# Do Remittances reduce vulnerability to climate variability in West African Countries? Evidence from panel vector autoregression

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# *Do Remittances reduce Vulnerability to Climate Variability in West African Countries? Evidence from Panel Vector Autoregression*

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Preliminary version

***Abstract:***
In this paper, we empirically examine the role of remittances in smoothing the GDP fluctuations induced by precipitation variability and both meteorological and natural shocks. To this end, we use a panel VAR to empirically study six West African countries from 1983 to 2009. Our evidence suggests that remittances are an important element of macroeconomic stability especially for those countries most vulnerable to precipitation variability. The estimated orthogonalized impulse responses show on one hand, that meteorological shocks and declining precipitation have both adverse consequences on GDP per capita. On the other hand, remittances are characterized by counter-cyclical patterns in cases of precipitation variability and climate shocks. Remittances inflows in the selected countries (countries of emigration) are also heavily dependent on economic shocks in host countries.



*Keywords:* Climatic variability, Panel VAR, Remittances, West Africa
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# 1. Introduction

The least developed countries (LDCs) of West Africa are at tremendous risk from climatic shocks such as shifting weather patterns and environmental degradation and suffer the greatest burden of adjusting to threats of climate change because they are already challenged by what is known as 'multiple vulnerabilities' on account of their low levels of economic and human development (UN-DESA, 2009a: 71). Clearly, West Africans face a future where a lack of social and physical infrastructure, missing institutions and a narrow economic base may be 'exposed not just to potentially catastrophic large-scale disasters but also to a more permanent state of economic stress as a result of higher average temperatures, reduced availability of water sources, more frequent flooding and intensified windstorms' (ibid).

Many studies have sought to analyse the impact of external shocks, especially climatic shocks, on gross domestic product (GDP) volatility in developing countries. Most of these studies have concluded that there is a relatively modest impact of external shocks, particularly climatic shocks on developing countries' GDP volatility. For example, Raddatz (2009) has argued that the low impact of external shocks on GDP fluctuations may be explained by domestic factors such as the level of inflation, overvalued real exchange rates, civil wars, corruption and/ or large public deficits. Another potential explanation concerns the existence of counter-cyclical factors[1] that smooth GDP fluctuations to climatic shocks. Noy (2009) using a sample of 109 countries for the period 1970-2003 includes structural factors such as the literacy rate, level of education, quality of institutions and trade openness in the analysis on the impact of shocks on GDP fluctuations using a variant of Raddatz's (2007) model. Noy (2009) concludes that countries with a higher literacy rate, better institutions, higher per capita income, a greater degree of openness to trade, higher levels of government spending, foreign exchange reserves, and levels of domestic credit, but with less open capital accounts are better able to withstand the initial shock of a climatic disaster and limit wider spill-over effects.



[1] In theory, any economic quantity that is positively correlated with the overall state of the economy is considered pro-cyclical. Thus, any quantity that tends to increase when the overall economy is growing is classified as pro-cyclical. Quantities that tend to increase when the overall economy is slowing down are classified as 'counter-cyclical'. Thus, in developing countries remittances tend to rise during periods of financial crises.

Using a generalised linear regression model Hochrainer (2009) highlights the role of aid and remittance inflows in reducing the adverse macroeconomic consequences of shocks. The author uses an autoregressive integrated moving average model (ARIMA) to forecast GDP into the medium term following a disaster event. In order to extrapolate GDP trends, the evolution of GDP following a shock is compared with GDP trends in the absence of a disaster. Hochrainer (2009) then tests several explanatory variables (termed vulnerability predictors) to explain variations in projected and observed GDP 5 years after a disaster event. Finally the limited impact of climatic shocks on GDP volatility may be explained by the nature of the shock itself. Loaysa et al. (2009) focus on the analysis of climate shocks and their impact on 94 developing countries from 1961 to 2005 on the basis of a Generalized Method of Moment (GMM) model. The authors identified different impacts according to the type of climate shock. Certain disasters (in particular low-span disasters e.g. low covariant disasters such as floods) can also have a positive economic impact, if they induce investment and the reconstruction of an economic sector. In contrast, more substantial span disasters (with a stronger covariance e.g. droughts) have negative consequences and an almost immediate impact on the economy of the poorest countries.

The paper aims to analyze the role of remittances in explaining the relationship between GDP instability and climate shocks in six West African countries. Thus, the paper seeks to examine the extent to which remittance receipts, climatic and biological shocks as well as rainfall patterns help to explain the volatility of GDP growth in West Africa after controlling for a number of climatic variables that have been cited in the literature as potential determinants of GDP volatility.

To do so, we elaborate a methodology which differs from the cited studies in several ways. First, in addition to the notion of shocks, we focus on climate variability by assessing the impact of shocks in precipitation patterns in relation to GDP fluctuations. Indeed, sub-Saharan Africa (SSA) is one of the most vulnerable continents to climate variability and in particular to both intra and inter-annual precipitation variability. This vulnerability to climate variability may also be aggravated by the interaction and occurrence of multiple stresses coupled to a relatively low adaptive capacity of SSA populations. The economic impact on the agricultural sector – an activity which accounts for 70 percent of the SSA labor-force and 30 percent of

GDP – is particularly important because of the predominance of rain-fed agriculture and thus an increased dependence on rainfall patterns.

Second, among the possible factors affecting the link between climate and biological shocks and GDP fluctuations, we take into account the impact of remittances on macroeconomic stability and their interactions with shocks and rainfalls. Remittances represent one of the main and most stable sources of financial inflows to West Africa. Between 2001 and 2008, official remittance inflows increased by 700% in Mali, Mauritania, Niger, Togo, Benin and Senegal. These countries received (on average) US$ 1.25 billion of remittances in 2008. Since 1990 remittances in West African countries have been a more important financial flow than Official Development Assistance (ODA). Third, we use a Panel Vector Autoregressive (PVAR) model which combines the traditional VAR model with a panel-data approach based on the PVAR routine written by I. Love (World Bank). To assess the role of the level of GDP in the spillover effects exerted by climatic shocks and precipitation variability, we consider two PVAR models on the six selected countries: the first PVAR model (PVAR1) assesses the contemporaneous and lagged impacts of both precipitation shortage and climate shocks on remittances per capita and GDP per capita while the second PVAR model (PVAR2) estimates the contemporaneous and lagged effects of GDP per capita in region of immigration on remittances inflows in the six West African countries. By comparing the PVAR1 and PVAR2 outputs from orthogonalized Impulse Response Functions (IRF) and Forecast Error Decomposition Variance (FEDV) we are able to:

i) Isolate the effect of precipitation variability on remittances inflows and GDP per capita and compare it to the impact of climate and biological shocks.
ii) To discuss the constraints on remittances inflows in order to smooth GDP fluctuations by taking account of exterior economic constraints.

Results from orthogonalized IRFs bring strong evidences that climate shocks and precipitation variability are strong explanatory factors amongst in GDP fluctuations in West African countries. Remittances responses to shocks on precipitation variability and climate shocks are significant and counter cycle whereas responses to GDP shocks remain non-significant. This suggests that remittances contributes directly to a high resilience to precipitation variability and climate shocks and then have indirect effects on GDP fluctuations. Results from FEDV also indicate that precipitation explains a large fraction of the GDP and remittances fluctuations compared to climate shocks and home GDP shocks. Whereas climate shocks explain almost 2.5% of the GDP variance, precipitation variance contributes to 1.6% in GDP fluctuations. Precipitation variability explains 1% of the remittances variances and 3.4% and 1.4% is explained by climate and GDP shocks respectively. Results from IRFs and FEDV indicate GDP shocks explain a low fraction of the remittances variance whereas GDP of countries of immigration explain the larger fraction of the remittances inflows in countries of emigration. A negative shock corresponding to -57%% to GDP of Western Europe correspond to a variation of 0.94% in remittances inflows and results from FEDV indicates that Western European GDP variance contributes to 6.1% of remittances variance.

The remainder of the paper is organized as follows: section 2 outlines the empirical and theoretical literature dealing with the impact of remittances on GDP volatility in West African countries. Section 3 presents the methodology and empirical results of the paper. We draw the main conclusions from the study in section 4.

## 2. The role of remittances in smoothing GDP fluctuations in West Africa

In West Africa, remittances are an integral part of household risk management strategies. According to Findley (1994), during the great drought (1984-1985), 63% of households depended on remittances sent by (non-resident) family members abroad. Of those, 47% were receiving money from migrants established in France and only 16% from migrants established in sub-Saharan Africa cities. These findings show first, the importance of international migration as a source of remittances collected by households in the region of origin and secondly, the importance of migration as a means of providing insurance against climatic hazards. Several case studies have shown a positive relationship between the occurrence of natural disasters and growth in remittances. In a study conducted in Jamaica, Clarke and Wallsten (2004) show that remittances tend to increase with the occurrence of a natural disaster. Similarly, Gupta (2004) shows the positive impact of droughts in India on the cyclical component of such transfers. Ratha (2006) finds that transfers tend to increase after the occurrence of a natural disaster in Bangladesh, the Dominican Republic, Haiti and the Honduras. However, no study addresses the importance of the characteristics of the seasonal distribution of precipitation at a particular location (i.e. the precipitation regime) in explaining the volume of remittances in West Africa.

In theory, an increase in the variability of precipitation should negatively affect the income of households predominantly occupied in the agricultural sector and therefore lead to an increase of remittance inflows. However, several studies have questioned this unidirectional relationship. First, as migration is an ex-ante and ex-post risk management process, an anticipated shock (such as drought) may give rise to compensation well before the occurrence of the shock. Some other shocks, which are less predictable, may instead, give rise to compensation after their occurrence (e.g. floods). Second, remittances may be sent because of seasonal variability (intra-annual) intrinsic to rainfall patterns in West Africa. Remittances also constitute a form of insurance against all types of shocks, whether climatic or economic (Ebeke, 2010).

Although it is now widely recognized that households benefit from remittance inflows (Gupta et al., 2007), their empirical macroeconomic consequences remain less well known. Despite a broad set of theoretical studies (see Rapoport and Docquier, 2006), *"empirical studies still lag behind and have mostly focused on growth, inequality and poverty, leaving issues of macroeconomic stability largely uninvestigated"* (Bugamelli and Paterno, 2008). Nevertheless, according to the IMF (2005), *"[...] the relatively stable and a-cyclical nature of remittances suggests that countries with access to significant remittance inflows may be less prone to damaging fluctuations, whether in output, consumption or investment*".

Recent empirical evidence has sought to demonstrate this hypothesis but the results are often ambiguous regarding the pro or counter-cyclical patterns of remittances to GDP fluctuations. Ebeke (2010) measures the role of insurance played by remittances against shocks using a measure of the cyclical nature of the transfers vis-à-vis real GDP. Ebeke (2010) found that half the sample examined was defined by a strong counter-cyclical relationship (particularly during the mid-1990s). Similarly, Gupta et al. (2009) test the cyclical nature of remittances on real GDP of sub-Saharan African countries identifying a counter-cyclical relationship during the period 1996-2006 and a pro-cyclical association during the previous period (1980-1995). These studies offer contrasting results according to the particular country or region surveyed. For example, Neagu and Schiff (2009) find a pro-cyclical relationship for 70% of their sample including 116 countries. However, Sayan (2006) estimated correlations between the cyclical components of remittances and GDP for 12 countries suggest that there is a counter-cyclical relationship between the two variables for the sample as a whole. However, Sayan country-by-country analysis also suggests a greater heterogeneity of cases as only India and Bangladesh had counter-cycles whilst the rest of the sample revealed a pro-cyclical relationship (especially in Senegal and the Côte d'Ivoire).

In theory, the smoothing role of remittances is justified by the assumption that individuals are guided by altruism. Under this assumption, remittances should be counter-cyclical because the migrants tend to remit more funds when the economy in the country of origin undergoes a shock. A portfolio approach would consider the transfers a form of investment which should be pro-cyclical. According to Elbadwi (1992) and Agarwal and Horowitz (2002), most empirical evidence suggests that remittance flows are based on altruistic motivations. Nevertheless, studies testing for a correlation between cyclical components of the transfers and GDP suffer from several drawbacks. First, descriptive statistics (e.g. correlation coefficients) cannot take into account multiple causality which requires sensitivity analyses based on econometric models (e.g. Forbes and Rigobon, 2002). Second, the pro-cyclical nature of transfers in relation to real GDP might have a more positive impact on the level of GDP given a country's relative dependence on remittances. In order to overcome these shortcomings, we use a Panel VAR model in order to analyse the dynamic patterns of shocks' impacts on GDP fluctuations and the dynamic responses of official remittance inflows to both GDP instability and the occurrence of shocks. The panel VAR model also enables an empirical exploration of the underlying incentives to remit not only as a consequence of significant fluctuations in GDP but also as a direct consequence of shocks, whether climatic or economic in West African countries.

The vector autoregressive model differs from the classical model because it exploits all the causal links between the components of a phenomenon, and within a time space (Meuriot, 2008). There is no distinction between endogenous and exogenous variables and each variable is expressed in terms of its own past values and past and current values of all other variables. In addition, the VAR model allows us to study the consequences of economic variables through the reaction functions of shock according to Granger causality tests (Grenne, 2005). It identifies different types of shocks in the analysis of transmission mechanisms of economic variables, through the study of the propagation of shocks or impulses. Also, since the contribution of Sims (1980), researchers believe VAR models as the most suitable methodological framework for analysis of fluctuations in terms of innovations (Ziky, 2005). Recent studies use VAR model to determine the impact of remittances on mid and long term growth (A. Tchokpon Medenou, 2010) and on the main determinants of remittances (Coulibaly, 2009)

# 3. GDP fluctuations, climate variability and remittances in West Africa: an investigation using a PVAR model

In this section, we assess the share of remittances received by six West African countries experiencing climatic shocks using a simple Panel VAR model. The model will also be used to explore the underlying incentives to remit not only as a consequence of significant fluctuations in GDP but also as a direct result of shocks and precipitation variability in West African countries and economic constraint in host countries.

## 3.1. Empirical methodology and data

We present an annual dataset comprising six West African countries (Mali, Niger, Mauritania, Togo, Benin, Senegal), and covering the period 1980 to 2009. In order to analyze the impact of climate shocks on GDP fluctuations and the potential role of remittances, we use a panel data Vector Autoregression (VAR) methodology based on I. Love and L. Zicchino (2006). This combines the traditional VAR model, which treats all the variables in the system as endogenous, with a panel-data approach, which allows for unobserved individual heterogeneity.

We specify a first-order four -variable VAR model as follows:

(1) $$Y_{it} = \Gamma(L)Y_{it} + u_i + \varepsilon + fi$$

where $Y_{it}$ is a vector of stationary variables, $\Gamma(L)$ is a matrix polynomial in the lag operator, $u_i$ is a vector of country specific effects and $\varepsilon_{it}$ is a vector of idiosyncratic errors. $Y_{it}$ is the four variables vectors: {PREC, CLIMAFF, REMIT and GDP} where GDP represents real GDP (purchasing power parity PPP adjusted) per capita[2], REMIT reflects remittances and the compensation of employees (earnings) per capita[3], CLIMAFF is a variable reporting the

[2] Real GDP per capita (PPP adjusted) come from Penn World tables. Real GDP per capita (GDPPC) is measured as the log of the Real GDP divided by the total population in each country.

[3] Remittances and compensation of employee received per capita (REMITPC) obtained from WDI, World Bank (2010). Worker remittances and the compensation of employees is comprised of current transfers by migrant

number of affected people climate shocks experienced in each country between 1983 and 2009. We then specify another four variables PVAR model where $Y_{it}$ is the four variables vectors: {GDPeur, GDPCI, REMIT and GDP}. GDPCI is the GDP (purchasing power parity PPP adjusted) per capita of the Côte d'Ivoire and GDPeur is the GDP (purchasing power parity PPP adjusted) per capita of Western Europe. These two variables aims at reflecting shocks on GDP per capita in the main countries capturing the bulk of West African migration.

We use two proxies for climatic factors from the CRED Emergency Disasters Database[4] (EM-DAT) data: (i) the number people affected[5] by droughts episodes experienced by countries; and (ii) the number of people affected by extreme temperature. We choose to not include floods event to approximate climate shocks since floods are well known to be low span events and because of their ambiguous effects on local economies[6]. A number of studies (Raddatz, 2007; Raddatz, 2009; Skidmore and Toya, 2002) have assessed the impact of climatic and natural disasters' on macroeconomic stability using the EM-DAT data. The EM-DAT database includes data on the occurrence and effects of over 12,800 mass- disasters in the world since 1900, compiled from a wide range of sources. In EM-DAT, disasters are divided into two main categories (technological and natural corresponding to human and natural determinants of disasters). The natural disaster category is divided into 5 sub-groups, which in turn covers 12 disaster types and more than 30 sub-types. The climatic disaster categories include floods, droughts, extreme temperatures, and wind storms. The occurrence of disasters is proxy by a dummy with a value equal to 1 in the case of a shock and 0 otherwise. In our article, we choose to approximate shocks by the number of people affected rather than using a dummy variable. We justify this choice by the following assumption: the more a shock is covariant and the individuals have incentives to remit. Thus, a variable including the number of affected people by a shock is more fitted to translate the dynamic properties of the model. However, the production of this type of data does have some limitations (UNDP, 2004). First, the data does not take into account the possibility that the occurrence of a particular shock can derive

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.

[4] Center for Research on the Epidemiology of Disasters Database, CRED (see http://www.emdat.be/).

[5] The number of affected people are approximate as the sum of People suffering from physical injuries, trauma, people needing immediate assistance for shelter and people requiring immediate assistance during a period of emergency; it can also include displaced or evacuated people as a direct result of the disaster.

[6] We performed multiples PVAR incorporing floods as a proxy of climate events. Results from IRFs function and FEDV showed no statistical differences.

from another shock[7]. A further limitation of the EM-DAT data concerns drought, which is a relatively slow onset of some natural hazards. For example, a drought may develop gradually over time and space and therefore its occurrence and economic impact cannot be simply translated into a single dummy variable. These limitations are inherent to a conception of disaster which places little emphasis on the temporal dimension. We propose to focus on this temporal dimension using precipitation (PREC) data derived directly from multiple weather stations[8] throughout sampled countries. Therefore, for each country in our sample, we have estimated the average of annual precipitations from a database of at least ten (uniformly distributed) meteorological stations per country.

The presence of fixed effects which are correlated with the regressors, due to lags of the dependent variable is a concern we address in estimating this model. In order to allow a fixed effect without biased coefficients, we follow Love and Zicchino (2006) procedure by Helmert transformed all variables. The Helmert procedure or forward mean-difference procedure allow us to estimate the coefficient by system GMM preserving the orthogonality between Helmert transformed variables and regressors (Arellano and Bover, 1995; Love and Zicchino, 2006). We focus our analysis on the orthogonalized impulse-response functions (IRFs) and Forecast Error Decomposition Variance (FEVD). IRFs describe the reaction of one variable in the system to the innovations in another variable in the system, while holding all other shocks at zero.

Standard errors of IRFs and confidence intervals (5th and 95th percentiles) are generated with Monte Carlo simulations with 90 repetitions. However, the actual variance-covariance matrix of the errors is unlikely to be diagonal; it is therefore necessary to decompose the residuals in such a way that they become orthogonal. The usual convention used is the Choleski decomposition which assumes that the variables which come earlier in the ordering affect the subsequent variables contemporaneously, and with a lag; whilst the variables that come later

[7] For example, the EM DAT database has identified two main droughts in Mali during 1978 and 1980 (which is regarded as the period of the great drought). However, many secondary sources indicate that Mali experienced the most dramatic consequences of drought in 1973 and 1984 because of famine. Moreover, the rainfall deficits between 1970 and 1985 negatively impacted local ecosystems resulting in a significant decline in cereal yields. The human consequences of this were serious as Mali experienced two major famines during this period.

[8] NOAA NCEP CPC EVE: Monthly station precipitation and temperature data from the Climate Prediction Center Resolution: 13701 stations; Longitude: global; Latitude: global; Time: [Sep 1982, Sep 2010]; monthly data.

only affect the previous variables with a lag[9]. For the purposes of this paper, we also order the variables according to the results of our Granger causality / bloc exogeneity Wald Tests. In each model, the Wald statistic for joint significance of all other lagged endogenous variables in the equation indicated under the $h_0$ non causality hypothesis has a probability < 5% for both remittances per capita and the log Real GDP per capita. These two variables are treated as endogenous to our model. We assume that disaster measures and precipitation are exogenous to the system since climate shocks and precipitation are not subject to any reverse causality from GDP and remittances[10]. The resulting Cholesky order for our variable ordering is as follows: PREC, CLIMAFF, REMITPC and GDPPC for the first PVAR model and GDPeur, GDPCI, REMIT and GDPPC for the second PVAR model.

### 3.2. Empirical results

In this section we estimate systems of equations using the GMM estimator to assess the dynamic response of remittances inflows and GDP to both climatic disasters and precipitation. As mentioned in the previous section, using a panel-modeling framework allow us to increase the power of the analysis given the data limitations. We, firstly concentrate our analysis on the response of GDP per capita to climatic disasters and precipitation variability. Secondly, we focus on the response of remittances inflows response to climate shocks and precipitation. In a first time we discuss the dynamic relationship between GDP per capita and remittances inflows taking into account the GDP fluctuations in regions of immigration.

Before estimating the structural VAR model, we tested for the stationarity of variables. To do this, we used several panel unit root tests: Levin, Lin and Chu (2002), Im, Pesaran and Shin (2003), Fisher-type tests using augmented dickey-fuller (ADF) and Phillips–Perron (PP) tests (Maddala and Wu (1999) and Choi (2001), and Hadri (1999). The tests results (see Table A.1 in Appendix A) show that all the variables are non-stationary in levels but stationary in first-differences for all countries. We set all endogenous variables in the model, fixed the sample period (1980 to 2009), and conducted diagnostic tests in order to verify the stability of the PVAR. The inverse roots of the characteristic autoregressive (AR) polynomial tables

[9] Variables that appear earlier in the system are exogenous and those which appear later are largely endogenous.
[10] For further details see the Granger causality / bloc exogeneity Wald Tests tables (tables XXXX) in Appendix.

(Lütkepohl (1991) is shown in table A2 (see Appendix A). The test has (p = 1, 2) as proposed in the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SC)[11].

### 3.2.1. GDP fluctuations and climate patterns in West African countries

IRFs are estimated on the basis of PVAR 1 model (see methodological description in section 3.1) of two lags because of the limited time dimension and the small number of countries in the sample. Figure B.1 and Table B.1 show results obtained from impulse response functions for GDP per capita to one standard deviation shocks to climatic and precipitation variables. Results obtained from IRFs allow us to identify the dynamics impacts of a negative shock to climate variable (resulting in a positive shock i.e. fewer people affected by a shock) and on precipitation (resulting in a decline in precipitation) on GDP. Our results strongly indicates that a positive shock corresponding to a decrease by 90% (one standard deviation innovation shock) in the number of people affected by a climate disaster results in a statistical significant increase in the GDP per capita immediately after the shock occurrence (a variation of 31.1 between year 0 and year 1). A one standard deviation shock on precipitation (by 73%) results in a significant decline of GDP per capita and a negative variation of -2.91. between year 0 and 1. Results from IRFs also indicate that the effect of a climatic disaster as well as a precipitation shock dies after 3 years.

The Forecast Error Variance Decomposition analysis presented in Table B.3 Shows that climatic disaster shocks are responsible for 2.4% percent of variance of GDP at the 10 and 20 year horizon and precipitation variable account for 1.62% of the variance of GDP. As mentioned by A.C. David (2010), climate shocks can be considered as weakly exogenous variable. Since they are approximate by their impacts on individuals, they take into account the capacity (or non capacity) of individuals to cope with those types of events. In terms of vulnerability conceptual framework, the measure of climate shocks take into account the socioeconomic capacity of individuals and cannot translate their real exposure to physical events. On the contrary, precipitation variable can be treated as a purely exogenous variable (see Granger causality test in Table A.2 in appendix A). These findings then suggest that the



[11] See Burnham, K. P., and Anderson, D.R., 2002. Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach, 2nd ed. Springer-Verlag. ISBN 0-387-95364-7.

selected West African countries are particularly exposed to physical factors such as precipitation variability.

According to Raddatz (2009), external shocks account only for a small fraction of the overall variance of real GDP in low-income countries. Even in the long run, they cannot explain more than 11 percent of this variance. The remaining 89 percent is accounted for by factors associated with endogenous shocks. Among the external shocks, climatic disasters explain 14% of the GDP variance. Without taking account of the remittances effect on such economies, our results are in line with those find by Raddatz (2009). Both climate disasters and precipitation variables account for 4% of the whole GDP variance. When taking account of the remittances effect, all variables included in the model explains 5.5% of the GDP variance. Thus, 94.5% of the GDP variance is explained by other factors (external i.e. such as commodity price, interest rate, or internal factors i.e. civil wars, corruption…) non-included in the model.

In the next section we give more details about the linkages between remittances inflows, climate disasters and precipitation. We show that remittances inflows have considerable indirect effects on GDP fluctuations acting as an external "stabilization" source of income.

### 3.2.2. Remittances and climate nexus

Emigrants may send money to home country in order to sustain consumption of their families. These remittances may be independent of economic conditions of home country or they may be countercyclical. At the microeconomic scales, research on the motives to migrate and remit impulse in the 80's by the New Economics of labor Migration (NELM) make distinction between remittances being primarily driven by altruistic motives versus remittances being driven by investment motives. According to Docquier and Rapoport (2006), «it is not only that different individuals may be heterogeneous in their motivations to remit, but also that different motivations to remit may coexist within the same individual." One of the positive effects of remittances by unanimity is the impact on poverty. This effect is through increasing the resources of households and by smoothing their consumption expenditure over time (Gupta, Pattillo and Wagh, 2007). The impact of remittances on household living conditions is reinforced by their counter-cyclical effect on the economy: increasing during periods of recession and decreasing during expansions. Remittances help households' recipients to maintain their level of well-being and a better allocation in their consumption spending over time, especially for those engaged in seasonal activities, such as farmers (Daffé, 2009). However, as mentioned in Section 2, empirical assessments do not agree on the counter cyclical nature of remittances.

Macroeconomic research assumes that pro cycle and counter cycle patterns between remittances and GDP is evidence of either investment or altruistic motives, respectively. Empirical research dealing with the compensatory or opportunistic nature of remittances finds different results depending on time scale and selected region. Chami, Fullenkamp and Jahjah (2005) have found some of the strongest evidence to date that remittances are better described as compensatory transfers than as opportunistic ones. Work by Frankel (2009) also finds them counter-cyclical. Neagu and Schiff (2009) find that remittances are pro-cyclical. Durdu and Sayan (2008) find them counter-cyclical in Mexico but pro-cyclical in Turkey.

Our results suggest remittances have countercyclical patterns with climate shocks and precipitation variable in WA countries whereas the direct link between remittances and home GDP seems more multifaceted. Results from IRFs functions in PVAR 1 show that remittances increase when climate and precipitation shocks occur in West African countries. A positive shock corresponding to a decrease by 90% (one standard deviation innovation shock) in the number of people affected by a climate disaster results in a statistical significant decrease in remittances per capita inflows the year after the shock (a variation of -11.24 between year 1 and year 2). A one standard deviation shock on precipitation (by 73%) results in a significant increase in remittances per capita and a positive variation of 10.16 between year 0 and 1. We can notice a difference in terms of time variation between remittances sent after a climate shock and remittances sent in case of precipitation shock. In the first case remittances tend to increase one year after the shock occurred whereas in the second case remittances increase in the same time.

Remittances variance is explained by 5.85% by all the variables included in the model and by 4.45% regarding both climate shocks and precipitation. Precipitation variable account for a smaller share in the variance of remittances (1%) than climate shocks and 94% of the remittances variance may be explained by other variables omitted in the PVAR model. These results may be explained by the fact that:

i) Precipitation variability has multiple effects on local economies and a decline in precipitation cannot be translated into a shock.

ii) In case of altruism or counter cyclical patterns, remittances are sent in case of different type of shocks. In our article dealing mainly with precipitation shortage and drought, we cannot take into account the effects of large natural disasters, geological disasters or internal shocks on remittances inflows. This could explain the high fraction of the remittances variance unexplained by the model.

iii) Incentives to remit are not only driven by altruism, in case of remittances driven by investment, the share of remittances sent after a shock may decrease.

iv) Remittances inflows strongly depend on foreign economies. In case of economic or political crisis in host countries, remittances inflows may decrease as was the case in West African countries right after the recent economic crisis.

### 3.2.3. Is the cyclical nature of remittances may be questioned by the economy of host countries?

In this section we focus on the relationship between GDP and remittances. As mentioned in the previous section, precipitation and climate shocks have a significant impact on GDP fluctuations. However, the response of remittances to GDP shocks seems less direct and more complex to analyze. PVAR 2 model aims at assessing the exterior economic constraints weighing on remittances inflows in sampled countries. Results from IRFs shows that the response of remittances to one standard deviation innovation on GDP per capita remains non significant over the time even if standard error bands (obtained by Monte Carlo simulation with 90 reps) are closed to the zero line at period 3 and 4 (s=3; 4). This suggest that remittances tend to increase after a shock on GDP if all other variables are maintain to zero 3 years after the initial shock.

The question we ask then is: if remittances increase in case of climate and precipitation shock which have a significant impact on GDP, we would be able to expect a significant response of remittances (upward) in case of negative shock to GDP. This latter relationship remains however unverified according to results obtained from IRFs in PVAR 2.

The lack of significant response of remittances to shock on home GDP can be explained theoretically by an arm's length of remittances to economic fluctuations (as policies) in countries (or regions) of immigration (search authors on the theory and empirical). This dependency may result in a disability situation of migrants living abroad to send money to their families remaining in countries of origin when they undergoes a shock. The theoretical literature identifies several potentially negative effects of remittances limiting their effectiveness. According to Azam and Gubert (2002) and Ndione and Lalou (2005), the presence of remittances may lead to a liquidity trap. Because of anticipations of recipients, flows of remittances are used to maintain the dissipation of resources. The relationship Poverty - Migration - Remittances – may be enhanced when remittances are no longer used only to smooth consumption expenditure, but when they participate to transform and diversify consumption needs.

Thus, a dependency to remittances can be favored in developing countries (Lipton 1980, Binford, 2003; Chami and al. 2003), encouraging the emigration of individuals of working age, so a massive outflow of labor, leading eventually to reduction in labor supply. In this case, risks of dependence on external economic conditions (economic cycles of host countries) and transmission of economic shocks may increase. According to the IMF (2009), the countries receiving remittances may see their economic condition deteriorated depending on the magnitude of the crisis in countries sending remittances. The probability of deteriorating economic conditions in these countries then depends on the likelihood of such countries to be affected by a crisis (the degree of exposure to economic crisis).

Our results strongly confirm the assumption that remittances inflows heavily depends on GDP fluctuations of sending countries. Results from IRFs in PVAR 2 model indicate that the economic conditions of the main host countries have a direct impact on the volume of remittances inflows in countries of origin. The response of the remittances variable significantly follows the simulated shock (one standard deviation innovation) on GDP of European countries with a lag of one year. Results from Error Forecast Variance Decomposition in PVAR 2 show that European GDP variance and GDP of Côte d'Ivoire contributes, respectively, to 6.1% and 7.2% of remittances inflows variance whereas Home GDP variance only contributes to a small fraction of the remittances inflows fluctuations (1.7%).

# 4. Conclusions

By comparing results from FEDV (with 10 reps) in PVAR 1 and PVAR 2 models, we assess the contribution of external economic shocks variance (approximated by the GDP of main countries of immigration) vis-à-vis climatic and precipitation shocks on home GDP and remittances inflows fluctuations. Results from FEDV are summarized in the following table.

***Table 1 Results from FEVD: climate and precipitation Vs. Countries of immigration GDP fluctuations***

| | *Prec* | *Climaff* | *Prec and ClimShock* | *GDPeur* | *GDPCI* | *GDPeur and GDPCI* | *Total* |
|---|---|---|---|---|---|---|---|
| **GDP** | 1,60% | 2,40% | 4,00% | 5% | 3,50% | 8,50% | 12,50% |
| **Remit** | 1% | 3,40% | 4,40% | 6,10% | 7,20% | 13,30% | 17,70% |

Both *GDPeur* and *GDPCI* variables contributes to a high fraction of the home GDP variance (8.50%) and remittances inflows variance (13.50%) if compared to the climate component (climate shocks and precipitation variable). Climate shocks and precipitation account for 4% of GDP variance and 4.40% of remittances variance. If the fraction of the variance of European GDP countries contributes to a higher volatility than GDP of Côte d'Ivoire in GDP of West Africa countries (respectively 5% and 3.50%), fluctuations of GDP in Côte d'Ivoire explain a larger fraction of remittances inflows to West Africa countries.  7.20% of the remittances variance is explained by the variable *GDPCI* after 10 lags whereas 6.10% is explained by GDP fluctuations in European countries. Results from Error Forecast Variance Decomposition in PVAR 1 show that 4% of GDP variance and 4.40% of remittances are explains by precipitation and climate shocks. The fraction of the GDP and remittances variances explained by precipitation only remains lower with respectively 1.60% and 1%.

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# Appendix A. Unit roots tests, estimation by GMM system and diagnostics tests

**Table A1: Unit root tests**

| | *Levin, Lin & Chu t** | | *Im, Pesaran and Shin W-stat* | | *ADF Ficher Chi square* | | *Hadri Z-stat* | |
|---|---|---|---|---|---|---|---|---|
| *Variables* | *Statistique de test* | *Prob.*** | *Statistique de test* | *Prob.*** | *Statistique de test* | *Prob.*** | *Statistique de test* | *Prob.*** |
| | | | | *In levels* | | | | |
| **GDP** | 1.19209 | 0.8834 | 1.12420 | 0.8695 | 12.2909 | 0.2661 | 6.16208 | 0.0000 |
| **Prec** | -1.79306 | 0.0365 | -4.12215 | 0.0000 | 36.4171 | 0.0001 | 8.00620 | 0.0000 |
| **GDPeur** | 7.73988 | 0.7056 | 9.55211 | 0.7642 | 0.10895 | 0.0908 | 8.26733 | 0.0000 |
| **GDPCI** | 6.46570 | 1.0000 | 5.92817 | 1.0000 | 0.67792 | 1.0000 | 6.47312 | 0.0000 |
| | | | | *1st difference* | | | | |
| **GDP** | -4.01785 | 0.0000 | -6.48380 | 0.0000 | 57.9795 | 0.0000 | 3.46774 | 0.0003 |
| **Remit** | -1.76963 | 0.0384 | -3.97804 | 0.0000 | 34.3585 | 0.0002 | 2.07497 | 0.0190 |
| **Prec** | -4.29408 | 0.0000 | -7.98664 | 0.0000 | 72.6967 | 0.0000 | -0.47231 | 0.6816 |
| **GDPeur** | -1.60460 | 0.0143 | -3.59515 | 0.0002 | 33.8442 | 0.0007 | 6.25741 | 0.1203 |
| **GDPCI** | -3.19640 | 0.0007 | -3.62071 | 0.0001 | 34.3823 | 0.0006 | 3.91757 | 0.0000 |
| **Climaff** | -0.88329 | 0.1885 | -13.8539 | 0.0000 | 130.950 | 0.0000 | 3.93529 | 0.0000 |
| | | | | *2nd difference* | | | | |
| **Remit** | -3.87267 | 0.0001 | -7.94819 | 0.0000 | 73.3555 | 0.0000 | 1.15061 | 0.1249 |
| **Climaff** | -16.1837 | 0.0000 | -19.0482 | 0.0000 | 144.862 | 0.0000 | 0.23544 | 0.4069 |

**Table A.2: VAR Granger Causality / Block Wald Exogeneity Test**

| Dependent variable: D(GDPCI) | | | | Dependent variable: D(GDPPC) | | | |
|---|---|---|---|---|---|---|---|
| Excluded | Chi-sq | df | Prob. | Excluded | Chi-sq | df | Prob. |
| **GDPPC** | 1.320597 | 2 | 0.5167 | **GDPCI** | 0.118341 | 2 | 0.9425 |
| **PIBEUR** | 22.90564 | 2 | 0.0000 | **PIBEUR** | 3.137121 | 2 | 0.2083 |
| **REMITPC** | 0.244792 | 2 | 0.8848 | **REMITPC** | 0.277574 | 2 | 0.8704 |
| **All** | 26.93260 | 8 | 0.0007 | All | 3.716872 | 8 | 0.8817 |
| Dependent variable: D(PIBEUR) | | | | Dependent variable: D(REMITPC) | | | |
| Excluded | Chi-sq | df | Prob. | Excluded | Chi-sq | df | Prob. |
| **GDPCI** | 8.101298 | 2 | 0.0174 | **GDPCI** | 3.702014 | 2 | 0.1571 |
| **GDPPC** | 1.090284 | 2 | 0.5798 | **GDPPC** | 0.306556 | 2 | 0.8579 |
| **REMITPC** | 7.832738 | 2 | 0.0199 | **PIBEUR** | 11.55238 | 2 | 0.0031 |
| **All** | 19.70006 | 8 | 0.0115 | **All** | 19.15764 | 8 | 0.0140 |

**Table A.3: Results of the Estimation by system GMM for PVAR 1*****

| | *Equation 1: dep.var h_prec* | | | | *Equation 2: dep.var h_climaff* | | |
|---|---|---|---|---|---|---|---|
| | b_GMM | se_GMM | t_GMM | | b_GMM | se_GMM | t_GMM |
| L.h_prec | .17243427 | .07831066 | 2.2019258 | L.h_prec | -454.78964 | 1039.3224 | .30245155 |
| L.h_climaff | -9.147e-06 | 9.362e-06 | -.97706655 | L.h_climaff | .08364657 | .27656188 | .30245155 |
| L.h_remit | .04918788 | .10501001 | .46841135 | L.h_remit | -920.55611 | 1377.766 | -.66815128 |
| L.h_gdp | .07088622 | .08087138 | .87653032 | L.h_gdp | 157.96685 | 649.8533 | .24308078 |
| L2.h_prec | -.14563746 | .07772399 | -1.8737774 | L2.h_prec | 1519.2628 | 1350.2165 | 1.1251994 |
| L2.h_climaff | 2.604e-06 | .00001431 | .18195575 | L2.h_climaff | -.01262607 | .30133079 | -.04190101 |
| L2.h_remit | .01457851 | .09624597 | .15147139 | L2.h_remit | -2506.3969 | 1464.5424 | -1.7113857 |
| L2.h_gdp | -.10837987 | .08611828 | -1.2585002 | L2.h_gdp | 573.78514 | 792.24303 | .72425394 |

| | *Equation 4: dep.var h_gdp* | | | | *Equation 3: dep.var h_remit* | | |
|---|---|---|---|---|---|---|---|
| | b_GMM | se_GMM | t_GMM | | b_GMM | se_GMM | t_GMM |
| L.h_prec | -.13084385 | .0769516 | -1.7003396 | L.h_prec | .08786628 | .07237914 | 1.2139723 |
| L.h_climaff | .00001346 | 6.768e-06 | 1.9887487 | L.h_climaff | -9.155e-07 | 8.390e-06 | -.10910943 |
| L.h_remit | .07919874 | .09360953 | .84605427 | L.h_remit | .18592129 | .08748801 | 2.125106 |
| L.h_gdp | .39245217 | .08193632 | 4.789722 | L.h_gdp | -.03547135 | .0783626 | -.45265664 |
| L2.h_prec | .01269925 | .0779736 | .16286602 | L2.h_prec | -.00680926 | .0754834 | -.09020873 |
| L2.h_climaff | -1.013e-06 | 8.213e-06 | -.123358 | L2.h_climaff | -.00001404 | 7.863e-06 | -1.7856739 |
| L2.h_remit | -.00448971 | .09632676 | -.04660918 | L2.h_remit | -.14849739 | .08818535 | -1.6839235 |
| L2.h_gdp | -.02404409 | .07534579 | -.3191166 | L2.h_gdp | .11663632 | .07916923 | 1.4732531 |

* Number of observations used: 144.

** estimation sample from 1983 to 2009, strongly balanced

**Table A.4: Results of the Estimation by system GMM for PVAR 2*****

| | *Equation 1: dep.var h_GDPeur* | | | | *Equation 2: dep.var h_GDPCI* | | |
|---|---|---|---|---|---|---|---|
| | b_GMM | se_GMM | t_GMM | | b_GMM | se_GMM | t_GMM |
| L.h_prec | 1.1272458 | .06774685 | 16.639089 | L.h_prec | .00012375 | .00034885 | .35473799 |
| L.h_climaff | 9.3475813 | 6.8508478 | 1.3644415 | L.h_climaff | 1.3545711 | .06911239 | 19.599539 |
| L.h_remit | -204.08517 | 127.51405 | -1.6004916 | L.h_remit | -.13052109 | .7938822 | -.16440864 |
| L.h_gdp | 44.050125 | 127.51405 | -1.6004916 | L.h_gdp | -.58580031 | .73599065 | -.79593445 |
| L2.h_prec | -.79849975 | .06541692 | -12.206319 | L2.h_prec | -.00055062 | .00037558 | -1.4660232 |
| L2.h_climaff | 2.9285851 | 8.0258221 | .36489535 | L2.h_climaff | -.56234947 | .07583894 | -7.4150494 |
| L2.h_remit | -143.89566 | 121.82946 | -1.1811237 | L2.h_remit | .09522354 | .77829639 | .12234869 |
| L2.h_gdp | 141.60404 | 107.58767 | 1.3161736 | L2.h_gdp | -.68142273 | .66337697 | -1.0272029 |

| | *Equation 4: dep.var h_gdp* | | | | *Equation 3: dep.var h_remit* | | |
|---|---|---|---|---|---|---|---|
| | b_GMM | se_GMM | t_GMM | | b_GMM | se_GMM | t_GMM |
| L.h_prec | .00002042 | .00004897 | .41707146 | L.h_prec | .00009362 | .00004378 | 2.1381741 |
| L.h_climaff | .00880181 | .00731318 | 1.3941333 | L.h_climaff | .00949287 | .00680916 | 1.3941333 |
| L.h_remit | .05452637 | .09920928 | .54960957 | L.h_remit | .20317607 | .08689615 | 2.3381482 |
| L.h_gdp | .34031169 | .0842326 | 4.0401423 | L.h_gdp | -.06592155 | .07678715 | -.85849714 |
| L2.h_prec | -.00007808 | .00005695 | -1.3709705 | L2.h_prec | -.0000244 | .00004693 | -.51985786 |
| L2.h_climaff | -.00858085 | .00803231 | -1.0682924 | L2.h_climaff | -.01719763 | .00729561 | -2.357258 |
| L2.h_remit | -.02566304 | .0958797 | -.26765876 | L2.h_remit | -.12473479 | .08276789 | -1.5070432 |
| L2.h_gdp | -.01216905 | .08005775 | -.15200335 | L2.h_gdp | .12049802 | .0766133 | 1.5728081 |

* Number of observation used: 144.

** estimation sample from 1983 to 2009, strongly balanced

# Appendix B. Impulse responses and decomposition variances



**Table B.1 : Results from Orthogonalized Impulse-Response Functions in PVAR 1****

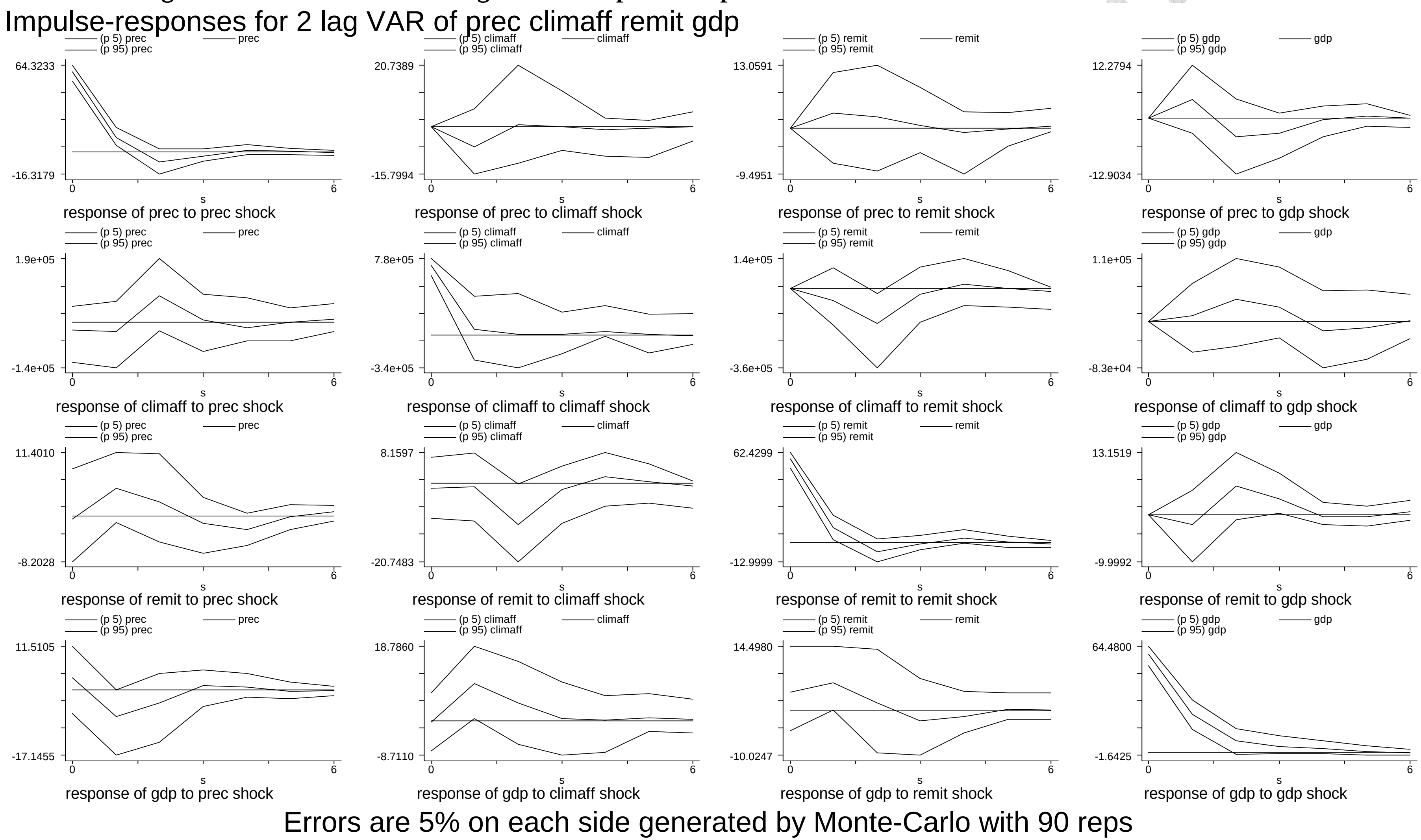
| | | *Response of Precipitation to Precipitation Shock* | | | | | *Response of Remittances to Precipitation Shock* | | |
|---|---|---|---|---|---|---|---|---|---|
| Varname | S | Prec_5 | Prec | Prec_95 | | S | Prec_5 | Prec | Prec_95 |
| Prec | 0 | 52,64 | 59,62 | 64,32 | Remit | 0 | -8,2 | -0,55 | 8,47 |
| Prec | 1 | 5,12 | 10,71 | 18,39 | Remit | 1 | -1,19 | 5,04 | 11,4 |
| Prec | 2 | -16,31 | -7,24 | 2,28 | Remit | 2 | -4,68 | 2,55 | 11,13 |
| Prec | 3 | -6 ,7 | -2,91 | 2,18 | Remit | 3 | -6,65 | -1,34 | 3,34 |
| Prec | 4 | -2,1 | 1,12 | 5,52 | Remit | 4 | -5,3 | -2,42 | 0,47 |
| Prec | 5 | -2,13 | 0,57 | 2,83 | Remit | 5 | -2,43 | -0,1 | 2,03 |
| Prec | 6 | -2,31 | -0,25 | 1,18 | Remit | 6 | -0,91 | 0,72 | 1,85 |
| | | *Response of GDP to Precipitation Shock* | | | | | *Response of Climate to Climate Shock* | | |
| | S | Prec_5 | Prec | Prec_95 | | S | Climaff_5 | Climaff | Climaff_95 |
| GDP | 0 | -6,12 | 3,28 | 11,5 | Climaff | 0 | 6.1e+05 | 7.1e+05 | 7.8e+05 |
| GDP | 1 | -17,12 | -6,88 | -0,08 | Climaff | 1 | -2.6e+05 | 6.1e+04 | 4.0e+05 |
| GDP | 2 | -13,65 | -3,37 | 4,38 | Climaff | 2 | -3.4e+05 | 4.7e+03 | 4.3e+05 |
| GDP | 3 | -4,22 | 1,22 | 5,25 | Climaff | 3 | -1.9e+05 | 7.7e+03 | 2.3e+05 |
| GDP | 4 | -1,95 | 0,74 | 4,41 | Climaff | 4 | -1.6e+04 | 3.4e+04 | 3.0e+05 |
| GDP | 5 | -2,19 | -0,34 | 2,04 | Climaff | 5 | -1.9e+05 | 6.1e+03 | 2.2e+05 |
| GDP | 6 | -1,49 | -0,19 | 1,01 | Climaff | 6 | -9.4e+04 | -5.6e+03 | 2.2e+05 |
| | | *Response of Remittances to Climate Shock* | | | | | *Response of GDP to Climate Shock* | | |
| | S | Climaff_5 | Climaff | Climaff_95 | | S | Climaff_5 | Climaff | Climaff_95 |
| Remit | 0 | -9.2812 | -1.3851 | 6.8959 | GDP | 0 | -7.5779 | -0.3129 | 7.0075 |
| Remit | 1 | -9.9294 | -0.8979 | 7.9957 | GDP | 1 | 0.4745 | 9.3463 | 18.7860 |
| Remit | 2 | -20.7483 | -10.9566 | -0.2356 | GDP | 2 | -5.9958 | 4.5709 | 14.9792 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Remit | 3 | -10.5927 | -1.7185 | 4.5859 | GDP | 3 | -8.7110 | 0.5197 | 9.7765 |
| Remit | 4 | -6.0633 | 1.7415 | 8.1597 | GDP | 4 | -7.8650 | 0.1192 | 6.3685 |
| Remit | 5 | -5.2548 | 0.4199 | 5.0910 | GDP | 5 | -2.6999 | 0.7386 | 6.9107 |
| Remit | 6 | -6.5232 | -0.7005 | 0.4978 | GDP | 6 | -3.1371 | -0.4044 | 5.4388 |
| | | *Response of GDP to GDP Shock* | | | | | *Response of Remittances to GDP* | | |
| | S | GDP_5 | GDP | GDP_95 | | S | GDP_5 | GDP | GDP_95 |
| GDP | 0 | 52.6724 | 59.6557 | 64.4800 | Remit | 0 | 0 | 0 | 0 |
| GDP | 1 | 14.2269 | 23.4120 | 32.0239 | Remit | 1 | -9.9992 | -2.1161 | 5.1046 |
| GDP | 2 | -0.9894 | 7.1597 | 14.5995 | Remit | 2 | -1.1074 | 6.0971 | 13.1519 |
| GDP | 3 | -0.8127 | 3.8632 | 10.1147 | Remit | 3 | 0.2740 | 3.3530 | 8.7161 |
| GDP | 4 | -0.7615 | 2.2856 | 6.9969 | Remit | 4 | -2.2060 | -0.4249 | 2.4901 |
| GDP | 5 | -1.6425 | 0.5045 | 4.1423 | Remit | 5 | -2.4195 | -0.5611 | 1.7746 |
| GDP | 6 | -1.3985 | -0.1083 | 2.0223 | Remit | 6 | -1.2711 | 0.4965 | 3.0265 |
| | | *Response of Remittances to Remittances Shock* | | | | | *Response of GDP to Remittances Shock* | | |
| | S | Remit_5 | Remit | Remit_95 | | S | Remit_5 | Remit | Remit_95 |
| Remit | 0 | 51.6455 | 58.0071 | 62.4299 | GDP | 0 | -4.5778 | 4.1158 | 14.4701 |
| Remit | 1 | 2.2263 | 10.6388 | 18.7594 | GDP | 1 | 0.1764 | 6.2093 | 14.4980 |
| Remit | 2 | -12.9999 | -6.0515 | 2.7514 | GDP | 2 | -9.4372 | 1.7985 | 13.8833 |
| Remit | 3 | -4.8942 | -0.9711 | 5.0029 | GDP | 3 | -10.0247 | -2.3120 | 7.2354 |
| Remit | 4 | -0.3165 | 3.2816 | 9.2398 | GDP | 4 | -5.0521 | -1.2360 | 4.3014 |
| Remit | 5 | -3.1106 | 0.7920 | 4.5785 | GDP | 5 | -1.9682 | 0.2563 | 3.9849 |
| Remit | 6 | -3.4800 | -0.7835 | 1.5787 | GDP | 6 | -1.9413 | 0.1859 | 4.0787 |

* Impulse-Responses for 2 lag Panel Vector AutoRegressive

** Errors are 5% on each side generated by Monte Carlo with 90 reps

**Figure B.1: Results from Orthogonalized Impulse-Responses Functions in PVAR 1**



## Table B.2 : Results from Orthogonalized Impulse-Response Functions in PVAR 2* **

| | | *Response of GDPeur to GDPeur Shock* | | | | | *Response of GDPCI to GDPeur* | | |
|---|---|---|---|---|---|---|---|---|---|
| Varname | S | GDPeur_5 | GDPeur | GDPeur_95 | | S | GDPeur_5 | GDPeur | GDPeur_95 |
| GDPeur | 0 | 6.5e+04 | 7.3e+04 | 7.9e+04 | GDPCI | 0 | -1.4e+02 | -66.5667 | 10.3324 |
| GDPeur | 1 | 7.0e+04 | 8.1e+04 | 9.3e+04 | GDPCI | 1 | -2.0e+02 | -86.1092 | 22.1605 |
| GDPeur | 2 | 1.7e+04 | 3.1e+04 | 3.1e+04 | GDPCI | 2 | -2.4e+02 | -1.2e+02 | 0.7574 |
| GDPeur | 3 | -5.0e+04 | -3.3e+04 | -1.1e+04 | GDPCI | 3 | -2.7e+02 | -1.5e+02 | -40.2377 |
| GDPeur | 4 | -8.2e+04 | -6.6e+04 | -4.9e+04 | GDPCI | 4 | -2.5e+02 | -1.6e+02 | -37.6650 |
| GDPeur | 5 | -7.3e+04 | -5.1e+04 | -2.9e+04 | GDPCI | 5 | -1.9e+02 | -1.1e+02 | 23.7464 |
| GDPeur | 6 | -3.4e+04 | -5.6e+03 | 1.6e+04 | GDPCI | 6 | -1.1e+02 | -21.8549 | 98.8109 |

| | | *Response of Remit to GDPeur Shock* | | | | | *Response of GDP to GDPeur Shock* | | |
|---|---|---|---|---|---|---|---|---|---|
| | S | GDPeur_5 | GDPeur | GDPeur_95 | | S | GDPeur_5 | GDPeur | GDPeur_95 |
| Remit | 0 | -2.1750 | 3.9183 | 12.1688 | GDP | 0 | -0.9352 | 7.5555 | 15.5883 |
| Remit | 1 | 1.5491 | 6.4729 | 12.1819 | GDP | 1 | -2.5515 | 3.6838 | 8.5651 |
| Remit | 2 | 7.6183 | 7.6183 | 12.1819 | GDP | 2 | -8.2371 | -2.7979 | 2.8850 |
| Remit | 3 | -3.7721 | 2.7102 | 8.6184 | GDP | 3 | -12.4989 | -6.7105 | -0.6246 |
| Remit | 4 | -10.2231 | -3.5398 | 2.0554 | GDP | 4 | -11.3516 | -5.7513 | 1.4622 |
| Remit | 5 | -10.8078 | -5.7231 | -1.6182 | GDP | 5 | -5.3088 | -1.0043 | 5.0179 |
| Remit | 6 | -8.2644 | -2.8619 | 2.6655 | GDP | 6 | -1.2624 | 4.0063 | 10.0077 |

| | | *Response of GDPCI to GDPCI Shock* | | | | | *Response of Remit to GDPCI Shock* | | |
|---|---|---|---|---|---|---|---|---|---|
| | S | GDPCI_5 | GDPCI | GDPCI_95 | | S | GDPCI_5 | GDPCI | GDPCI_95 |
| GDPCI | 0 | 476.0078 | 531.5793 | 582.6257 | GDP | 0 | -19.9822 | -13.1255 | -5.4306 |
| GDPCI | 1 | 637.2252 | 718.0287 | 807.1901 | GDP | 1 | -3.7244 | 1.9578 | 9.5571 |
| GDPCI | 2 | 536.9348 | 665.2090 | 785.1393 | GDP | 2 | -6.1124 | -3.9934 | 2.5850 |
| GDPCI | 3 | 327.4001 | 488.7159 | 662.8708 | GDP | 3 | 327.4001 | 488.7159 | 662.8708 |
| GDPCI | 4 | 90.0735 | 277.1693 | 481.1832 | GDP | 4 | -10.9682 | -5.3894 | 0.4783 |
| GDPCI | 5 | -1.1e+02 | 90.4923 | 334.5506 | GDP | 5 | -10.4010 | -4.8226 | 0.1223 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| GDPCI | 6 | -2.3e+02 | -39.0411 | 203.3766 | GDP | 6 | -9.1678 | -3.9197 | -0.3306 |

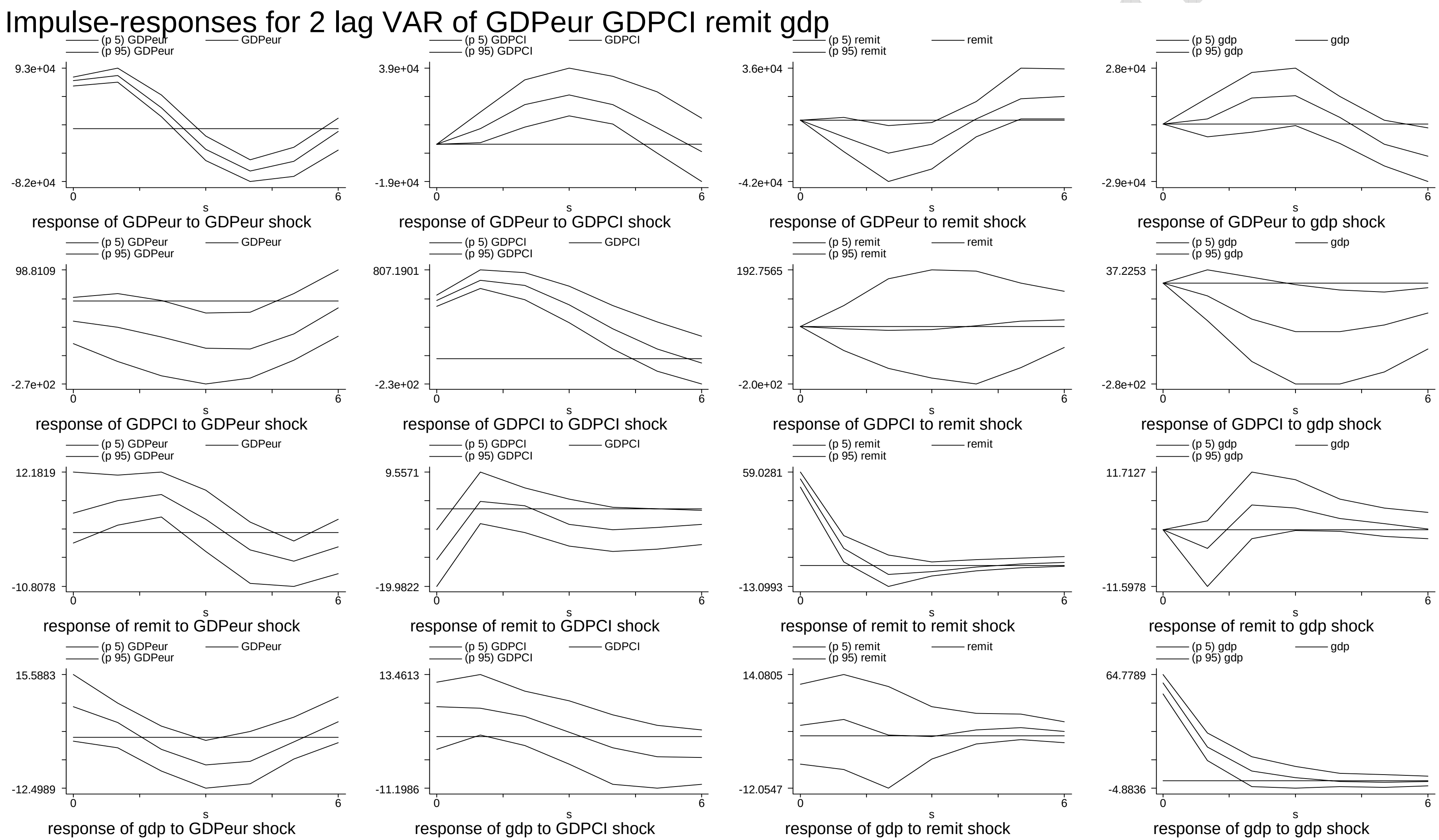
| | | *Response of GDP to GDPCI Shock* | | | | | *Response of GDP to GDP* | | |
|---|---|---|---|---|---|---|---|---|---|
| | S | GDPCI_5 | GDPCI | GDPCI_95 | | S | GDP_5 | GDP | GDP_95 |
| GDP | 0 | -2.7214 | 6.3952 | 11.7475 | GDP | 0 | 52.7954 | 59.6049 | 64.7789 |
| GDP | 1 | 0.3769 | 6.1395 | 13.4613 | GDP | 1 | 12.0844 | 20.2842 | 29.0821 |
| GDP | 2 | -1.9852 | 4.3756 | 9.7976 | GDP | 2 | -3.6153 | 5.7097 | 14.5436 |
| GDP | 3 | -5.9456 | 0.8892 | 7.6981 | GDP | 3 | -4.8836 | 1.5520 | 8.3468 |
| GDP | 4 | -10.2782 | -2.4368 | 4.6622 | GDP | 4 | -3.7751 | -0.4599 | 4.2301 |
| GDP | 5 | -11.1986 | -4.3254 | 2.3969 | GDP | 5 | -4.1350 | -1.2271 | 3.2901 |
| GDP | 6 | -10.4083 | -4.5515 | 1.5330 | GDP | 6 | -3.5866 | -0.7316 | 2.3815 |

| | | *Response of Remittances to GDP Shock* | | |
|---|---|---|---|---|
| | S | GDP_5 | GDP | GDP_95 |
| Remit | 0 | 0.0000 | 0.0000 | 0.0000 |
| Remit | 1 | -11.5978 | -3.9292 | 1.8113 |
| Remit | 2 | -1.8487 | 4.9611 | 11.7127 |
| Remit | 3 | -0.1583 | 4.3584 | 10.1219 |
| Remit | 4 | -0.3551 | 2.2909 | 6.1732 |
| Remit | 5 | -1.4864 | 1.1112 | 4.3530 |
| Remit | 6 | -1.8767 | 0.1639 | 3.4070 |

* Impulse-Responses for 2 lag Panel Vector AutoRegressive.

** Errors are 5% on each side generated by Monte Carlo with 90 reps.

**Figure B.2: Results from Orthogonalized Impulse-Responses Functions in PVAR 1**




Errors are 5% on each side generated by Monte-Carlo with 90 reps

**Table B.3: Results from Decomposition Variance Functions in PVAR 1***

| | S | Prec | Climaff | Remit | GDP |
|---|---|---|---|---|---|
| Prec | 10 | .97125971 | .01175851 | .00441656 | .01256523 |
| Climaff | 10 | .01525844 | .92750396 | .05234303 | .00489457 |
| Remit | 10 | .01080319 | .03452022 | .9403333 | .01434329 |
| GDP | 10 | .01624611 | .02470672 | .01485959 | .94418757 |
| Prec | 20 | .97125913 | .01175867 | .00441692 | .01256528 |
| Climaff | 20 | .0152597 | .92750076 | .05234472 | .00489483 |
| Remit | 20 | .01080486 | .0345213 | .94032999 | .01434385 |
| GDP | 20 | .01624629 | .02470697 | .01485988 | .94418686 |

* Decomposition Forecast Error Variance Functions are calculated with 10 and 20 reps

**Table B.4: Results from Decomposition Variance Functions in PVAR 2***

| | S | GDPeur | GDPCI | Remit | gdp |
|---|---|---|---|---|---|
| GDPeur | 10 | .85197443 | .06140248 | .05453555 | .03208754 |
| GDPCI | 10 | .05660771 | .90347065 | .00094864 | .03897299 |
| Remit | 10 | .06100112 | .07244104 | .84881688 | .01774096 |
| Gdp | 10 | .05094001 | .03586547 | .00687577 | .90631874 |
| GDPeur | 20 | .85008015 | .05645895 | .05725824 | .03620266 |
| GDPCI | 20 | .05906279 | .89963176 | .00131994 | .03998551 |
| Remit | 20 | .07253643 | .07272446 | .83596251 | .0187766 |
| Gdp | 20 | .06002879 | .03597359 | .00749534 | .89650228 |

* Decomposition Forecast Error Variance Functions are calculated with 10 and 20 reps