# EconomiX

# Document de Travail
## Working Paper
## 2014-37

The ambiguous role of remittances
in West African countries facing climate variability

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# The ambiguous role of remittances
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**Abstract:** We investigate the consequences of remittances inflows on macroeconomic performance of West African countries over the 1985 - 2007 period. We take into account the exposition of those countries to climate variability by estimating a PCHVAR model which allows heterogeneity between countries' responses to rainfall shocks. Our results show that the impact of remittances on macroeconomic performances is highly sensitive to those shocks. In particular, when drought conditions prevail, remittances do not longer exert any short-term spillover effects on growth and may increase a situation of economic dependence, by spurring agricultural imports.

**JEL Classification:** C33; F24; O11

**Keywords:** Climate variability; Remittances; PCHVAR model; West Africa

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# 1. Introduction

Among developing countries, many West African ones are seen as the most vulnerable to climate shocks. These shocks do not only include potentially catastrophic large-scale disasters, but also testify to a more permanent state of economic stress which results from higher average temperatures, reduced availability of water sources, more frequent flooding, and intensified windstorms (UNDP, 2004). Moreover, the burden of adjusting to the threats from climate shocks is the heaviest for those economies. Indeed, they have already suffered what is known as 'multiple vulnerabilities' because of their low level of resilience to shocks (Guillaumont, 2009).

A recent literature has analyzed the impact of climate shocks and natural disasters in order to assess their contribution to the volatility of GDP in developing countries (Loayza et al., 2009 ; Hochrainer, 2009 ; Raddatz, 2007). Results show that the macroeconomic performance of developing countries are highly exposed to climate shocks, and especially to droughts in the short term.[1] Other contributions have shown how population may use migration and remittances in order to cope with negative impacts of bad weather conditions (Ebeke and Combes, 2013 ; Findley, 1994).

Although it is now widely recognized that remittance inflows may benefit to households at a microeconomic level (Gupta et al., 2009), their empirical macroeconomic consequences remain less investigated (Rapoport and Docquier, 2005) and few studies have highlighted their countercyclical role in mitigating the effects of negative shocks (Ebeke and Combes, 2013 ; IMF, 2005). Indeed, the consequences of remittances depend on whether they are consumed or invested (Ratha, 2007). They are expected to have either direct positive effects, when they directly contribute to productive investments, or indirect ones, when they are used by households to consume goods and services produced locally. Otherwise, if they result in demand exceeding domestic production capacities, they may spur imports, and especially imports of agricultural goods, in order to satisfy new consumption habits or to maintain a vital level of consumption (Jovičić and Mitrović, 2006).

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1. See Cavallo and Noy (2010) for a detailed survey of the literature.

This paper parallels these issues by investigating the impact of remittances on macroeconomic performance in West African countries undergoing climate stress. Accordingly, we estimate the relationship between droughts, remittances and economic performance for a sample of eight West African countries over the period 1985-2007, relying on a PCHVAR (Panel conditional homogeneous Vector Autoregressive) model, which has the advantage (i) of exploiting the panel nature of the data and (ii) of shaping heterogeneities in countries' dynamics conditionally to an exogenous variable (Georgiadis, 2012).

Our analysis is distinctive of the existing literature in many respects. Firstly, we seek to identify the direct impact of remittances on macroeconomic performance and their indirect impact through their financial deepening effect. Secondly, the role of remittances is assessed by taking into account potential non-linearities and heterogeneities caused by climatic conditions of West African economies. Finally, we focus on climate stress through the computation of the Standardized Precipitation Index (SPI) by using precipitation data from the Climate Research Unit (CRU). This index allows us to assess more accurately the impact of a purely physical shock, comparatively to proxies of climate shocks widely used in the literature.

The main results of this article are the following. First, remittances do not exert spillover effects on the agricultural value added and tend instead to increase agricultural imports, especially when countries face negative rainfall shocks. Secondly, our findings show that remittances may have a positive effect on financial development only when cumulative precipitation deviates positively from the climatological average. This relationship becomes negative in case of stress conditions such as droughts. Finally, we find a negative impact of financial development on GDP per capita pointing out the lack of complementarity between remittances, financial development and growth.

The remainder of the paper is organized as follows. Section 2 outlines the empirical literature dealing with the impact of remittances on macroeconomic performance in developing countries. In Section 3, we present the design of the PCHVAR model employed in this article. In Section 4, we describe the data and the empirical specification of the model. Section 5 displays our different results. Finally, section 6 concludes.

# 2. Literature review

Regional and international population mobility has a major impact on economic development in West Africa (De Haas, 2010). Recent migration patterns and their motives are linked to multiples forces, among which remittances constitute a 'bond' connecting migrants to their families. Between 1996 and 2009, West African countries received 30% of the official remittances sent to sub-Saharan African countries. Their share in the regional GDP has averaged 3.2% over the same period and rose from 2.1% to 4.3% in 2009.[2]

Several theoretical and empirical studies initiated by the New Economics of Labor Migration (Lucas and Starks, 1985) show that migration and remittances are an integral part of a household's risk management strategies. According to Findley (1994), during the great drought (1984-1985), 63% of agricultural households in Mali depended on remittances sent by non-resident family members abroad, suggesting the importance of those transfers as a means of providing insurance against climate hazards. In theory, droughts should affect negatively the income of households predominantly occupied in the agricultural sector, and we may therefore expect remittance inflows to support basic consumption and/or productive investments.

The question of whether remittances inflows have beneficial or detrimental effects on economic development is the subject of an extensive literature, and of a controversial debate. It has mainly focused on how remittances are used, i.e., whether they are mainly consumed or spent in productive investment.

The multiplier effect exerted by remittances on national income can only take place in a context where the additional demand induced by remittances inflows can be satisfied by domestic production. In that case, a share of those transfers is injected into the economy through productive investment. On the contrary, if remittances cannot be absorbed by domestic production, their multiplier effect will be severely limited (Glytsos, 1993). Empirical studies fail to reach clear-cut results at a microeconomic level. They show that remittances can foster productive investments but also allow households to maintain

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2. Based on authors' calculations from the database World Development Indicators, World Bank (2013a).

consumption through a process of inter-temporal smoothing.

Adams (2002) finds that Pakistani households receiving international remittances have a greater saving propensity than households benefiting from a pension. According to Taylor (1999), remittances serve as insurance against risks associated with new production activities. According to Lucas and Starks (1985), remittances tend to reduce labor supply and cereal production in the short run in sub-Saharan Africa whereas in the long run, they are invested and thus promote cereal productivity and livestock accumulation. Yang and Choi (2005), testing the role of remittances in insuring against rainfall shocks in the Philippines, show that 60% of the households' income loss due to these shocks is offset by remittances, which help consumption to stabilize. Remittances can also stimulate subsistence consumption if the income of households is below a certain threshold after a negative shock (Yang, 2008). Similar behaviour is displayed when households are facing a crisis or a shock pressuring their previous level of consumption. Case studies undertaken on Mali, Senegal, Morocco and the Comoros show that only 10% of the households receiving remittances used them for productive investments (IFDA, 2009). Those findings support the conclusion reached by Chami et al. (2003) that rural households tend to rely heavily on remittances to improve their living conditions through the satisfaction of basic needs.

The fact that households use remittances to smooth consumption raises the question of whether an additional demand induced by remittances may be satisfied by domestic production. Indeed, if demand rises without a stimulation of the supply side, remittances can foster an increase in imports and then lead to a deterioration of the trade balance. Furthermore, when imports financed by remittances involve basic necessities, their multiplier effect is small. Thus, although remittances can tackle risks of increasing poverty, they cannot necessarily allow countries to be more resilient to future shocks if they spur imports.

Recently, studies examining the role of remittances on economic development have underlined their effect on growth through their interaction with financial development. These studies are also debated and reach different conclusions (Aggarwal et al., 2011). According

to Mundaca (2005) and Ahamada and Coulibaly (2011), remittances may be better used in countries showing high financial development, and they may thus have a positive effect on growth. Therefore, large remittances inflows could have non-significant or smaller effects on growth in less financially developed countries.

However, remittances may also promote growth in such countries. Indeed, they may compensate for the lack of financial markets in rural areas by easing liquidity constraints and supporting productive investment. In this case, remittances are assumed to promote growth in less financially developed countries (Giuliano and Ruiz-Arranz, 2009). Finally, remittances can help foster financial development in developing countries (Aggarwal et al., 2011 ; Demirgüç-Kunt et al., 2010).

# 3. Methodology: the PCHVAR specification

In order to analyze the multiple causality and spillover effects between remittances and economic performance in a context of climate shocks, we use a panel conditionally homogeneous vector auto-regressive (PCHVAR) model which extends the traditional panel vector autoregressive (PVAR) model. The PCHVAR model offers several advantages, by allowing for unobserved individual heterogeneity, cross-section dependency and exogenous conditioning variables.

The dynamics in standard panel vector autoregressive frameworks (PVAR) is assumed to be fully homogeneous across cross-sectional units. This assumption is usually maintained for the sake of parsimony and to gain degrees of freedom by pooling the data of cross-sectional units. However, this restriction may not hold in a macroeconomic setting since countries may be subject to asymmetrical shocks, and may implement different policy measures and/or responses to cope with those shocks (Canova and Cicarelli, 2013).

In this case, using fixed effects to allow heterogeneity between the panels' units may be problematic since OLS and standard fixed effect estimator (LSDV) are known to be biased in panels that include lagged endogenous variables (Holtz-Eakin et al., 1988). Even if this problem is eliminated when the time dimension $T$ is relatively large compared to the

cross sectional dimension $N$ ($T > 2N$), OLS and LSDV estimations can still show bias when the time dimension is large if the coefficients on the lagged endogenous variables vary greatly across countries.

Macroeconomic studies have made extensive use of Generalized Method of Moments (GMM) techniques in order to estimate panel VARs. By employing a forward orthogonal deviations transformation so as to eliminate time-invariant individual fixed effects, lagged level variables can be thus used as instruments in GMM estimations (Love and Zicchino, 2006). However, GMM and extended GMM estimators are designed for the case of a large cross-sectional dimension ($N$) relatively to the time dimension ($T$) and have been shown to perform poorly when $T \to \infty$ and particularly when the ratio of the variance of the individual effects to the variance of the innovations increases (Juessen and Linnemann, 2012).

To address these concerns, we then set up a panel conditionally homogeneous vector auto-regressive (PCHVAR) model, allowing for heterogeneous cross-sectional dynamics (Georgiadis, 2012) :

$$Y_{it} = \sum_{j=1}^{p} A_j(z_{it})Y_{i,t-j} + \delta_i + B_q w_{t-q} + \varepsilon_{it} \qquad \varepsilon_{it} \ i.i.d. \ (0, \Sigma_\varepsilon) \qquad (1)$$

Where $Y_{it}$, the vector of five endogenous regressors, comprises the real GDP (PPP adjusted) per capita ($y$), the agricultural value added per capita ($y_{agr}$), remittances and compensation of employee per capita ($R_i$) inflows ($R_i$), agricultural imports per capita ($M_{agr}$) and a financial sector development index ($F_d$). $z_{it}$ is a $M \times 1$ matrix of exogenous variables comprises the drought probability index; $\delta_i$ is a $d \times 1$ vector of fixed effect and unit specific time trend and $w_t$, a $L \times 1$ vector of exogenous variable affecting all countries at the same time (homogeneous effect), comprises the GDP per capita of developed countries.[3]

Unlike the standard Panel VAR, the panel conditionally homogeneous vector autoregressive model (PCHVAR) allows for different cross-sectional dynamics. The time series are

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3. GDP per capita in developed countries is used to control for common shocks and particularly for shocks on remittances inflows since economic performances in developed countries, as shown by the recent economic crisis, may act as a constraint on the capacity of migrants to send remittances.

pooled, but impulse responses differ based on the values of one exogenous conditioning variable $z_{it}$. Assuming that each scalar coefficient $a_{j,sm}$ in the matrix of coefficients $A_j$ can be approximated by a scalar polynomial in the conditioning exogenous variable $z_{it}$ (with $j = 1, ..., p$, $s = 1, ..., K$ and $m = 1, ..., K$):

$$a_{j,sm}(z_{it}) \approx \pi(z_{it})\gamma_{j,sm} \tag{2}$$

With $\pi(z_{it}) = [\pi_1(z_{it}), \pi_2(z_{it}), ..., \pi_\tau(z_{it})]$ is a vector with polynomials in $(z_{it})$ and $\gamma_{j,sm} = (\gamma_{j,sm_1}, \gamma_{j,sm_2}, ..., \gamma_{j,sm_\tau})$ is a vector of polynomial coefficients. $A_j(.)$ can then be rewritten:

$$
\begin{aligned}
A_j(z_{it}) &= \begin{bmatrix} \pi(z_{it}).\gamma_{j,11} & \cdots & \pi(z_{it}).\gamma_{j,1K} \\ \vdots & \ddots & \vdots \\ \pi(z_{it}).\gamma_{j,K1} & \cdots & \pi(z_{it}).\gamma_{j,KK} \end{bmatrix} \\
\\
&= \begin{bmatrix} \gamma'_{j,11} & \cdots & \gamma'_{j,1K} \\ \vdots & \ddots & \vdots \\ \gamma'_{j,K1} & \cdots & \gamma'_{j,KK} \end{bmatrix} . [I_K \otimes \pi'(z_{it})] \\
\\
&= \Gamma_j . [I_K \otimes \pi'(z_{it})]
\end{aligned} \tag{3}
$$

The model in equation (1) can be written as follows:

$$
\begin{aligned}
Y_{it} &= \sum_{j=1}^{p} \Gamma_j.[I_K \otimes \pi'(z_{it})]Y_{i,t-j} + \delta_i + B_q w_{t-q} + \varepsilon_{it} \tag{4} \\
\\
&= \sum_{j=1}^{p} \Gamma_j.x_{i,t-j} + \delta_i + B_q w_{t-q} + \varepsilon_{it} \tag{5} \\
\\
&= \Gamma_j.X_{i,t-1} + \delta_i + B_q w_{t-q} + \varepsilon_{it} \tag{6}
\end{aligned}
$$

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Following Georgiadis (2012), the model in equation (6) can be interpreted as a standard multiple equations panel time series model and is estimated using OLS. Once the polynomial coefficients in the matrix $\Gamma$ are estimated, the reduced form coefficient matrix $A_j(.)$ is calculated for multiple values of the conditioning variable.

In case of cross-section dependency across panels' units, the model given by equation (6) may be estimated using the technique proposed by Pesaran (2006). Pesaran tackles the issue of cross-sectional dependency in panel dynamics model by approximating the common component of the data by the cross-sectional averages of the dependent and explanatory variables, and then augmenting the panel regression with these averages.

The lag order is chosen by minimizing the Akaike Information Criterion (AIC) and the Schwarz Criterion (SC). In accordance with the AIC and SC results and the limited size of our sample, we include only one lag in the vector of endogenous regressors $y_{it}$ and in the vector of exogenous variables with homogeneous effects ($w_t$). Stability test indicates that the model given by equation 6 is stationary.[4] Once the unknown parameters are estimated, dynamic simulations can be performed as Orthogonalized Impulse Response Functions (OIRFs), as well as Forecast Error Variance Decompositions (FEVD), allowing for the examination of the impact which innovations or shocks affecting any particular variable have on other variables in the system.

Because of the dependence of the coefficient matrices on the conditioning variable $A_j(z_{it})$, OIRFs and FEVD in the PCHVAR model are function of the conditioning variable and are interpreted for a grid of values of the conditioning variable. To obtain OIRFs, we decompose the residuals in a way that makes them orthogonal, by adopting the Choleski decomposition. This decomposition involves a particular ordering of variables where the variables that appear earlier affect the following variables contemporaneously and with lags, while the variables that appear later only affect the previous variables with lag. The variables order in the vector of endogenous regressors is based upon the Granger causality test on panel data proposed by Emirmahmutoglu and Kose (2011).

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4. Results are shown in appendix A.1.

# 4. Estimation of the PCHVAR Model

## 4.1. The sample

Given the availability of data, our study relies on annual data covering the 1985 - 2007 period and eight West African countries.[5] All data are log transformed. Real GDP per capita (PPP adjusted) is extracted from PennWorld tables. GDP per capita of developed countries (PPP adjusted), total agricultural imports per capita (Current $US), agricultural value added per capita (Constant $US), remittances and compensation of employee data come from the World Bank database, World Development Indicators, World Bank (2013a). Worker remittances and compensation of employees include current remittances by migrant workers, plus wages and salaries earned by non-resident workers. Per capita remittances are obtained by dividing the total amount of remittance inflows by the total population of each country.

Following Ahamada and Coulibaly (2011) and Beck et al. (2006), we use private credit by deposit money banks and other financial institutions as percentage of GDP as a measure of financial development. Data are extracted from the World Bank Global Financial Development Database, World Bank (2013b).[6]

Several studies (Raddatz, 2007; Raddatz, 2009; Skidmore and Toya, 2002) assess the impact of natural and climate disasters on the macroeconomic stability of developing countries using the International Disaster (EM-DAT) database developed by the Centre for Research on the Epidemiology of Disasters (CRED). However EM-DAT data shows some limitations (UNDP, 2004). Firstly, such data does not take into account the potential correlation between shocks (a shock coming from another shock). Some climate shocks, like droughts,

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5. The PCHVAR framework requires balanced panel data. List of the countries included: Mali, Benin, Togo, Senegal, Côte d'Ivoire, Niger, Burkina Faso and Ghana.

6. Financial development refers to a set of phenomena acting on the financial system and may indeed be proxied by various indicators. Unfortunately, working on a sample of African countries and on a balanced panel obviously reduces the potential measures due to data availability issues. We thus retain the indicator for which data are available for all countries and for all time periods of our sample, i.e. private credit to GDP ratio. This variable represents financial resources that are channeled to the private sector. However, it may not capture the extent of actual access to financial services since credit can be unequally distributed.

are also problematic because they tend to develop gradually over time and space. Thus, their occurrence and their economic impact cannot be approximated by a binary variable. Another limitation is related to the endogeneity problem inherent to the production of such data. Indeed, a disaster is defined by the number of people affected by the shock during a year. Thus, this measure relies on the ability or inability of individuals to cope with the shock and does not take into account the physical dimension of the shock. These various limits are closely related to the concept of disaster, which gives only limited importance to the temporal dimension of climate shocks.

Therefore, we propose to use rainfall data from the Climate Research Unit (CRU)[7] in order to measure the impact of shocks on remittances since rainfall variability constitutes the primary source of income risk in many African countries (Gubert, 2002). Following McKee et al (1993), we compute the Standardized Precipitation Index (SPI) with a 6-month time scale.[8] The SPI is commonly used for defining and monitoring droughts. It captures the occurrence and the severity of droughts at a given time scale (temporal resolution) for any rainfall station with historical data and can also be used to determine periods of anomalous wet events. The SPI is the transformation of the precipitation time series into a standardized normal distribution (z-distribution) and has several advantages compared to other drought indicators such as the Palmer Drought Severity Index (PDSI). In particular, since the SPI uses normalized rainfall data and compares the current rainfall with the average, different areas with different rainfall characteristics can be compared in terms of how badly they are experiencing drought conditions (Edwards and McKee, 1997). The index is negative for drought, and positive for wet conditions. As the dry or wet conditions become more severe, the index tends to 3 or -3.

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7. CRU time-series datasets comprise month-by-month variations in climate over the last century or so. These are calculated on high-resolution ($0.5° \times 0.5°$) grids, which are based on an archive of monthly mean temperatures provided by more than 4000 weather stations distributed around the world. They allow variations in climate to be studied, and include variables such as cloud cover, diurnal temperature range, frost day frequency, precipitation, daily mean temperature, monthly average daily maximum temperature, vapor pressure and wet day frequency. We use the version 3.10.01 from which precipitation data in mm can be extracted over the period 1901-2009.

8. The methodology used to compute the SPI is shown in appendix A.2. SPI are calculated with a 6-month time scaled because meteorological and soil moisture conditions (agriculture) respond to precipitation anomalies on relatively short timescales, 1-6 months, whereas streamflow, reservoirs, and groundwater respond to longer term precipitation anomalies of the order of from 6-months to 24-months or longer.

## 4.2. Unit roots, cointegration and causality tests

Climate shock occurrence in a specific country may have macroeconomic consequences in the neighboring countries. For instance, precipitation shocks in sending countries (such as Côte d'Ivoire) may reduce remittances inflows in receiving countries, and in turn affect overall economic performance. Similarly, climate shocks may reduce domestic production capacities and constrain exports to neighboring countries. Thus, the potential correlation between macroeconomic performances on a regional scale after a climate shock requires taking into account the dependence hypothesis between countries.

Results of the cross-sectional dependence (CD) test of Pesaran (2004) confirm the presence of dependence between cross-sectional units (see appendix A.3). This therefore requires the use of the technique proposed by Pesaran (2006), which takes into account the cross-section dependence between countries in order to estimate the model given by equation (6), and the use of second generation panel unit root tests like the cross-sectionally augmented panel unit root test (CIPS) proposed by Pesaran (2007) in order to analyze the time properties of variables. The CIPS test has the advantage of taking into account dependence between countries in the stochastic process of the series and has also good properties in finite samples, i.e., samples that remain relatively strong with a limited number of observations.

Results of the CIPS test (table 1) show that GDP per capita, total agricultural imports per capita and remittances per capita are $I(0)$ when expressed in their first difference, whereas precipitation (SPI) and financial development (private credit by deposit money banks and other financial institutions as percentage of GDP) variables are stationary variables when expressed in level.

**Table 1.** *Panel unit root test results*

| Variables | Specification | Lag | Level | First difference |
|---|---|---|---|---|
| $SPI$ | Constant | 0 | -6.36 (0.002) | . |
| | | 1 | -2.82 (0.000) | . |
| | Constant & trend | 0 | -6.76 (0.000) | . |
| | | 1 | -4.14 (0.000) | . |
| $R_i$ | Constant | 0 | 1.87 (0.969) | -5.38 (0.000) |
| | | 1 | 1.05 (0.854) | -2.98 (0.001) |
| | Constant & trend | 0 | 2.40 (0.992) | -4.09 (0.000) |
| | | 1 | 2.07 (0.981) | -1.78 (0.037) |
| $F_d$ | Constant | 0 | -2.58 (0.005) | . |
| | | 1 | -3.67 (0.000) | . |
| | Constant & trend | 0 | -2.31 (0.011) | . |
| | | 1 | -4.34 (0.000) | . |
| $y_{agr}$ | Constant | 0 | -3.27 (0.001) | . |
| | | 1 | -3.15 (0.001) | . |
| | Constant & trend | 0 | -3.82 (0.000) | . |
| | | 1 | -4.65 (0.000) | . |
| $y$ | Constant | 0 | 1.97 (0.976) | -8.08 (0.000) |
| | | 1 | 2.86 (0.998) | -3.83 (0.000) |
| | Constant & trend | 0 | -0.95 (0.170) | -7.48 (0.000) |
| | | 1 | -0.36 (0.359) | -3.49 (0.000) |
| $M_{agr}$ | Constant | 0 | -1.18 (0.117) | -7.89 (0.000) |
| | | 1 | -0.41 (0.341) | -3.27 (0.001) |
| | Constant & trend | 0 | -0.24 (0.403) | -6.50 (0.000) |
| | | 1 | -0.86 (0.806) | -1.73 (0.042) |

*Series are I(1) under the null hypothesis and p-values are reported in parenthesis.*

Using first differenced variables in a VAR model may result in a loss of the long run information in presence of a cointegration relationship between the variables. We then use the four panel cointegration tests of Westerlund (2007), which have good small-sample properties and high power relative to popular residual-based panel cointegration tests such as the Pedroni test (2004). Furthermore, bootstrap p-values are computed making inference possible under cross-sectional dependence.[9]

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9. The Westerlund (2007) tests are designed to test the null hypothesis of no cointegration by testing whether the error correction term in a conditional error correction model is equal to zero. If the null hypothesis of no error correction is rejected, then the null hypothesis of no cointegration is also rejected. The panel cointegration tests of Westerlund (2007) are able to accommodate serially correlated error terms, country-specific intercept and trend terms, and country-specific slope parameters.

The $G_t$ and $G_a$ statistics test the null hypothesis of no cointegration for all cross-sectional units against the alternative that there is cointegration for at least one cross-sectional unit ($H_0 : \rho_i = 0$ for all $i$ versus $H_0 : \rho_i = 0$ for at least one $i$). The $P_t$ and $P_a$ statistics pool information over all the cross-sectional units to test the null of no cointegration for all cross-sectional units against the alternative of cointegration for all cross-sectional units ((i.e. $H_0 : \rho_i = 0$ versus $H_0 : \rho_i = \rho < 0$ for all $i$).[10]

For small samples like ours, Westerlund (2007) warns that the results of the tests may be sensitive to the specific choice of lag and lead lengths. Hence, to avoid over-parametrization and the resulting lack of sufficient degrees of freedom, we hold the short-run dynamics by setting up one lag and one lead length (i.e. $p_i = p = 1$) in the panel cointegration test model. The lag order choice is also confirmed by the AIC criterion. Pooled and panel statistics, reported in table 2, indicate no rejection of the null hypothesis that the series are not cointegrated.

The panel causality test proposed by Emirmahmuoglu and Kose (2011) is based on the meta-analysis of Fisher (1932)[11] and has several advantages. First, it allows taking into account heterogeneities in the cross-sectional units. A Granger causality test for each unit is calculated with different lag orders (the maximum lag order is set to 2 lags) based on the AIC criterion. The panel Fisher test statistic ($\lambda$) is obtained by combining the p-values corresponding to the Wald statistic for each cross-sectional unit. Secondly, the test allows for cross-sectional dependency. In the case of cross-section dependency in the panel, a bootstrap method is applied to generate the empirical distributions of the Fisher test. The bootstrap distribution of the Fisher test statistics is derived from 5000 replications and bootstrap critical values are obtained at the 1%, 5% and 10% levels.

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10. For more details on the test-statistics and their derivation, see Persyn and Westerlund (2008).

11. The meta-analysis developed by Fisher (1932) is a statistical technique which has been planned to obtain a common result combining the results of a number of independent studies which test the same hypothesis.

**Table 2.** *Panel cointegration test results*

|  | Statistics | Value | Z-value | P-value |
|---|---|---|---|---|
| $y$ | $G_a$ | -0.448 | 4.229 | 0.953 |
|  | $G_t$ | 0.735 | 4.497 | 0.888 |
|  | $P_a$ | -0.044 | 3.199 | 0.963 |
|  | $P_t$ | -0.293 | 4.864 | 0.963 |
| $F_d$ | $G_a$ | -0.396 | 4.250 | 0.978 |
|  | $G_t$ | -0.469 | 5.293 | 0.975 |
|  | $P_a$ | -0.745 | 2.896 | 0.718 |
|  | $P_t$ | -0.413 | 2.857 | 0.730 |
| $M_{agr}$ | $G_a$ | -1.381 | 3.854 | 0.450 |
|  | $G_t$ | -2.192 | 0.125 | 0.340 |
|  | $P_a$ | -1.115 | 2.737 | 0.475 |
|  | $P_t$ | -5.157 | 0.261 | 0.235 |
| $R_i$ | $G_a$ | -0.500 | 4.208 | 0.915 |
|  | $G_t$ | -0.317 | 5.749 | 0.990 |
|  | $P_a$ | -0.094 | 3.177 | 0.933 |
|  | $P_t$ | -0.405 | 4.757 | 0.925 |
| $y_{agr}$ | $G_a$ | -0.662 | 4.143 | 0.520 |
|  | $G_t$ | -1.626 | 1.820 | 0.760 |
|  | $P_a$ | -0.618 | 2.951 | 0.480 |
|  | $P_t$ | –2.725 | 2.562 | 0.520 |

*Each error-correction model includes a constant and no trend under the null hypothesis of no cointegration. Robust critical values are obtained through bootstrapping with 800 replications.*

Results in table 3 confirm that remittances inflows may have positive or negative effect on the domestic credit provided by the banking sector which, in turn, may contributes to GDP growth. By positioning remittances before financial sector development and GDP variables in the PCHVAR model, we address the potential immediate and lagged spill-over effects of remittances on domestic production capacities. Furthermore, Granger causality test results in table 3 show that agricultural imports are Granger-caused by remittances and GDP variables. Agricultural imports are then considered as the most endogenous variable in the system. They are contemporaneously affected by remittances, financial sector development and GDP. Thus the 5 variables of the system are ordered as follows :

$$Y_{it} : \left[ R_i; F_d; y_{agr}; y; M_{agr} \right] \tag{7}$$

**Table 3.** *Granger causality test results*

| Null hypothesis | $\lambda$ | Bootstrapped critical values | | |
| --- | --- | --- | --- | --- |
| | | CV 1% | CV 5% | CV 10% |
| $F_i \nrightarrow R_i$ | 25.865 | 43.505 | 32.994 | 28.037 |
| $R_i \nrightarrow F_i$ | 38.156 | 42.577 | 30.962 | 26.976 |
| $F_i \nrightarrow y$ | 35.082 | 41.782 | 33.629 | 29.137 |
| $y \nrightarrow F_i$ | 30.150 | 40.212 | 30.925 | 27.223 |
| $y_{agr} \nrightarrow y$ | 50.416 | 39.363 | 31.076 | 27.248 |
| $y \nrightarrow y_{agr}$ | 32.632 | 38.063 | 30.524 | 26.972 |
| $M_{agr} \nrightarrow y$ | 19.264 | 37.880 | 30.553 | 27.086 |
| $y \nrightarrow M_{agr}$ | 34.323 | 48.015 | 34.476 | 29.418 |
| $R_i \nrightarrow M_{agr}$ | 37.454 | 37.324 | 31.209 | 26.864 |
| $M_{agr} \nrightarrow R_i$ | 12.091 | 40.477 | 31.510 | 27.298 |

# 5. Empirical results

We determine the effects of drought severity and remittances shocks on the set of the considered macroeconomic variables by estimating the PCHVAR model given by equation 6. We compute Orthogonalized Impulse-Response Functions (OIRFs) giving the $s$th-period response when the system is shocked by a one-standard deviation shock, and we also perform a standard variance decomposition exercise (FEDV) for the variables included in the PCHVAR model. Since the model is estimated in logs, the OIRFs show the log deviations of variables with respect to their baseline level, so they can be interpreted as percentage changes.

Results from the estimated PCHVAR model show the various potential impacts of remittances. On the supply side, agents receiving remittances may be pushed to move away from their main activity or to diversify their agricultural production. On the demand side, they can spend remittances to maintain a minimum level of consumption during precipitation shocks and drought periods (Yang and Choi, 2005; Quisumbing et al., 2008). The macroeconomic consequences of such behaviors remain undetermined. Remittances may well promote growth, if they are used to purchase domestically produced goods and

services (Glytsos, 1993), but such consumption smoothing behaviours may also induce an increase in imports, including imports of essential goods (Jovičić and Mitrović, 2006).

However, macroeconomic impacts exerted by remittances may also be influenced by precipitation shocks, which have direct consequences on agricultural production capacities. In other words, remittances may exert spill-over effects on growth during normal periods but may have a pernicious macroeconomic impact when shocks occur. Our findings confirm this conjecture by evidencing that the macroeconomic impact of remittances in West Africa is highly sensitive to drought conditions. Indeed, results from OIRFs and FEDV show that a positive shock in remittances has various macroeconomic effects depending on the level of the 6-month Standardized Precipitation Index.

Remittances exert no spillover effects in the countries studied here since they only explain 5.94% of the GDP variance (table 4). This low contribution of remittances inflows to innovations in GDP remains constant for all values taken by the conditioning variable (i.e. the Standardized Precipitation Index). Impulse response functions indicate that a one standard deviation positive shock on remittances has no effect on the real GDP per capita, whatever the weather conditions (figure 1). On the contrary, responses of agricultural value added to remittances positive shocks vary greatly according to the Standardized Precipitation Index (figure 1). Indeed, a one standard deviation positive shock on remittances results in an increase in agriculture value added by 0.98% and in a decline by -0.83% in case of abnormal wet conditions ($SPI = 1$) and moderate droughts ($SPI = -1$) respectively one year after the shock. By contrast, the response of agricultural value added to a positive shock on remittances is found to be non-significant for median values of the Standardized Precipitation Index ($SPI = 0$).

**Figure 1.** *Agricultural value added and GDP responses to a shock on remittances*



$y_{agr}/R_i \ (SPI = -1)$

$y_{agr}/R_i \ (SPI = 0)$
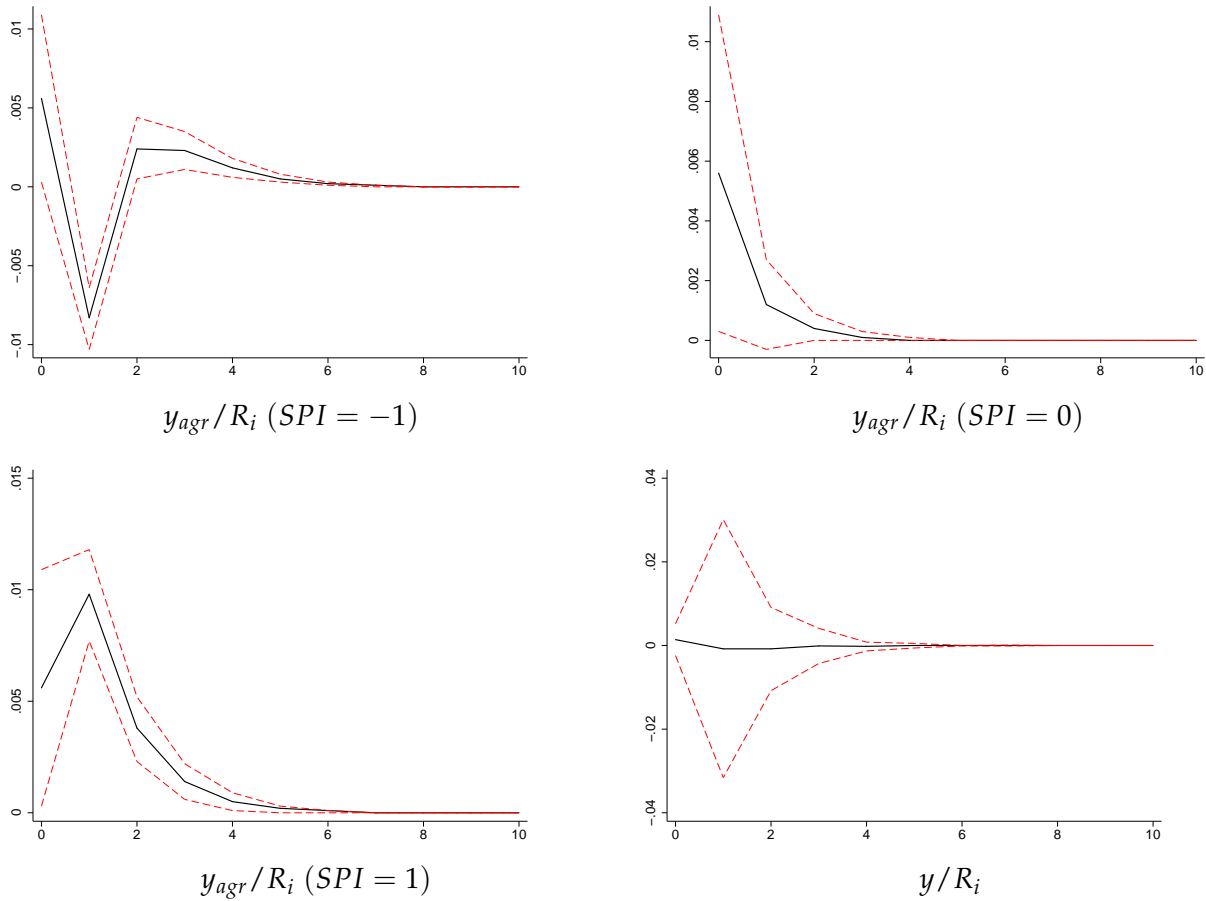
$y_{agr}/R_i \ (SPI = 1)$

$y/R_i$

*Figure 1 exhibits the response functions of (log) real GDP per capita and agricultural value added per capita to a one standard deviation shock to log remittances per capita variable. The continuous line depicts the point estimate of the IRF, and the broken lines show the 95% asymptotic confidence bands.*

Our results also confirm that remittances inflows may spur agricultural imports especially for low SPI values. The dynamic response of agricultural imports to a shock on remittances is depicted in Figure 2. In case of abnormal wet conditions ($SPI = 1$), impulse response functions show that a positive shock on remittances has a negative impact of -7.35% on agricultural imports one year after the shock. For median values of the SPI ($SPI = 0$), a one standard deviation positive shock on remittances results in a non-significant response of agricultural imports. Conversely, the effect of such a shock is positive and significant for values of the SPI lower than $-0.4$. Thus, in case of moderate droughts ($SPI = -1$) a positive shock on remittances leads to an increase in agricultural imports of 9.23% one year after the shock, gradually returning to normal levels the following year as the initial

shock of remittances is diluted. This increase in agricultural imports appears to be a response to the decline in agricultural supply after a rainfall shock, a decline which is not entirely compensated by the rise following remittances inflows.

**Figure 2.** *Agricultural imports responses to a shock on remittances*



$M_{agr}/R_i \; (SPI = -1)$

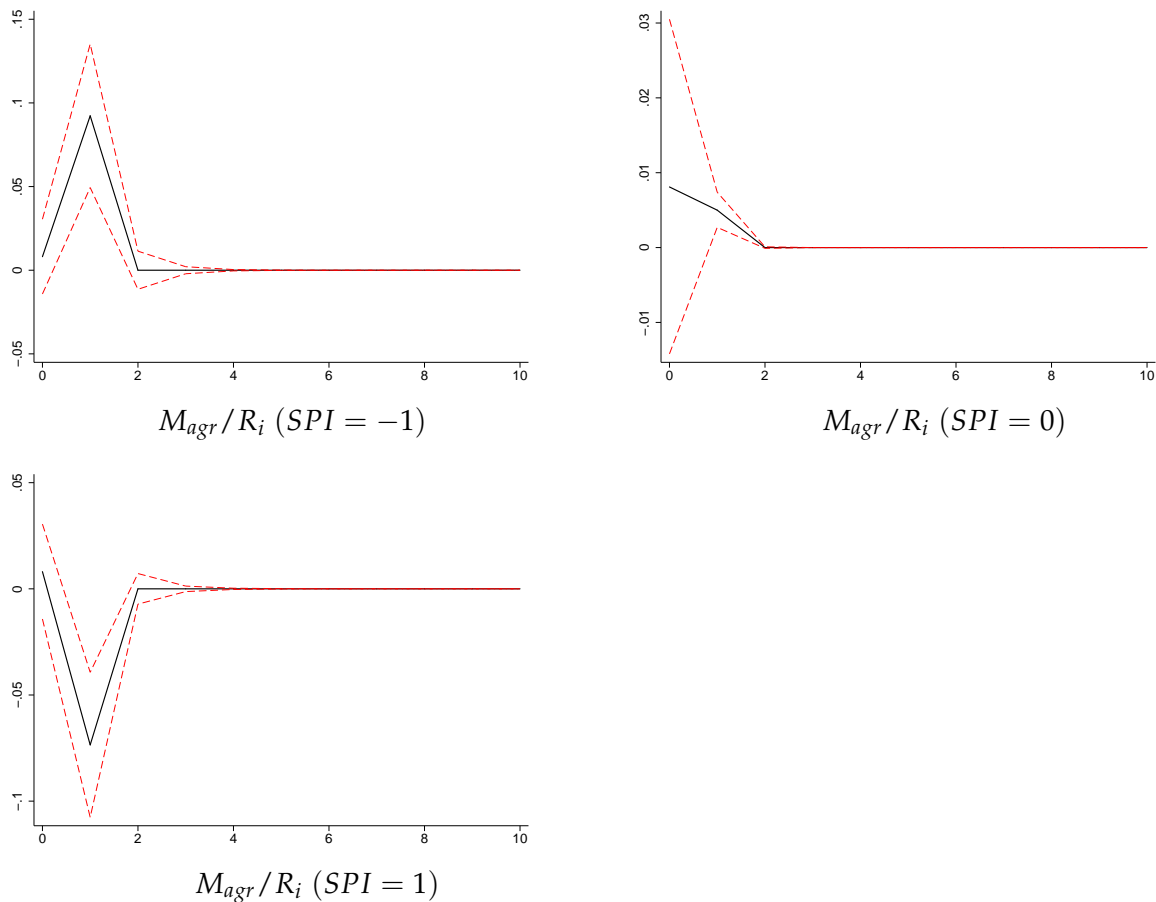$M_{agr}/R_i \; (SPI = 0)$

$M_{agr}/R_i \; (SPI = 1)$

*Figure 2 exhibits the response functions of (log) real total agricultural imports per capita to a one standard deviation shock to (log) remittances per capita variable. The continuous line depicts the point estimate of the IRF, and the broken lines show the 95% asymptotic confidence bands.*

Analysis of the FEDVs in table 4 corroborates those results. Indeed, remittances only explain a low percentage of the fraction of the variance of agricultural imports in countries characterized by normal SPI values (7.92% for $SPI = 0$). This contribution increases as the Standardized Precipitation Index deviates from its baseline. Remittances explain 42.95% and 23.87% of the fraction of the variance of agricultural imports in case of moderate

droughts ($SPI = -1$) and abnormal humid conditions ($SPI = 1$) respectively.

Thus, our results bring some evidence that imports responses to remittances shocks can be interpreted as part of income strategies of intertemporal smoothing in a context of agricultural supply constraints. In case of adverse weather conditions, the negative response of the agricultural value added to a positive shock in remittances supports previous empirical studies: it shows that remittances inflows may generate moral hazard and then have a negative effect on economic growth (Azam and Gubert, 2005 ; Chami et al., 2003).

A key question is whether remittances have an impact on the financial development of our sampled countries. We find a significant link between remittances and financial development but this link appears to be non-linear, depending also on weather conditions. After controlling for climate shocks, our results are contrary to the view of a positive impact of remittances on financial development in sub-Saharan countries (Aggarwal et al., 2011 ; Gupta et al., 2009). Indeed, we find that adverse weather conditions act as a constraint on the complementarity link between remittances and financial development. Therefore, in West Africa and especially in rural areas characterized by low financial institutions, poorer and most exposed households may prefer to rely on informal services when they face adverse weather events because of high transaction costs in formal financial services, and particularly in credit.

FEDVs show that shocks on remittances account for a large share in the variance of the financial development indicator for extreme values of the standardized precipitation index. This contribution in the variance of the financial development indicator increases from 0.36% when the SPI is equal to 0 to 12.26% when $SPI = -1$ and to 13.29% when $SPI = 1$. Results from OIRFs in figure 3 indicate that a positive shock on remittances leads to an increase in financial development (4.01%) the year following the shock in case of abnormal humid conditions ($SPI = 1$) and to a decrease (-4.30%) in case of moderate droughts ($SPI = -1$).

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**Figure 3.** *Financial sector development responses to a shock on remittances*



$F_d/R_i \; (SPI = -1)$

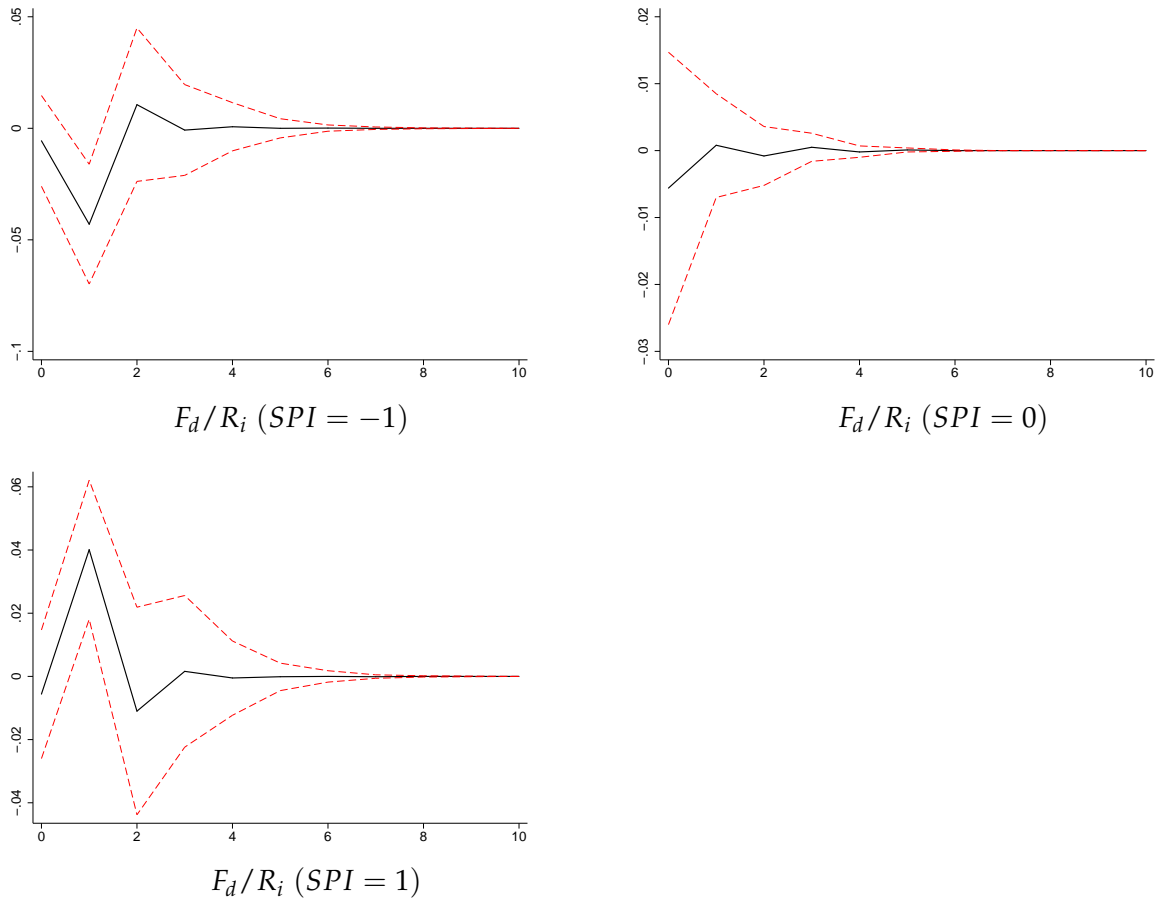$F_d/R_i \; (SPI = 0)$

$F_d/R_i \; (SPI = 1)$

*Figure 3 exhibits the response functions of the (log) private credit by deposit money banks and other financial institutions (as percentage of GDP) to a one standard deviation shock to (log) remittances per capita variable. The continuous line depicts the point estimate of the IRF, and the broken lines show the 95% asymptotic confidence bands.*

Furthermore, our results also show that GDP per capita responds negatively to positive shocks on financial development. According to FEDVs, the index of financial development contributes to 11.13% in the variance of GDP and OIRFs indicate that a one standard deviation positive shock on private credit to GDP ratio results in an immediate 0.5% decrease in GDP per capita. This response remains negative and significant for every values of the SPI. This confirms previous results showing that the relationship between financial development and growth can be negative in the case of developing countries where strong fragmentation exists between formal and informal financial sectors (Aryeetey et al., 1997). Recent studies have also showed that low level of economic development can

limit the efficiency of the financial sector (Méon and Weill, 2010).

**Figure 4.** *GDP response to a shock on financial sector development*
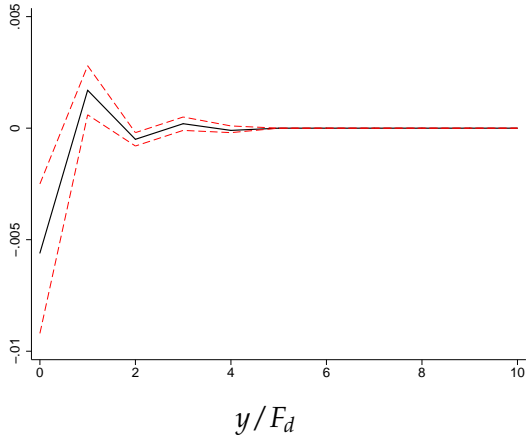


$$y/F_d$$

*Figure 4 exhibits the response functions of the (log) GDP per capita to a one standard deviation shock to the (log) private credit by deposit money banks and other financial institutions (as percentage of GDP). The continuous line depicts the point estimate of the IRF, and the broken lines show the 95% asymptotic confidence bands.*

**Table 4.** *Forecast Error Decomposition Variance*

|           | $R_i$  | $F_d$  | $y_{agr}$ | $y$    | $M_{agr}$ |
|-----------|--------|--------|-----------|--------|-----------|
| $SPI = -1$ |        |        |           |        |           |
| $R_i$     | 96.13  | 3.87   | 0.00      | 0.00   | 0.00      |
| $F_d$     | 12.26  | 87.74  | 0.00      | 0.00   | 0.00      |
| $y_{agr}$ | 11.68  | 0.22   | 85.95     | 0.12   | 2.03      |
| $y$       | 5.94   | 11.13  | 18.20     | 62.65  | 2.08      |
| $M_{agr}$ | 42.85  | 7.74   | 2.62      | 3.69   | 43.09     |
| $SPI = 0$ |        |        |           |        |           |
| $R_i$     | 95.35  | 4.65   | 0.00      | 0.00   | 0.00      |
| $F_d$     | 0.36   | 99.64  | 0.00      | 0.00   | 0.00      |
| $y_{agr}$ | 3.35   | 0.09   | 96.55     | 0.00   | 0.00      |
| $y$       | 5.94   | 11.13  | 26.89     | 53.96  | 2.08      |
| $M_{agr}$ | 7.92   | 7.05   | 4.42      | 6.49   | 74.12     |
| $SPI = 1$ |        |        |           |        |           |
| $R_i$     | 87.26  | 12.74  | 0.00      | 0.00   | 0.00      |
| $F_d$     | 13.29  | 86.71  | 0.00      | 0.00   | 0.00      |
| $y_{agr}$ | 10.89  | 0.16   | 87.50     | 0.08   | 1.37      |
| $y$       | 5.94   | 11.13  | 28.13     | 52.72  | 2.08      |
| $M_{agr}$ | 23.87  | 24.25  | 2.65      | 4.05   | 45.18     |

*The columns of the table show the fraction of the ten year ahead forecast error that can be explained by all considered variables in the PCHVAR model. The variance of the ten year ahead forecast error is almost identical to the unconditional variance of variables. So, figures show the fraction of the total variance of variables that can be accounted by each type of shock.*

# 6. Conclusion

The aim of this paper was to investigate the consequences of remittances inflows on macroeconomic performance for a sample of West African countries facing climate variability. Accordingly, we have implemented an empirical framework based on the estimation of a PCHVAR model where effects of remittances are conditional to rainfall shocks. Rainfall shocks have been computed based on a Standardized Precipitation Index using time series of precipitation data extracted from the Climate Research Unit.

Our results show that remittances have a significant impact on the macroeconomic performance of West African economies. Yet this impact is highly sensitive to rainfall shocks in a context of vulnerability to climate stress. In case of humid conditions, a positive shock on remittances leads to an immediate increase in agricultural value added and to a negative response of agricultural imports the year following the shock. Moreover, remittances are found to have a positive role on financial development.

However, this positive role of the remittances on West African macroeconomic performance is no longer observed for lower values of the Standardized Precipitation Index. Indeed, if remittances help increasing the households' resilience to rainfall shocks by smoothing consumption over time, this process leads to a rise of agricultural imports when countries face adverse weather events. In this case, remittances have a negative impact on agricultural value added and financial development and do not exert any short-term spillover effects on growth. The immediate rise of agricultural imports following the remittances 'boom' confirms the possibility that remittances may increase a situation of economic dependence particularly when drought conditions prevail.

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# Appendix

## A.1 Lag selection and stability test results
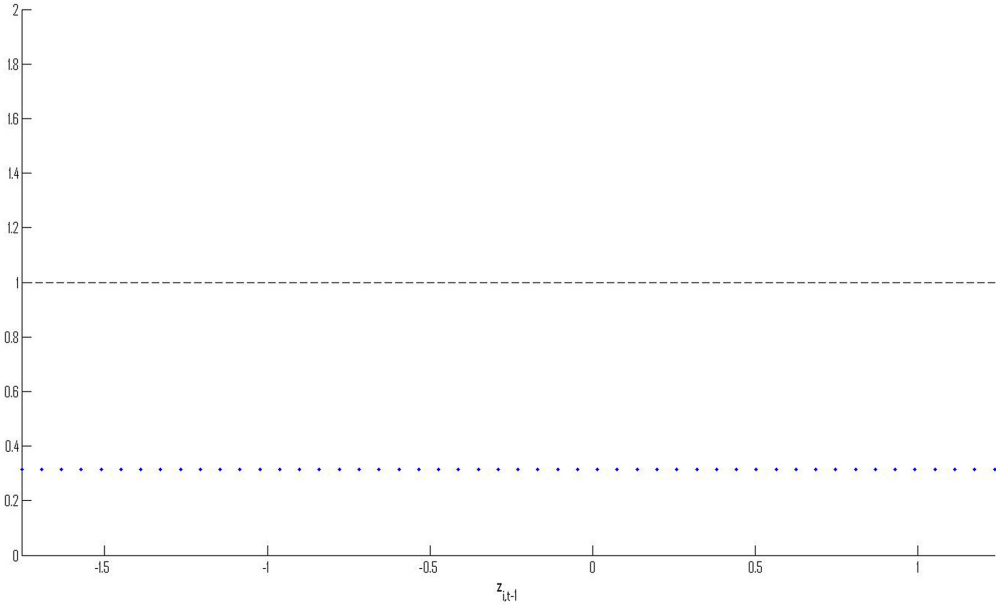
**Figure A.1.** *PCHVAR stability test*



**Table A.1.** *Lag order decision rule*

| Lag order | AIC | SC |
| --- | --- | --- |
| 1 | -6.8229 | -5.9825 |
| 2 | -6.5657 | -5.2856 |

## A.2 SPI methodology

Following Edwards and McKee (1997), the calculation of SPI is done by fitting each climatological precipitation time series to the gamma probability density function:[12]

$$g(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \qquad \text{for } x > 0 \tag{8}$$

Where $\alpha$ is a shape parameter, $\beta$ is a scale parameter and $x$ is the monthly precipitation amount ($\alpha > 0$ and $\beta > 0$). For $\alpha > 0$ the gamma function $\Gamma(\alpha)$ is defined by:

$$\Gamma(\alpha) = \int_0^\infty x^{\alpha-1} e^{-x} dx \tag{9}$$

Computation of the SPI involves fitting a gamma probability density function to a given frequency distribution of precipitation totals for a station. The alpha and beta parameters of the gamma probability density function are estimated for each station, for one or different time scales of interest (1, 2, 3, 6, 12, 24 months) and for each month of the year. From Thorn (1966), the maximum likelihood solutions are used to optimally estimate $\alpha$ and $\beta$:

$$\hat{\alpha} = \frac{1}{4A} \left( 1 + \sqrt{1 + \frac{4A}{3}} \right) \tag{10}$$

$$\hat{\beta} = \frac{\bar{x}}{\hat{\alpha}} \tag{11}$$

Where,

$$A = \ln(\bar{x}) - \frac{\sum \ln(x)}{n} \tag{12}$$

With $n$ the number of precipitation observation. Integrating the probability density function with respect to $x$ and attach $\alpha$ and $\beta$ parameters yields the cumulative probability

---

12. The first step in the calculation of the SPI is to determine a probability density function that describes the long-term series of observations (Guttman, 1999). Gamma distribution and Pearson type III distribution are the most commonly used probability density function to compute SPI. Some authors have found that Pearson type III distribution seems to be a better choice than the gamma distribution in describing the long-term rainfall series (Guttman, 1999; Wu et al., 2007) while others find non significant and averaged zero differences between SPI final values based on both Pearson type III distribution and gamma distributions (Kumar et al., 2009; Blain, 2005).

distribution function $G(x)$:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\hat{\beta}^{\hat{\alpha}}\Gamma(\hat{\alpha})} \int_0^x x^{\hat{\alpha}-1}e^{-x/\hat{\beta}}dx \tag{13}$$

Substituting $t$ for $-\frac{x}{\hat{\beta}}$ yields the incomplete gamma function:

$$G(x) = \frac{1}{\Gamma(\hat{\alpha})} \int_0^x t^{\hat{\alpha}-1}e^{-t}dt \tag{14}$$

Since the gamma function is undefined for $x = 0$ and a precipitation distribution may contain zeros, the cumulative probability becomes:

$$H(x) = q + (1-q)\,G(x) \tag{15}$$

Where $q = P(x = 0)$ is the probability of zero (null) monthly precipitation. The cumulative probability distribution $H(x)$ is then transformed into the standard normal random variable $Z$ to yield the SPI (Edwards and McKee, 1997; Abramowitz and Stegun, 1965).

$$Z = SPI = -\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \qquad \text{for } 0 < H(x) \le 0.5 \tag{16}$$

$$Z = SPI = +\left(t - \frac{c_0 + c_1 t + c_2 t^2}{1 + d_1 t + d_2 t^2 + d_3 t^3}\right) \qquad \text{for } 0.5 < H(x) < 1.0 \tag{17}$$

Where,

$$t = \sqrt{\ln\left(\frac{1}{(H(x))^2}\right)} \qquad \text{for } 0 < H(x) \le 0.5 \tag{18}$$

$$t = \sqrt{\ln\left(\frac{1}{1-(H(x))^2}\right)} \qquad \text{for } 0.5 < H(x) < 1.0 \tag{19}$$

$$c_0 = 2.5155 \quad c_1 = 0.8028 \quad c_2 = 0.0103$$

$$d_1 = 1.4327 \quad d_2 = 0.1892 \quad d_3 = 0.0013$$

For the purposes of this article studying larges areas (countries), SPI is applied equally to wet and dry areas characterized by different types of climates. We calculate SPI using the monthly amount of precipitation (in *mm*) between 1960 and 2010 for multiple precipitation grid point on a 6-month time resolution basis using data from the Climate Research Unit (CRU). We then use the SPI averages at the national scale as the conditioning variable in the PCHVAR model in equation (6).

## A.3   Pesaran Cross-Section Dependence test (2004)

**Table A.2.** *Pesaran CD test results*

|  | Variable in level | | First diff. variable | |
| --- | --- | --- | --- | --- |
| Variable | CD-test | p-value | CD-test | p-value |
| $M_{agr}$ | 4.62 | 0.000 | 4.67 | 0.000 |
| $y_{agr}$ | -0.87 | 0.385 | 2.54 | 0.011 |
| $R_i$ | 0.64 | 0.522 | 2.20 | 0.028 |
| $y$ | 0.80 | 0.424 | 4.56 | 0.000 |
| $F_d$ | 9.26 | 0.000 | 1.06 | 0.287 |

*Series are assumed to be cross-section independent under the null hypothesis.*