indicate the total spillovers to country *i* from country *j*[3].

Focussing first of all on the direct effects, the impulse response effects translate into considerable differences across countries. Anomalous precipitation has the strongest direct effects when occurring in Costa Rica (cumulative price effect is 35 per cent) which is not surprising given the impulse response effects reported in Figure 2 above. The direct effects are also notable for the Dominican Republic, Ecuador and the Côte d'Ivoire. For other exporting countries, the impact of precipitation anomalies is relatively weak taken over a 12 month period following the precipitation shock.

There can be several reasons for this diverse pattern of price effects. First, the different effect is likely to be tied to the untypical rainfall patterns experiences in each of the banana exporting countries reflecting the data presented in Figure 1. Second, there may be other confounding factors that may account for the diversity, ranging from temperature variations to the characteristics of the export sector in each country, the use of contracts, the role of multinational firms, the market shares, geographic proximity and spatial dependence and so on, factors that are all accounted for in the model specification since we include fixed effects. These factors may also impact on the magnitude of the spillover effects which we report below.

The off-diagonal entries report the spillover effects for each competing exporting country; these entries highlight the importance of addressing the spillover effects in fully gauging the impact of weather shocks. Take the case first of all of Costa Rica which generates the highest direct effects.

[3] Prices are normalised at 100 for each exporting country with the cumulative effects relating to the percentage change in prices from the impulse response coefficients.

Although the direct cumulative effect is to increase export prices by 35 per cent, prices from other exporters also increase significantly: the spillover effects from the Costa Rica precipitation shock is strong across all other Central and Latin American exporters and relatively weaker, but nevertheless strong, for Cameroon and the Côte d'Ivoire; this result may suggest both the presence of spatial dependences (these two countries are the only African countries) and the relevance of the market shares (Cameroon and Côte d'Ivoire are minor exporters towards the UK compared to other Latin American countries). For the Central and Latin American exporters, the spillover effects for each exporter are (approximately) as strong as direct effect on Costa Rica. Ecuador (the world's leading banana exporter) also has a significant impact on banana prices with the spillover effects being as strong as the direct effect; in the case of Colombia (the leading exporter to the UK), the spillover effects are stronger than the direct effect though for both Ecuador and Colombia both the cumulative direct and spillover effects are considerably weaker than the Costa Rica impact.

A second observation from Table 2 is to highlight that for some countries, the source of export price volatility is more likely to be other countries' anomalous weather patterns than its own. For example, in the case of Belize, the impact of precipitation anomalies arising from Colombia, the Dominican Republic and Ecuador is stronger than the direct-Belize effect. A similar observation can be made about the impact of spillover effects impacting on Cameroon. These two examples highlight, once, again, the importance of market shares, leading role in the market and geography.

Table 2: Cumulative Impact of Precipitation Shocks Originating in Export Countries

Source of Weather Anomaly:	**Cumulative (12 Month) Price Impact Originating from:**						
	Belize	Colombia	Costa Rica	Dom. Rep.	Ecuador	Cameroon	Ivory Coast
Belize	**98.63**	102.88	136.65	101.73	102.18	98.67	100.26
Colombia	99.37	**99.75**	128.17	101.33	101.88	99.39	100.09
Costa Rica	99.37	102.34	**135.29**	102.59	102.85	98.78	97.87
Dom. Rep.	99.15	103.86	133.14	**103.66**	102.44	98.97	99.99
Ecuador	99.42	102.47	133.04	100.98	**102.92**	98.45	100.68
Cameroon	103.63	99.98	113.05	102.65	100.87	**97.21**	100.06
Côte d'Ivoire	98.51	100.98	112.79	101.58	101.24	98.50	**103.84**

It is important to put these numbers in context. Two observations can be made. First, Cashin *et al.* (2017) reported ENSO-related increases in (an index of world) commodity prices of 4 per cent after 4 quarters. This is in the ball-park of the results reported here. But our results show that the magnitude of the price increases depend on where the weather anomaly arises, that the price effect can vary quite substantially and part of the commodity price effect is likely to arise through spillover effects. Second, precipitation anomalies occur with high frequency as is evident from Figure 1. Given that the results reported above relate to a one-off shock to precipitation anomalies from specific countries, the results reported in Figures 1 and 2 and Table 2 suggest that weather-related impacts on prices are important sources of price volatility both across all exporting countries and for the importing country.

6. Summary and Conclusions

In this paper, we have applied a panel VAR approach to measure the impact of weather fluctuations on export prices: our specific focus has been on banana exports from the leading export countries to the UK. This approach offers a number of new insights into the impact of weather shocks. First, by using time series data, we can identify the impact of weather events on export prices. Second, the panel structure allows us to identify not only the direct but also the spillover effects of weather shocks. Using detailed data on untypical rainfall patterns in the main exporting countries, our results show, in aggregate, these spillover effects are important and, taken together, can dominate the direct effects.

Several implications arise from these insights. First, the data indicates that untypical rainfall patterns vary across the main banana exporting countries that therefore warrants the use of detailed crop-weather specific data as opposed to more aggregate ENSO anomaly data that have been employed in recent research on climate and commodity price impacts. Second, given the spatial dimension of weather patterns, export price volatility for a specific exporter can arise either due to the weather effect in the source country or due to weather fluctuations in competing exporters. Contingent on weather patterns across exporters, the spillover effect from competing exporters may be a more important source of price volatility than own-country weather fluctuations. Our approach offers a means to gauge the relative importance of these effects. Third, our results suggest that both the direct and spillover effects likely depend on market shares, the role of the countries in the international commodity network, and the geographic location. Finally, from the importing country's perspective, weather fluctuations are a significant source of volatility: untypical weather fluctuations are not necessarily strongly correlated which implies that weather fluctuations due to climate events are an on-going source of price variability to export markets; despite the country-specific nature of untypical weather fluctuations, the aggregate price effects faced by importers are aggravated by the spillover effects.

There are a number of future directions for research on climate shocks and resulting price effects using this methodology: most obvious in this regard is the use of detailed weather data for specific commodity sectors that will be more insightful than aggregate data that has been recently applied. Extending the definition of the export market will have the potential to give a more complete assessment of the spillover effects. Our results indicate the importance of spillovers for specific markets; the extent to which exports are directed from other sources will be picked up in the price impacts on a specific importing country, but the implications for exporting countries may be more contingent on exports to other destination markets.

References

Anselin, L. (1988) *Spatial Econometrics: Methods and Models*. Kluwer Academic Publisher.

Brunner, A.D. (2002) "El Niño and World Primary Commodity Prices: Warm Water or Hot Air?" *Review of Economics and Statistics*, 84: 176-183

Canova, F. and M. Ciccarelli. (2004) "Forecasting and Turning Point Prediction in a Bayesian Panel VAR Model." *Journal of Econometrics*, 120(2): 327-359.

Canova, F. and M. Ciccarelli. (2009) "Estimating Multi-country VAR Models. *International Economic Review*, 50(3): 929-959.

Carleton, T.A. and S. M. Hsiang (2016) "Social and Economic Effects of Climate" *Science*, 353 (6304)

Cashin, P., K. Mohaddes and M. Raissi (2017) "Fair Weather or Foul? The Macroeconomic Effects of El Niño" *Journal of International Economics*, 106(1): 37-54

Chen, S-L., J.D. Jackson, H. Kim and P. Resiandini (2014) "What Drives Commodity Prices?" *American Journal of Agricultural Economics*, 96(5): 1455-1468

Chib, S. (1995) "Marginal Likelihood from the Gibbs Output." *Journal of the American Statistical Association*, 90(432): 1313-1321.

Chudik, A. and M. H. Pesaran. (2011). "Infinite-Dimensional VARs and Factor Models." *Journal of Econometrics*, 163(1): 4{22.

Chudik, A. and M. H. Pesaran. (2014). "Theory and Practice of GVA Modelling." *Journal of Economic Surveys*, 30(1): 165-197.

Dell, M., B.F. Jones and B.A. Olken (2014) "What Do We Learn from the Weather? The New Climate-Economy Literature" *Journal of Economic Literature*, 52: 740-798

FAO (2018) *The State of Agricultural Commodity Markets: Agricultural Trade, Climate Change and Food Security*. Food and Agriculture Organisation, Rome.

Georgiadis, G. (2017). "To Bi, or Not to Bi? Differences between Spillover Estimates from Bilateral and Multilateral Multi-country Models." *Journal of International Economics*, 107: 1-18.

Gouel, C. and D. Laborde (2018) "The Crucial Role of International Trade in Adaptation to Climate Change" Mimeo, INRA, Paris

Koop, G. and D. Korobilis. (2016) "Model Uncertainty in Panel Vector Autoregressive Models." *European Economic Review*, 81(C): 115-131.

Machovina, B. and K.J. Feeley (2013) "Climate Change Driven Shifts in the Extent and Location of Areas Suitable for Export Banana Production" *Ecological Economics*, 95: 83-95

Newton, M.A., and A.E. Raftery. (1994). "Approximate Bayesian Inference by the Weighted Likelihood Bootstrap." *Journal of the Royal Statistical Society, Series B*, 56: 3-48.

Pesaran, M.H., T. Schuermann, and S.M. Weiner. (2004) "Modelling Regional Interdependences using a Global Error-Correcting Macro-econometric Model." *Journal of Business and Economics Statistics*, 22(2): 129-162.

Ramirez-Villegas, J., A. Jarvis, I. Van den Bergh, C. Staver and D. Turner, D. (2011). "Changing Climates: Effects on Growing Conditions for Banana and Plantain (*Musa* spp.) and Possible Responses". In S. S. Yadav, R. Redden, H. Lotze-Campen and A. Hall (Eds.), *Crop adaptation to climate change* (pp. 426–438). Oxford: Wiley-Blackwell.

Ropelewski, C.F. and M.S. Halpert (1987) "Global and Regional Scale Precipitation Patterns Associated with EL Niño/Southern Oscillation" *Monthly Weather Review*, 115: 1606-1626

Ubiliva, D. (2017) "The Role of EL Niño Southern Oscillation in Commodity Price Movement and Predictability" *American Journal of Agricultural Economics*, 100(1): 239-263

Van den Bergh, I., J. Ramirez, C. Staver, D. Turner, A. Jarvis and D. Brown, (2012). "Climate Change in the Sub-Tropics: The Impacts of Projected Averages and Variability on Banana Productivity". *Acta Horticulturae, 928*, 89–99.

Appendix

Table A1 presents the results for the model selection. The results represent the likelihood statistics for alternative specifications based on estimates of the models with different seeds. The test results reported are the average likelihoods for 10 different seeds. The results show that Model 1 can be considered a suitable model specification. Consequently, Model 1 was selected as the preferred model and the results in the text relate to this specification.

Table A1: Results from Model Selection

	Model Selection			
	Model 1	Model 2	Model 3	Model 4
Chib	-2.172.5	-2,198.33	-1,874.84	-2,420.57
nse	8.92	17.51	271.42	20.66
Schwartz	-2,186.91	-2,193.59	-2,183.39	-2,246.33
nse	1.32	1.11	1.93	0.95
Harmonic Mean	-2,247.84	-2,303.62	-2,408.08	-2,365.67
nse	0.30	2.30	17.51	1.60