Rainfall, Financial Development, and Remittances: Evidence from Sub-Saharan Africa

by

Rabah Arezki and Markus Brückner

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Abstract: We use annual variations in rainfall to examine the effects that exogenous, transitory income shocks have on remittances in a panel of 41 Sub-Saharan African countries during the period 1970-2007. Our main finding is that on average rainfall shocks have an insignificant contemporaneous effect on remittances. However, the marginal effect is significantly decreasing in the share of domestic credit to GDP. So much so, that at high levels of credit to GDP rainfall shocks have a significant negative effect on remittances, while at low levels of credit to GDP the effect of rainfall on remittances is significantly positive.

Key words: Transitory Income Shocks, Remittances, Financial Development

JEL codes: F24, F30, O10

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* International Monetary Fund (Arezki), and School of Economics, University of Adelaide (Brückner). Contact e-mail: rarezki@imf.org; markus.brueckner@adelaide.edu.au. The paper has significantly benefited from comments and suggestions received by two anonymous referees and the editor Ariel Burstein. Brückner gratefully acknowledges the financial support of the Spanish Ministry of Science and Technology provided by CICYTECO2008-04997. The views in this paper are those of the authors alone and do not necessarily represent those of the IMF or IMF policy.

1. Introduction

For many developing countries and most importantly for Sub-Saharan African countries, remittances constitute a significant source of foreign exchange and income. According to the World Bank, "tens of millions of African migrants scattered around the world could mobilize more than \$100 billion a year to help develop the impoverished continent". The World Bank says "there's around \$40 billion a year in officially recorded remittances -- cash sent by migrants back to their home countries -- and an estimated \$50 billion in diaspora savings that could be leveraged for low-cost project finance".[1] Given the economic significance of remittances to the developing world, the causes of remittances to these countries is an issue of key importance for both academics who study the determinants of economic growth in the developing world and economic policy makers. In particular, for the economic policy response to transitory income shocks it is key to understand whether the response of remittances to transitory income shocks is positive, negative, or zero.

Obtaining an estimate of the causal effect that transitory income shocks have on remittances is complicated by a possible reverse causal effect of remittances on income. Remittances may have a positive effect on income if they are used to increase investment, yet they could equally have a negative income effect if they are spent to finance consumption (inducing a real exchange rate appreciation) or lead to a reduction in labor supply because of positive wealth effects.[2] The empirical literature on remittances is well aware of this simultaneity problem and has addressed it using instrumental variables techniques.[3] However, a second key issue when dealing with identifying the causal relationship between transitory income shocks and remittances that has not received sufficient attention in the literature is whether the transitory change in income is due to a transitory change in productivity, or whether it is due to a transitory but abrupt change in the capital stock that could be the consequence of

1 See http://www.smartmoney.com/news/on/?story=on-20110330-000243.
2 See for example Amuedo-Dorantes and Pozo (2006), Bansak and Chezum (2009), or Acosta et al. (2009).
3 See for example Yang (2007) and Yang and Choi (2007).

events such as natural disasters or wars. The reason why this distinction matters is that basic economic theory tells us that beyond the transitory change in income, it is the marginal product of capital that is relevant for the decision to send remittances if these remittances are driven by an investment motive. If the remittances are on the other hand driven by an insurance motive, then it is solely the transitory nature of the income shock that matters. At the macroeconomic level, there are events (for example, natural disasters or wars) where a decrease in income may be associated with an increase in the marginal product of capital. Observing an average within-country relationship between transitory income changes and remittances does not allow to distinguish, therefore, whether at the macroeconomic level remittances are driven by an investment, an insurance motive, or both.[4]

The starting point of our empirical analysis of Sub-Saharan African countries is that year-to-year variation in rainfall is a shock to agricultural productivity. According to the World Development Indicators (2010), the average share of agriculture in value added is about one third in the Sub-Saharan African countries. Hence, year-to-year variation in rainfall can have large effects on aggregate incomes per capita and on the return to capital, that do not go in opposite directions, through rainfall's effect on agricultural productivity. Moreover, year-to-year variation in rainfall is a plausibly exogenous shock to Sub-Saharan African economies that is of highly transitory nature: the sample average AR(1)

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4 To see this formally, consider an economy operating under a simple constant returns to scale production function $Y = AK^{\alpha} L^{1-\alpha}$, with 0<α<1. In this economy average income per capita $y \equiv \frac{Y}{L} = A\left(\frac{K}{L}\right)^{\alpha}$ decreases if, say, due to a natural disaster there is a decrease in the capital stock K that decreases the capital labor ratio. Notice that this reduction in K increases the marginal product of capital $MPK \equiv \frac{\partial Y}{\partial K} = A\left(\frac{K}{L}\right)^{\alpha - 1}$ and hence the incentives to send remittances in order to exploit higher returns. A positive average response of remittances to negative changes in income can therefore be consistent with both, an insurance and an investment motive. However, an estimation approach that uses an exogenous variable which does not affect income and the return to capital in opposite ways can overcome this problem.

coefficient on rainfall is about 0.18 and a distributed lag model shows that the significant effect on income per capita vanishes after about one year.

Our panel fixed effects analysis that uses the within-country variation in remittances and rainfall yields two main results. First, year-to-year variations in rainfall have on average an insignificant contemporaneous effect on remittances to Sub-Saharan African countries. This result is robust to controlling for country and year fixed effects, country-specific linear time trends, as well as the exclusion of extreme rainfall observations (i.e. droughts and floods), a distributed lag model that allows to distinguish short-run from medium/long-run responses, and a dynamic panel data model that controls for adjustment dynamics in remittances.

Our second main finding is that the marginal effect of transitory rainfall driven income shocks on remittances significantly varies across Sub-Saharan African countries' GDP share of domestic credit to the private sector. This difference in marginal effects is so strong that at high levels of credit to the private sector transitory increases in income had a significant negative effect on remittances. Hence, while in countries with low domestic private capital remittances responded significantly positively to transitory income shocks, in countries where domestic private capital as a share of GDP was relatively high the remittance flow response was significantly negative.

One possible interpretation of our findings is that they are consistent with an investment motive of remittance flows. The reason is that, if farmers' ability to obtain finance is a function of their wealth then a positive rainfall shock that increases farmers' income will slacken finance constraints and lead to an increase in investment. Therefore, when domestic capital to the private sector is thin, so that the percentage share of domestic private sector finance for each investment project is small and the percentage share of remittance finance is relatively large, a positive rainfall shock that increases investment will induce a particularly large remittance response (which, according to the investment motive, has the purpose to partially finance investment projects). On the other hand, as the percentage share of domestic private sector finance increases, the role of remittances in exploiting domestic investment opportunities diminishes. Thus, an increase in domestic finance to the private sector makes it less likely that the observed remittance flow response behaves as if it follows an investment motive.

Given this interpretation of why domestic credit to the private sector plays an important role in shaping the effect of rainfall on remittance flows, it is important to note that our findings are not inconsistent with the presence of an insurance motive of remittances. This is because in Sub-Saharan African countries with relatively high domestic credit to the private sector (where the investment motive should be less relevant as argued above) we find that the remittance response is significantly negative. Hence, in Sub-Saharan African countries where investors have relatively good access to credit, the obtained remittance response to exogenous rainfall shocks is consistent with an insurance motive of remittance flows.

There exist several papers on the determinants of remittances that are related to our study. Using a sample of middle and low income countries and focusing on cross-country variation Freund and Spatafora (2008) show that remittances are significantly lower in countries where transaction costs are higher. Sayan (2006) investigates the business-cycle behavior of remittances for 12 developing countries and fails to find strong evidence for a significant average countercyclical relationship. Sayan's study does not use exogenous, transitory rainfall shocks to examine the effects that within-country changes in income have on remittances however. On the other hand, Yang (2007) documents that exogenous income shocks due to hurricanes lead to a significant increase in workers' remittances to poor countries.

Yang's (2007) study and focus on hurricanes is closely related to our focus on rainfall driven income shocks. This is because hurricanes, like rainfall, are a transitory shock to income. However, a crucial difference between rainfall and hurricanes is that the later has a large negative (destruction) effect on the economy's capital stock. This means that an analysis that uses hurricanes as an exogenous, negative transitory income shock to examine the insurance motive of remittances is problematic because the response can also be consistent with an investment motive since the hurricane may be associated with a higher, transitory return to capital. A further key difference between our study and Yang (2007) is that Yang (2007) does not focus on the role of cross-country differences in financial development. In light of our focus on these cross-country differences, it is important to note that the negative relationship between rainfall and remittances, that Yang and Choi (2007) document in their micro-data study of the Philippines during July 1997 to October 1998, is consistent with our second main finding that at relatively high levels of the GDP share of domestic credit to the private sector the relationship between rainfall and remittances is significantly negative.[5]

There are a number of reasons why our empirical analysis focuses on the group of Sub-Saharan African countries. First, recent research on the macroeconomic effects of rainfall on income has shown that the significant effects of rainfall on GDP per capita are limited to the Sub-Saharan African region (see for example Barrios et al. 2010). That is, for other regions such as Asia and Latin America there is no significant average effect of rainfall on aggregate income. Second, according to PWT and WDI data the average ratio of remittance flows over total investment is about one-quarter in these economies. This suggests that remittances flows could be an important source of finance for the group of Sub-Saharan African countries.[6] Third, there is a significant policy debate on the causes of Sub-Saharan Africa's poor growth performance when measured over the past half century. Part of this debate has recently considered the role of remittances in reducing poverty in the Sub-Saharan African region (see,

5 According to WDI (2010), the average ratio of private sector credit to GDP in the Philippines during the 1997-1998 period was 0.58. Plugging this value into our estimates yields a negative relationship between rainfall and remittances that is significant at the 5 percent level. Thus, our macro panel data results are consistent with the micro panel data evidence that is provided by Yang and Choi (2007) on rainfall and remittances in the Philippines.

6 According to WDI (2010), in 2007 the total volume of remittances flows to Sub-Saharan African countries was US$18.6 billion; US$63.3 billion for Latin American countries, US$133.8 billion for South-East Asian countries; and US$33.4 for Middle East and North African countries. While Sub-Saharan Africa thus plays a more minor part in terms of the total global flow of remittances, this does not mean that for the Sub-Saharan African region remittance flows are an unimportant source of finance. To the contrary, the 2007 GDP share of remittances for Sub-Saharan Africa was 2.4 percent, 1.7 percent for Latin America, 0.7 percent for East Asia and the Pacific, 4.4 percent for South Asia; and 2.2 percent for the Middle East and North Africa.

for example, Gupta et al., 2009).

The remainder of our paper is organized as follows. In section 2 we explain our estimation strategy and data. In Section 3 we discuss our main empirical results. In Section 4 we conclude.

2. Data and Estimation Strategy

We examine the reduced-form effects that rainfall has on real workers' remittances per capita by estimating the following model:

$$\ln(Remittances_{it}) = \alpha_i + \beta_t + \gamma_i t + \eta \ln(Rainfall_{it}) + u_{it}$$

where α_i are country fixed effects, $\gamma_i t$ are country-specific linear time trends, and β_t are year fixed effects. u_{it} is an error term that is clustered at the country level.

As a baseline regression, we estimate the average marginal impact effect η that rainfall has on remittances. We then examine how the marginal effect of rainfall on remittances varies as a function of cross-country differences in financial development by estimating an interaction model of the form:

$$\ln(Remittances_{it}) = a_i + b_t + c_i t + d\ln(Rainfall_{it}) + e\ln(Rainfall_{it})*FD_{it-1} + hFD_{it-1} + k_{it}$$

where FD_{it-1} is a measure for cross-country differences in financial development. In order to reduce concern that our estimates on the interaction effect are biased due to reverse causality of remittances on financial development, we use the time-varying measure of financial development lagged one year. Because this is a predetermined variable, it is less likely that the measure is affected by within-country variations in rainfall or remittance flows.[7] To strengthen this point, we will also report dynamic panel data estimates that control for lagged remittances on the right-hand side of the regression.

Our data sources for the estimation of the above equations are as follows. The annual rainfall data are from Terrestrial Air Temperature and Precipitation: 1900-2006 Gridded Monthly Time Series,

7 In our working paper, Arezki and Brückner (2011), we reported estimates that were based on using the average (and thus time-invariant) GDP share of domestic credit to the private sector. The estimates obtained there were very similar to the ones reported in this paper.

Version 1.01 (Matsuura and Willmott, 2007). These rainfall data come at a high resolution (0.5°x0.5° latitude-longitude grid) and each rainfall observation in a given grid is constructed by interpolation of rainfall observed by all stations operating in that grid. The rainfall data are then aggregated to the country level by assigning grids to the geographic borders of countries. The annual investment and real GDP per capita data are from the Penn World Tables, version 6.3 (Heston et al. 2009). The data on the GDP share of domestic credit to the private sector and workers' remittances are from WDI (2010). Summary statistics on these variables are provided in Tables 1 and 2.

3. Main Results

Table 3 presents our estimates of the average reduced-form effect that rainfall has on remittances to Sub-Saharan African countries. Column (1) shows estimates where the control variables are country fixed effects only. Column (2) adds year fixed effects and column (3) adds country-specific linear time trends. The main finding is that the average effect that rainfall has on remittances is quantitatively small and statistically insignificant. Column (4) shows that this continues to be the case when the sample excludes observations that fall in the pre-1990 period (when remittance data might have been of poor quality). And column (5) shows that the effect of rainfall on remittances continues to be quantitatively small and statistically insignificant when we exclude extreme rainfall observations that fall in the bottom/top 5th percentile of the within-country rainfall distribution (i.e. droughts or floods)

As a first piece of evidence that cross-country differences in credit to the private sector play an important role for the marginal effect that rainfall has on remittances, we present in Table 4 estimates that split the sample. Column (1) presents estimates for observations that are in the bottom 25th percentile of the GDP share of credit to the private sector. The coefficient on rainfall for this sub-sample is positive and statistically significant at the 5 percent level. Column (2) reports the estimates for the bottom 50th percentile. These estimates show that in the sub-sample with below median credit to the private sector rainfall had also a positive effect on remittance flows. The estimated coefficient is statistically significant at the 10 percent level, but quantitatively it is less than half the size of the estimated coefficient in column (1). Moving to the top 50th percentile of the GDP share of credit to the private sector, column (3) shows that the estimated coefficient on rainfall is negative in sign but statistically insignificant. A comparison between columns (2) and (3) shows that the marginal effect of rainfall on remittances is significantly larger in the sample with below median credit to the private sector than in the above median sample. In addition to this, column (4) shows that in the top 25th percentile the effect of rainfall on remittances is negative and significant at the 10 percent level. Table 4 is therefore a first indication that: (i) the effect of rainfall on remittances varies significantly across the GDP share of credit to the private sector; (ii) the effect of rainfall on remittances is significantly positive at low levels of credit to the private sector but significantly negative at high levels of private sector credit.

In Table 5 we document that similar results are obtained if we interact rainfall with the time-varying measure of the GDP share of credit to the private sector (lagged one year). Because both variables on the interaction term are time varying we have to also directly include them on the right-hand side of the regression. There are three main results worth noting. First, the interaction between rainfall and the credit to GDP ratio is negative and statistically significant at the 5 percent level. Second, the estimates imply that at high levels of credit to GDP the relationship between rainfall and remittances is significantly negative. Third, the average effect of increases in credit to the private sector on remittances flows is positive though not statistically significant at the conventional confidence levels.

Taking partial derivatives of the estimates reported in column (1) of Table 5 with respect to rainfall yields:

$$\frac{\partial\,(\text{Remittances})}{\partial\,(\text{Rainfall})} = 0.68 - 0.028(\frac{\text{Credit}}{\text{GDP}})$$

This equation implies that at zero private credit to GDP ratios the estimates in column (1) predict a positive response of remittances to rainfall; and a negative and significant response at high credit to GDP ratios. In Figure 1, we plot this estimated relationship for the relevant sample range of the credit to GDP ratio.

Column (2) of Table 5 shows that importantly the estimates do not change significantly when we exclude country-year observations that fall in the pre-1990 period. The coefficient on the interaction between rainfall and credit to the private sector continues to be negative and statistically significant at the 5 percent level. We also note that the standard errors on the estimates in column (2) imply that we cannot reject for any of the right-hand-side variables that the effects are the same for the post-1990 period.[8] Column (3) of Table 5 also shows that the interaction between rainfall and credit to the private sector continues to be significant when we exclude extreme rainfall observations that fall in the bottom/top 5th percentile of the within-country rainfall distribution (i.e. droughts or floods). Thus, column (3) provides reassuring evidence that the estimates are driven by smooth within-country variations in rainfall and not by extreme weather events that could lead to an atypically large influx of remittances.

Previous studies of the effects of rainfall in Sub-Saharan African countries have documented a significant effect of rainfall on political institutions and civil war (e.g Miguel et al. 2004; Bruckner and Ciccone, 2011). To document that the effects of rainfall on remittances are robust to controlling for these within-country variations in political institutions and civil war, Table 6 reports estimates that

8 In Appendix Table 1 we show that similar results are obtained if we split the sample into the pre- and post-1990 (1980) period. The coefficients are only significant for the post-1990 (1980) period, but we cannot reject for any of the specifications that the coefficients in the different sub-periods are the same. In Appendix 2 we show that, if measurement error in the remittance data is higher for countries with a low GDP share of credit to the private sector, this type of measurement error will not lead to a bias of the estimated coefficients.

include the Polity2 score and a civil war incidence indicator variable on the right-hand side of the estimating equation.[9] The main result is that the effects of rainfall and the interaction between rainfall and financial development continues to be significant while these additional control variables turn out to be insignificant.

A further issue is whether the interaction estimate between rainfall and the GDP share of domestic credit to the private sector is robust to controlling for an interaction between rainfall and cross-country differences in GDP per capita as well as an interaction between rainfall and the GDP share of agricultural value added. In the cross-section, GDP per capita and the agricultural value added share are positively correlated with the GDP share of domestic credit to the private sector. Hence, reporting estimates where as additional control variables we include interactions between rainfall and GDP per capita and rainfall and the GDP share of agricultural value added is an important robustness check.

Table 7 shows that our main finding of a significant negative interaction effect between rainfall and the GDP share of credit to the private sector survives the control for such additional interaction terms. The estimates show that at low levels of credit to the private sector improved rainfall conditions have a positive effect on remittances while at high levels of credit to the private sector the relationship between rainfall and remittances is negative.[10] Moreover, the interactions between rainfall and GDP per capita, and rainfall and the agricultural value added share turn out to be insignificant in these regressions.

The interaction estimates use the time-varying GDP share of credit to the private sector, lagged one year to reduce concerns that this variable is affected by changes in remittances. In Table 8 we

9 We obtain the Polity2 variable from the Polity IV database and the civil war incidence indicator variable from the PRIO/UPSALLA database.

10 Appendix Table 2 shows that using in addition to a linear term a quadratic term of credit to the private sector yields very similar results. The interaction between rainfall and the linear GDP share of credit to the private sector is significantly negative while the interaction with the quadratic term is insignificant.

report estimates that control for lagged remittances, in order to provide additional support for the assumption that the lagged GDP share of credit to the private sector is exogenous to contemporaneous within-country variations in remittances. Both the least squares and GMM estimates show that there is quite a bit of persistence in remittance flows. The AR(1) coefficient is about 0.5 and highly statistically significant. However, including lagged remittances on the right-hand side of the regression does not change significantly the estimate on the interaction between rainfall and the GDP share of credit to the private sector. Table 9 also shows that, when including further lags of rainfall, the GDP share of credit to the private sector, and remittances the contemporaneous effect of rainfall and the interaction term continue to be significant while the lagged effects of rainfall and the interaction term are insignificant.

Table 10 documents that rainfall has a highly significant positive effect on investment. The coefficient on the contemporaneous effect of rainfall implies that a one percent increase in rainfall significantly increases the investment to GDP ratio by over 2 percent on average. The lagged effects of rainfall on investment are declining in size, and are statistically insignificant. Table 11 also documents that improved rainfall conditions are associated with significantly higher GDP per capita. The significant effect of rainfall on income occurs on impact; and the lagged effects are declining in size and are statistically insignificant. Hence, despite rainfall being a transitory ex-post shock to agricultural productivity, Tables 10 and 11 show that rainfall is associated with higher incomes and in particular with higher investment. Given these results, we provide in Appendix 1 a simple model that illustrates one possible reason for why the effects of rainfall on remittances are significantly decreasing in countries' GDP share of credit to the private sector.

4. Summary

We examined in this paper the effects that year-to-year variations in rainfall have on remittances in a panel of 41 Sub-Saharan African countries during the period 1970-2007. Our main finding was that the effects of rainfall on remittances are significantly decreasing in countries' GDP share of domestic credit to the private sector. This effect is so strong, that at low levels of domestic credit to the private sector improved rainfall conditions have a significant positive effect on remittances. However, rainfall has a significant negative effect on remittances in countries with relatively high levels of credit to the private sector, suggesting that in these countries there exists a counter-cyclical relationship between income and remittance flows. Our finding regarding a heterogeneous effect of rainfall on remittance flows highlights the role of domestic credit markets in shaping the response of remittance flows to country-specific income shocks.

References

Acosta, P., E. Lartey, and F. Mandelman (2009). "Remittances and the Dutch Disease." *Journal of International Economics* 79: 102-116.

Arezki, R. and M. Brückner (2011). "Rainfall, Financial Development, and Remittances: Evidence from Sub-Saharan Africa." IMF WP 11153.

Amuedo-Dorantes, C. and S. Pozo (2006). "Migration, Remittances, and Male and Female Employment Patterns." *American Economic Review* 96: 222-226.

Bansak, C. and B. Chezum (2009). "How Do Remittances Affect Human Capital Formation of School-Age Boys and Girls? *American Economic Review* 99: 145-148.

Barrios, S., L. Bertinelli, E. Strobl (2010). "Trends in Rainfall and Economic Growth in Africa: A Neglected Cause of the African Growth Tragedy." *Review of Economics and Statistics* 92: 350-366.

Brückner, M., K. Gerling, and H. Grüner (2010). "Wealth Inequality and Credit Markets: Empirical Evidence from Three Industrialized Countries." *Journal of Economic Growth* 15: 155-176.

Brückner, M. and A. Ciccone (2011). "Rainfall and the Democratic Window of Opportunity." *Econometrica* 79: 923-947.

Ciccone, A. (2011). "Economic Shocks and Civil Conflict: A Comment." *American Economic Journal: Applied Economics* (forthcoming).

Freund, C. and N. Spatafora (2008). "Remittances, Transaction Costs, and Informality." *Journal of Development Economics* 86: 356-366.

Gupta, S., C. Pattillo, and S. Wagh (2009). "Effect of Remittances on Poverty and Financial Development in Sub-Saharan Africa." *World Development* 37: 104-155.

Heston, A., R. Summers, and B. Aten (2009). Penn World Table Version 6.3. Center for International Comparisons of Production, Income and Prices. University of Pennsylvania, http://pwt.econ.upenn.edu.

Matsuura and Willmott (2007). Terrestrial Air Temperature and Precipitation: 1900-2006 Gridded Monthly Time Series, Version 1.01. University of Delaware, http://climate.geog.udel.edu/~climate/.

Miguel, E., S. Satyanath, and E. Sergenti (2004). "Economic Shocks and Civil Conflict: An Instrumental Variables Approach." *Journal of Political Economy* 112 (41): 725-753.

Sayan, S. (2006). "Business Cycles and Workers' Remittances: How Do Migrant Workers Respond to Cyclical Movements of GDP at Home?" IMF WP 06/52.

World Bank (2010). World Development Indicators. Online Database.

Yang, D. and H. Choi (2007). "Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines." *World Bank Economic Review* 21: 219–48.

Yang, D. (2008) "Coping with Disaster: The Impact of Hurricanes on International Financial Flows, 1970-2002." *The B.E. Journal of Economic Analysis & Policy* 8 (Advances), Article 13.

Appendix 1. A Simple Model

In this appendix we provide a simple model for why rainfall can have a particularly large, positive effect on remittance flows in countries with low credit to the private sector.

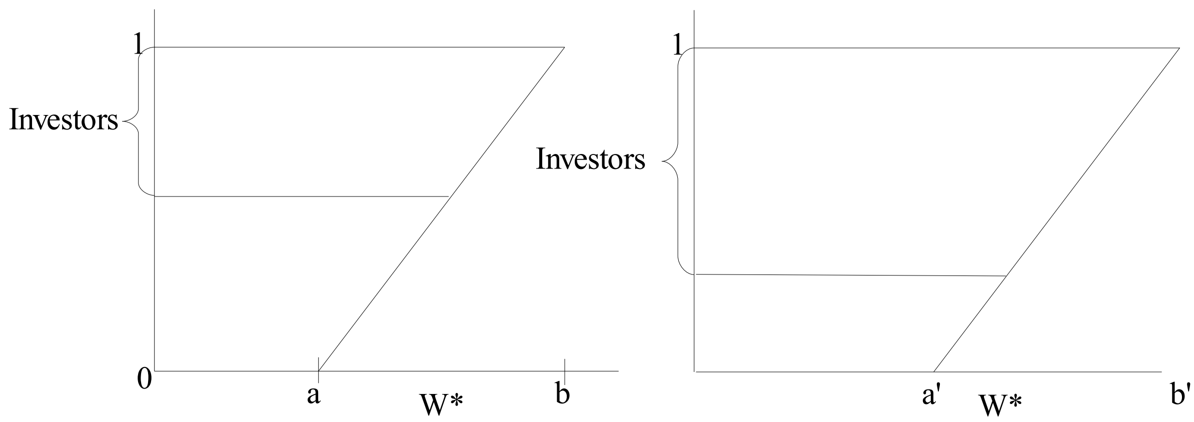
The starting point of our model is that, if investors' ability to obtain finance is a function of their wealth (i.e. there are credit market imperfections that imply that only investors with sufficient wealth can obtain finance) then positive rainfall shocks can lead to an increase in investment. The reason is that a positive rainfall shock, by increasing investors' wealth, will slacken finance constraints and hence will lead to an increase in the number of investors.

To be precise on the above point, suppose that a farmer wants to start a project of fixed size and cost I. He can obtain a loan for this investment project either from a local financial institution $L_{Domestic}$ or in form of a remittance flow $L_{Remittance}$. In either case, the total amount of the loan is assumed to be less than the investment project. The simple inequality below summarizes this assumption:

$$L_{Domestic}+L_{Remittance}=L_{Total}<I$$

The inequality implies that only farmers with sufficient wealth $W>I-L_{Total}$ start an investment project. This inequality is a common feature of models with moral hazard, see for example Bruckner et al. (2010) and the references cited therein. The assumption that the total amount of the loan is less than the investment project is thus nothing more than a short cut to ensure that only sufficiently wealthy agents start an investment project.

Again, for simplicity, suppose that wealth in an economy is distributed uniformly $W \sim U[a,b]$. The left-hand side figure on the next page illustrates how the distribution and amount of wealth in the economy affects the number of investors, and hence investment. Only farmers above W* have sufficient wealth to start an investment project.



If the rainfall shock increases farmers' income, then there would be a right-shift in the distribution of wealth to a' and b'. This right-shift is presented in the right-hand side of the figure. As the figure shows there would be more farmers that start the investment project *I*.[11] The reason is that the increase in farmers' wealth slackens finance constraints and more farmers will be able to obtain finance for their investment projects.

In order to illustrate in the above framework the importance of domestic credit to the private sector, it is useful to consider the extreme case where $L_{Domestic}=0$; i.e. all investment projects are financed by remittance flows (note that still it is assumed that only a fraction of each investment project is financed by remittances). In that case where domestic credit to investors is zero, a positive rainfall shock slackens finance constraints for investors and this will lead to a large increase in remittance flows. On the other hand, if the share of domestic lending for each investment project is already large, then remittance flows will respond little to rainfall shocks (think of the extreme case where $L_{Domestic}=I$). Intuitively, the reason for this result is that if domestic financial markets for investors are already moderately functioning the remittance flow that has the purpose to ease financing of investment projects plays only a minor role. Within this framework, the marginal effect of rainfall on remittance flows (via farmers' incomes) is therefore a decreasing function of credit to the private sector.

11 Note that the exact size of the increase in investment will depend on how wealth is distributed in the economy and how the rainfall shock affects income in that distribution.

Appendix 2. Measurement Error in Remittance Data

In this appendix we show that measurement error in remittance data that varies as a function of countries' GDP share of credit to the private sector (but not as a function of rainfall) does not lead to a bias of the least squares estimate. To see this, consider the simplest case where we split countries into above and below median sample credit to the private sector (as we do in columns (2) and (3) of Table 4). In particular, suppose that in the above median group there is no measurement error, while in the below median group remittance flows are observed with error. That is,

(1) $R_1 = R_1^*$ (High Credit to Private Sector)

(2) $R_2 = R_2^* + e_2$ (Low Credit to Private Sector)

where the variable e_2 in equation (2) reflects that remittances R_2 in the below median group are measured with some error e_2. Suppose then that the true model is:

(3) $R_1^* = a\text{Rain}^* + u_1$ (High Credit to Private Sector)

(4) $R_2^* = b\text{Rain}^* + u_2$ (Low Credit to Private Sector)

Least squares estimation of equation (3) yields that:

(5) $a^{LS} = \text{cov}(\text{Rain}^*, R_1^*)/\text{var}(\text{Rain}^*) = \text{cov}(\text{Rain}^*, a\text{Rain}^* + u_1)/\text{var}(\text{Rain}^*) = a$

where the last line uses the standard assumption that $\text{cov}(\text{Rain}^*, u_1)=0$; (i.e. rainfall is exogenous to remittances).

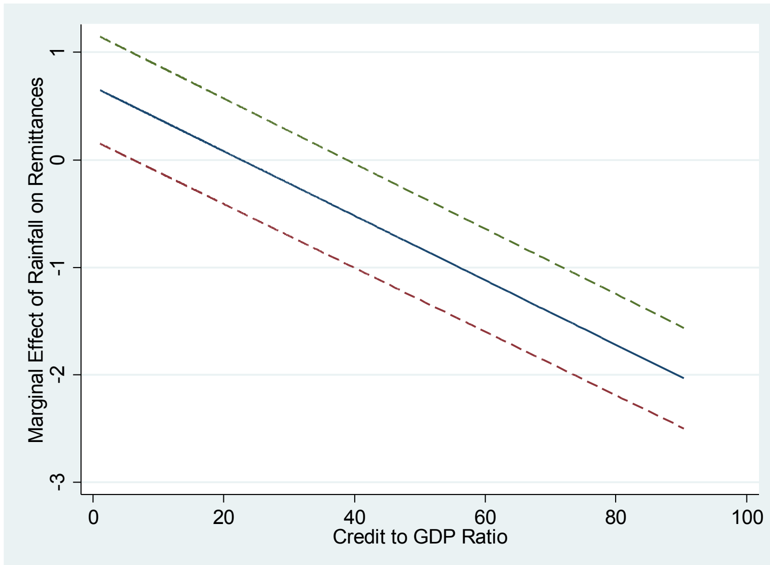
Likewise, least squares estimation of equation (4) yields that:

(6)
$$
\begin{aligned}
b^{LS} &= \text{cov}(\text{Rain}^*, R_2)/\text{var}(\text{Rain}^*) = \text{cov}(\text{Rain}^*, R_2^* + e_2)/\text{var}(\text{Rain}^*) \\
&= \text{cov}(\text{Rain}^*, b\text{Rain}^* + u_2 + e_2)/\text{var}(\text{Rain}^*) \\
&= b + \text{cov}(e_2, \text{Rain}^*)
\end{aligned}
$$

where the first line simply uses (2), the second line uses (4), and the last line uses the same assumption as above, namely that $\text{cov}(\text{Rain}^*, u_2)=0$.

Therefore, even if errors in remittance flows are larger for countries with low credit to the private sector, this measurement error will not lead to a bias in the least squares estimate as long as the measurement error in remittance flows is not a systematic function of rainfall.

Figure 1. Marginal Effect of Rainfall on Remittances as a Function of Credit to the Private Sector



Note: The figure reports the marginal effect that rainfall has on remittances as a function of the credit to GDP ratio (measured in percentage points). Results are based on the estimates shown in column (1) of Table 5. Dashed lines represent 95 percent confidence bands.

Table 1. Descriptive Statistics

	Mean	Std. Dev.	Min	Max
Share of Remittances in GDP (in %)	4	13	1	63
Share of Agricultural VA in GDP (in %)	31	13	5	55
Share of Domestic Credit in GDP (in %)	19	16	4	92

Table 2. Time-Series Properties

	AR(1) Coefficient	P-Value Fisher Panel Unit Root Test
Ln(Rainfall)	0.18	0.000
Ln(Remittances)	0.75	0.000
Ln(Investment/GDP)	0.56	0.000
Ln(GDP p.c.)	0.95	0.192
ΔLn(GDP p.c.)	0.09	0.000

Table 3. Rainfall and Remittances

	ln(Remittances)				
				Excl. Pre-1990 Period	Excl. Extreme Rain Obs.
	(1)	(2)	(3)	(4)	(5)
	LS	LS	LS	LS	LS
ln(Rain), t	0.14	0.17	0.06	-0.08	0.28
	(0.23)	(0.27)	(0.17)	(0.15)	(0.31)
Country FE	Yes	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Country Trends	No	No	Yes	Yes	Yes
Observations	899	899	899	506	798

Note: The dependent variable is the log of real remittances per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 4. Rainfall, Private Sector Credit, and Remittances
(Sample Split)

	ln(Remittances)			
	Bottom 25th Percentile	Bottom 50th Percentile	Top 50th Percentile	Top 25th Percentile
	(1)	(2)	(3)	(4)
	LS	LS	LS	LS
ln(Rain), t	1.32**	0.55*	-0.18	-0.26*
	(0.65)	(0.28)	(0.19)	(0.16)
Country FE	Yes	Ye	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country Trends	Yes	Yes	Yes	Yes
Observations	217	442	457	217

Note: The dependent variable is the log of real remittances per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. Column (1) reports estimates for the set of countries that are in the bottom 25th percentile of the GDP share of domestic credit to the private sector. Column (2) reports estimates for the set of countries that are in the bottom 50th percentile of the GDP share of domestic credit to the private sector. Column (3) reports estimates for the set of countries that are in the top 50th percentile of the GDP share of domestic credit to the private sector. Column (4) reports estimates for the set of countries that are in the top 25th percentile of the GDP share of domestic credit to the private sector. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 5. Rainfall, Private Sector Credit, and Remittances
(Interaction Estimates)

	ln(Remittances)		
		Excl. Pre-1990 Period	Excl. Extreme Rain Obs.
	(1)	(2)	(3)
	LS	LS	LS
ln(Rain), t	0.681***	0.294	0.928***
	(0.249)	(0.236)	(0.326)
ln(Rain), t * Private Credit GDP Share, t-1	-0.028***	-0.018**	-0.029***
	(0.009)	(0.009)	(0.010)
Private Credit GDP Share, t-1	-0.006	-0.006	-0.011
	(0.009)	(0.006)	(0.011)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country Trends	Yes	Yes	Yes
Observations	899	506	798

Note: The dependent variable is the log of real remittances per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 6. Rainfall, Financial Development, and Remittances
(Robustness to Controlling for Within-Country Changes in Civil War and Democracy)

	ln(Remittances)		
	(1)	(2)	(3)
	LS	LS	LS
ln(Rain), t	0.704*** (0.258)	0.686*** (0.259)	0.691*** (0.261)
ln(Rain), t * Private Credit GDP Share, t-1	-0.029*** (0.009)	-0.029*** (0.009)	-0.029*** (0.009)
Private Credit GDP Share, t-1	-0.006 (0.009)	-0.006 (0.009)	-0.006 (0.009)
Civil War, t-1	0.118 (0.206)		0.147 (0.163)
Democracy, t		0.147 (0.163)	0.117 (0.207)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country Trends	Yes	Yes	Yes
Observations	899	899	899

Note: The dependent variable is the log of real remittances per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 7. Rainfall, Financial Development, and Remittances
(Robustness to Interactions with Agricultural GDP Share and GDP Per Capita)

	ln(Remittances)		
	(1)	(2)	(3)
	LS	LS	LS
ln(Rain), t	0.612** (0.251)	0.712*** (0.261)	0.632*** (0.255)
ln(Rain), t * Private Credit GDP Share, t-1	-0.028*** (0.010)	-0.027*** (0.01)	-0.027** (0.011)
Private Credit GDP Share, t-1	-0.004 (0.009)	-0.005 (0.010)	-0.003 (0.10)
ln(Rain), t * Share of Agricultural VA, t-1	-0.000 (0.010)		-0.005 (0.010)
Share of Agricultural VA, t-1	0.011 (0.100)		0.062 (0.096)
ln(Rain), t * ln(GDP Per Capita), t-1		-0.345 (0.310)	-0.372 (0.344)
ln(GDP Per Capita), t-1		4.152 (2.931)	4.408 (3.163)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	853	899	853

Note: The dependent variable is the log of real remittances per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 8. Rainfall, Financial Development, and Remittances
(Robustness to Controlling for Lagged Remittances)

	ln(Remittances)	
	(1)	(2)
	LS	GMM
ln(Rain)	0.338* (0.189)	0.281* (0.166)
ln(Rain), t * Private Credit GDP Share, t-1	-0.012** (0.006)	-0.013** (0.006)
Private Credit GDP Share, t-1	-0.002 (0.005)	-0.001 (0.004)
ln(Remittances), t-1	0.538*** (0.059)	0.432*** (0.095)
Country FE	Yes	Yes
Year FE	Yes	Yes
Country Trends	Yes	Yes
Observations	855	855

Note: The dependent variable is the log of real remittances per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 9. Rainfall, Financial Development, and Remittances
(Robustness Additional Rainfall Lags)

	ln(Remittances)		
	(1)	(2)	(3)
	LS	LS	GMM
ln(Rain), t	0.658*** (0.239)	0.402* (0.21)	0.391** (0.185)
ln(Rain), t-1	0.141 (0.229)	-0.064 (0.193)	-0.024 (0.171)
ln(Rain), t-2	0.202 (0.281)	0.249 (0.202)	0.201 (0.191)
ln(Rain), t * Private Credit GDP Share, t-1	-0.029*** (0.009)	-0.015** (0.008)	-0.016** (0.007)
ln(Rain), t -1* Private Credit GDP Share, t-2	0.000 (0.007)	0.012 (0.008)	0.008 (0.007)
ln(Rain), t-2 * Private Credit GDP Share, t-3	-0.004 (0.008)	-0.005 (0.005)	-0.004 (0.005)
Private Credit GDP Share, t-1	-0.014 (0.011)	0.001 (0.005)	0.002 (0.005)
Private Credit GDP Share, t-2	-0.001 (0.09)	0.001 (0.007)	-0.002 (0.006)
Private Credit GDP Share, t-3	0.013 (0.009)	0.002 (0.007)	0.004 (0.005)
ln(Remittances), t-1		0.503*** (0.077)	0.419*** (0.111)
ln(Remittances), t-2		0.042 (0.054)	-0.044 (0.094)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country Trends	Yes	Yes	Yes
Observations	878	800	800

Note: The dependent variable is the log of real remittances per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 10. Rainfall and Investment

	ln(Investment)	
	(1)	(2)
	LS	GMM
ln(Rain), t	2.205**	1.735***
	(0.988)	(0.712)
ln(Rain), t-1	0.644	0.596
	(0.887)	(0.701)
ln(Rain), t-2	-0.036	0.057
	(0.759)	(0.744)
ln(Investment), t-1	0.582***	0.520***
	(0.071)	(0.050)
Country FE	Yes	Yes
Year FE	Yes	Yes
Country Trends	Yes	Yes
Observations	897	897

Note: The dependent variable is the log of the investment to GDP ratio. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 11. Rainfall and Income Growth

	Δln(GDP)	
	(1)	(2)
	LS	GMM
ln(Rain), t	0.029**	0.027*
	(0.013)	(0.014)
ln(Rain), t-1	0.007	0.006
	(0.012)	(0.013)
ln(Rain), t-2	-0.003	-0.013
	(0.014)	(0.014)
Δln(GDP), t-1	-0.097	-0.022
	(0.061)	(0.077)
Country FE	Yes	Yes
Year FE	Yes	Yes
Country Trends	Yes	Yes
Observations	897	897

Note: The dependent variable is the change in the log of real GDP per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Appendix Table 1. Different Time Periods

	ln(Remittances)			
	Post-1990	Post-1980	Pre-1990	Pre-1980
	(1)	(2)	(3)	(4)
	LS	LS	LS	LS
ln(Rain), t	0.29	0.63**	0.13	0.30
	(0.24)	(0.28)	(0.35)	(0.52)
ln(Rain), t * Private Credit GDP Share, t-1	-0.02**	-0.03***	-0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.02)
Private Credit GDP Share, t-1	0.18**	0.28***	0.10	-0.10
	(0.09)	(0.09)	(0.10)	(0.22)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country Trends	Yes	Yes	Yes	Yes
Observations	506	791	393	108

Note: The dependent variable is the log of real remittances per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Appendix Table 2. Quadratic Interaction Term

	ln(Remittances)		
		Excl. Pre-1990 Period	Excl. Extreme Rain Obs.
	(1)	(2)	(3)
	LS	LS	LS
ln(Rain), t	0.734**	0.436	0.954***
	(0.294)	(0.334)	(0.356)
ln(Rain), t * Private Credit GDP Share, t-1	-0.034**	-0.031*	-0.032*
	(0.015)	(0.018)	(0.018)
ln(Rain), t * Private Credit GDP Share Squared, t-1	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0002)
Private Credit GDP Share, t-1	-0.011	-0.012	-0.016
	(0.019)	(0.016)	(0.021)
Private Credit GDP Share Squared, t-1	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country Trends	Yes	Yes	Yes
Observations	899	506	798

Note: The dependent variable is the log of real remittances per capita. Huber robust standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.