Remittances and Domestic Output in the Long Run*

Abstract

The Sustainable Development Goals identify remittances as a lifeline for families and communities in developing countries. However, empirical studies have difficulty detecting their aggregate effect on output. We employ data from 80 developing countries and cointegration-panel techniques to uncover the long-run impact of remittance on output. Our approach addresses endogeneity bias and potential measurement errors— issues that make it challenging to detect a positive remittance-output effect. More importantly, because cross-country growth regressions may lack power to detect growth effects of remittance on output, we deviate from them and instead utilize the rich and informative non-stationary properties of the level data to uncover the long run relationship between output and remittance. We find that there exists a long-run relationship between remittance and output, and on average, a 1% increase in remittances raises output by approximately 0.07%. Overall, this result is robust to alternative estimators, issues related to cross-sectional dependence, potential outliers, sampling bias, and periodisation. Furthermore, we find that there exists long-run bi-directional causal relationship between remittance and output. This implies that that a rise in remittance increases output and that, in turn, higher output induces an increase in remittance inflows. Policy-wise, the results suggest that policies that seek to lower transaction costs of, or ease the transfer of remittance can induce a positive impact of remittance on real GDP in the long run.

JEL Classification: E1, E20, F43
Keywords: Remittances, Output, heterogeneous panel cointegration, Developing economies

*We have received helpful comments and suggestions from Stephen O'Connell, David McKenzie, Markus Eberhardt, Justin Kakeu, John Hoddinott, Juan Munoz, Alberto Posso, Kwabena Gyimah-Brempong, Anne Barthel, and Eric Hoffmann that have significantly improved the paper. We also thank conference participants and discussants at the 2019 North East Universities Development Consortium meeting at Northwestern University for useful discussions and feedback. We are solely responsible for any remaining errors.

1 Introduction

"*Remittances are dollars wrapped with care*" — Dilip Ratha

According to the 2019 World Bank's Migration and Development Brief, annual remittances to low and middle-income countries reached a record high of $529 billion in 2018—a 9.6 percent jump from the 2017 record. In the last decade, remittances have exceeded foreign aid to developing countries and are catching up to foreign direct investment (Barajas et al., 2018; Clemens and McKenzie, 2018).[1] Although aid and foreign direct investment remain important sources of capital flow in developing countries, the household-to-household nature of remittances makes them a unique source of revenue (Chami et al., 2008). Indeed, the United Nations' Sustainable Development Goals (SDGs) identify remittances as a lifeline for many families and communities as well as a potential driver of growth and development in developing countries.[2] Interestingly, the links between remittance and development at the aggregate level are, both theoretically and empirically, ambivalent (Clemens and McKenzie, 2018; Faini, 2007).

This paper studies the long-run relationship of remittance on output in developing countries. We employ data from 80 developing countries over the period 1974-2014 and utilize recently developed heterogeneous cointegration-panel techniques, which account for both endogeneity and measurement error issues to estimate a bivariate cointegration relation between remittance and output. An advantage of our bivariate cointegration specification is that the coefficient of remittance in the regression equation measures the total effect of remittance on output, which also means that we do not preclude any potential channel through which remittance can affect output. More specifically, we lend a structural interpretation to our empirical specification by deriving a steady state relationship between output and remittance in a general equilibrium model where households receive remittance as an additional source of income. Here, the long run association between remittance and output is succinctly captured through its effect investment, multi-factor productivity, private consumption, and labor supply.

[1] It is worth mentioning that excluding China, remittances to low- and middle-income countries ($462 billion) were significantly larger than foreign direct investment flows in 2018 ($344 billion). See, https://www.worldbank.org/en/news/press-release/2019/04/08/record-high-remittances-sent-globally-in-2018 for more details on the World Bank Migration and Development Brief.

[2] See, https://www.un.org/en/events/family-remittances-day/un-action.shtml a discussion on the importance of remittances in achieving the SDGs at both the micro- and macro-level.

We find that there exists a positive and statistically significant long-run relationship between remittances and output. In particular, our baseline estimate reveals that, on average, a 1 percent increase in remittance induces a 0.066 percent increase in real GDP in the long run. This result is robust to alternative estimators, potential outliers, sampling bias, and periodisation. Specifically, the robustness exercises uncover a consistently positive and statistically significant long-run relationship between remittances on output suggesting that a one percent increase in remittances can raise output by 0.02–0.12 percent. Additionally, in pursuing a narrower Granger causality approach for our panel, we find that there exists a long-run bi-directional causal relationship between remittance and output. This implies that a rise in remittance increases output and that, in turn, higher output induces an increase in remmittance inflows. An important and direct implication of these findings is that ongoing policy efforts to lower transaction costs to ease the transfer of remittances (see for example, World Bank, 2017), can generate a permanent and positive impact of remittance on real GDP. This can contribute non-trivially to sustainable development in these developing economies.

In the quest to understand the aggregate impact of remittance, the existing literature has predominantly focused on growth analysis. The results have generally been mixed, with findings ranging from small positive, zero, and negative effects (e.g. Chami et al., 2008; Giuliano and Ruiz-Arranz, 2009; Pradhan et al., 2008; Rao and Hassan, 2011). Existing studies have attempted to explain these mixed results by arguing that a positive remittance-growth effect is likely to be offset by, among other things, the negative impact of remittance on labor supply (e.g., Posso, 2012) or components of muliti-factor productivity such as institutions (Abdih et al., 2012).[3] More recently, Clemens and McKenzie (2018) succinctly explain three new reasons for why a positive remittance-growth relationship may be difficult to detect. The reasons include: (1) Endogeneity bias due to the omitted variable, rising emigration. This variable is correlated with rising remittances, and it is also an opportunity cost to GDP. (2) Cross-country growth regressions may lack the power to detect growth effects of remittances. (3) Measurement errors in remittance primarily driven by changes in the measurement of remittance. The authors show that these three issues can individually expunge

[3] There are a number of studies that do not find a negative effect of remittance on labor supply (see for instance, Vadean, Randazzo, and Piracha, 2019, for the case of Tajikistan). Additionally, studies such as Behzadan and Chisik (2018) also show that remittance can interact with within-country income distribution to generate differences in spending patterns, production patterns, and the pattern of international trade. They find that remittances have the tendency to foster economic growth.

the positive effect of remittance on output in empirical studies independent of prior explanations. Thus, despite providing great insight into the remittance-output nexus, existing empirical studies are likely to be subjected to at least one of these three new issues. We take the issues laid out in Clemens and McKenzie (2018) seriously and attempt to account for them in our study.

Against this backdrop, this paper pushes the empirical literature on the aggregate effect of remittance forward in the following ways: First, we focus exclusively on the long-run impact of remittances on output. In this sense, the cointegration techniques we employ allows us to use level data, which in turn permits us to utilize the rich and informative non-stationarity properties of output and remittance. This empirical strategy naturally removes the drawback of using growth rates. Studies that use cross-country growth regressions to quantify the impact of remittance on growth may lack power to detect a positive effect due to the high variance feature in measured growth and remittances (Clemens and McKenzie, 2018). Growth is a complex process that depends on a host of variables other than the inflow of external funds (Herzer and Morrissey, 2013). Consequently, to study the impact of remittance on growth, one needs to control for a host of potential determinants of growth such as investment and institutional quality, which may not only lead to overcontrolling but also induce the risk of precluding other potential channels through which remittance can affect growth. Furthermore, growth rates show little persistence over time while remittances, in levels or relative to GDP, have exhibited persistent trends.[4] A regression involving growth (which is stationary) as the dependent variable and the remittances/GDP ratio (which is non-stationary) as an independent variable will therefore be unbalanced and can lead to misleading results (see Ericsson et al., 2001; Herzer and Morrissey, 2013).[5] This unbalanced analysis is avoided in a cointegration estimation as both the regressand (i.e., output) and regressor (i.e., remittance) are permitted to be in levels, thereby utilizing their non-stationary properties.

Second, cointegration techniques are designed to address omitted variables and endogeneity issues that generally affect cross-country studies. Notice that remittances rise primarily with rising emigration, whose opportunity cost to GDP creates endogeneity bias. Consequently, migration itself becomes an omitted variable correlated with remittances and the error term in the regression,

[4]Notice that output and remittance exhibit non-stationary properties; hence, using growth rates or differencing the data means one loses important long run information in the data and only estimates a short run model.

[5]It is important to point out that we do not use remittance as a percentage of GDP in our empirical analysis. We use the natural logarithm of remittances as the regressor to avoid the issues of dividing by GDP as discussed in Clemens and McKenzie (2018).

inducing a downward bias of the coefficient on remittance (Clemens and McKenzie, 2018). While cross-country regressions attempt to alleviate or circumvent the endogeneity issues by utilizing instrumental variables regressions, such strategies may lead to spurious results in the scenario where the instruments are weak or invalid.[6] Moreover, in certain cases it is challenging, and sometimes even impossible to find variables that qualify as valid instruments (Temple, 1999). Cointegration techniques do not require the use of instrumental variables, and by employing them, we circumvent the issue of endogeneity usually present in existing cross-country growth-remittance studies.

Relatedly, as illustrated in (Clemens and McKenzie, 2018), much of the estimated aggregate growth in remittances at the global level during the 1990-2010 period was driven by changes in measurement rather than genuine growth in remittance flow. The measurement error issue is likely to lead to non-classical error, which can cloud the true growth-remittance relationship in panel regressions even if remittances are exogenous and the test has high power.[7] Consequently, overstating the growth in remittance flows, then, means that the true effect of that flow on GDP is smaller than would be expected without mis-measurement. However, Hassler and Kuzin (2009) show that even in the presence of measurement errors, cointegration techniques perform better than other competing estimators, making them a desirable estimator in such scenarios.[8]

Beyond addressing the issues discussed in Clemens and McKenzie (2018), we attempt to deal with challenges related to heterogeneity and cross-sectional dependence in panel data head-on. Specifically, existing studies make the stringent assumption of homogeneous coefficient for all cross-sectional units in a panel and hence, assume a common relationship between remittance and output for all the countries in the panel. However, remittances affect output through key observable inputs (e.g., labor and capital) and unobservable inputs such as the multi-factors that affect the level of productivity. Heterogeneity in the relationship between output and remittances is likely to arise due to heterogeneity in technology parameter, indicating differential production function parameters

[6]See, Herzer and Morrissey (2013) for the case of foreign aid effectiveness.

[7]Non-classical errors occur when there is a potential correlation of the measurement error with the true, unobserved dependent variable itself, with the true values of other variables in the model, or with the errors in measuring those values (Bound et al., 2001).

[8]Miller (2010) also considers a cointegrating regression in which the integrated regressors are messy in the sense that they contain data that may be mismeasured, missing, and observed at mixed frequencies— factors that can generate additional noise that may violate covariance stationarity assumptions on the model error. Miller shows that covariance-based methods for estimating cointegrating regressions may be valid even when the error term is not covariance stationary.

on inputs across countries (see, Eberhardt and Teal, 2010, for a detailed discussion). In our baseline estimation, we employ the between-group dynamic OLS (DOLS) estimator, which allows the remittance-output coefficients to be different across each country. The overall remittances-output relationship is therefore interpreted as an average long-run effect in these developing countries.

Furthermore, there have been strong arguments that cross-sectional dependence arising from unobserved common factors, economic spillovers, or global shocks is likely to be the norm in panel data rather than the exception (see for example, Baltagi and Pesaran, 2007, for a discussion). More precisely, with a highly integrated global economy, countries interact through among other things trade, immigration, culture and politics. This generates a web of interdependencies within and across countries (Eberhardt and Teal, 2010).[9] In this sense, assuming cross-sectional independence, which standard panel estimators assume, can lead to inaccurate inferences. We attempt to deal with cross-sectional dependence in our baseline estimation by employing the cross-sectionally demeaned data as in Francois and Keinsley (2019) and Herzer and Morrissey (2013), for instance. This strategy can address potential weak cross-sectional dependence. However, to ensure that even in the presence of strong or more complex cross-sectional dependence our baseline findings do not change, we employ the Pesaran (2006) common correlated effects mean group (CCEMG) estimator, and the augmented mean group (AMG) estimator introduced by Eberhardt and Teal (2010).[10]

The rest of the paper is organized as follows: Section 2 introduces the simple general equilibrium model to lend a structural interpretation to our econometric specification. Section 3 presents the econometric methodology, which is based on a panel cointegrating regression model of output and remittance interpreted as a long run relationship derived from a general equilibrium setting. Section 4 presents and discusses the results. Section 5 conducts robustness exercises. Section 7 discusses potential policy implications of the results and concludes.

2 Theoretical consideration of how remittances impact output

The goal of this section is to lend a structural interpretation to our bivariate cointegration regression that follow in the empirical section. We layout a simple general equilibrium model with remittances

[9] In the context of our study, assume Ghanaian immigrants in South Africa consistently send money back home to support their families in Ghana. If these immigrants lose their jobs due to an economic downturn in South Africa, this can affect the amount of remittances that they send back home negative. This in turn can affect economic well-being of these families.

[10] See Eberhardt and Presbitero (2015) for recent application of these estimators.

as an additional source of income to households, and work out the steady state relationship between remittance and output. To this end, the representative household faces the flow budget constraint

$$c_t + i_t \leq w_t l_t + r_t k_t + Rem_t \tag{1}$$

where Rem_t is real remittance received by households, i is investment and it is given as $i_t = k_{t+1} - (1-\delta)k_t$ with δ as the rate of depreciation, c_t is private consumption, w_t is wages from labor services l_t and r_t is rental rate from capital stock k_t. We assume that remittance can respond to changes in macroeconomic factors over the business cycle. However, in steady state, it is equal to its long run value of Rem.

In words, Eq. (1) suggests that the presence of remittance relaxes the household's budget constraint such that they can finance part of their consumption or investment even if they see reduction in the other sources of income— e.g., labor income. This is possible because remittance can substitute for other income sources including labor income. It is straightforward to infer the potential opposing effects remittance can have on output. More precisely, a possibility exists that remittance can reduce labor hours worked, which impacts output negatively, but also finance investment and consumption, both of which positively contribute to aggregate demand.

To formally show the discussion above, suppose the household has an instantaneous utility of $U(c_t, l_t) = \ln c_t - \frac{l_t^{1+\phi}}{1+\phi}$, where $\phi > 0$ governs the Frisch elasticity of substitution. The household maximizes lifetime utility by choosing c_t and l_t subject to Eq.(1). We therefore obtain the following optimality conditions:

$$l_t^{\phi} = \frac{w_t}{c_t} \tag{2}$$

and

$$1 = \beta \mathbb{E}_t \left[\frac{c_t}{c_{t+1}} (1 - \delta + r_{t+1}) \right], \tag{3}$$

Eqs. (2) and (3) represent the intratemporal and intertemporal Euler equation of labor and capital, respectively. For $\phi > 0$, Eq.(2) shows that there is a labor-consumption trade off such that all else equal, an increase in consumption reduces labor effort, and vice-versa. This means an increase in remittance that finances consumption can reduce labor effort.[11]

Output in this economy is produced through the Cobb-Douglas production function $y_t = A_t k_t^{\alpha} l_t^{1-\alpha}$ where $\alpha \in (0,1)$ is the output elasticity with respect to capital and A_t is the total- (or multi-) factor productivity (TFP). In our setup, remittance affects A_t in the manner of Rao and Hassan (2011) and Abdih et al. (2012), for instance. It is therefore evident that since remittances affects the input in the production function, it can directly or indirectly impact output in the economy.

In equilibrium, marginal product of labor and capital coincide with their respective factor prices such that

$$w_t = (1-\alpha)\frac{y_t}{l_t} \tag{4}$$

and

$$r_t = \alpha\frac{y_t}{k_t} \tag{5}$$

Finally, the aggregate resource constraint in the economy is given as

$$y_t + Rem_t = c_t + i_t. \tag{6}$$

2.1 Steady State Analysis

Here, we focus on the long run relationship between remittance and output by working with the steady state of the system. To this end, we eliminate the factor prices r and w by combining Eq.(2), Eq.(3), Eq.(4) and Eq.(5). Taking model parameters as given, log-differentiating the resulting system and after some algebra, we obtain:

$$d\ln y = \lambda_k d\ln k + \lambda_l d\ln l + \lambda_a d\ln A + \mu_m d\ln Rem, \tag{7}$$

where $\lambda_l = \frac{2+\phi-\alpha}{3\varepsilon_c-1}$, $\lambda_a = \frac{\varepsilon_c}{3\varepsilon_c-1}$, $\lambda_k = \frac{(1+\alpha)\varepsilon_c-\varepsilon_k}{3\varepsilon_c-1}$, and $\mu_m = -\frac{\varepsilon_m}{3\varepsilon_c-1}$ are scaling parameters. Under a standard calibration, it easy to show that all four of these parameters are greater than zero.

[11] Consider a back-of-the-envelope calculation of the potential relationship between labor supply and remittance. To this end, suppose a fraction of remittance, $\rho > 0$, finances consumption so that $c_t = \rho Rem_t$ and set $\phi = 1$, Eq. (2) becomes $l_t = \frac{w_t}{\rho Rem_t}$. Clearly, as remittance increases, holding other factors constant, labor supply falls (i.e., $\partial l/\partial Rem < 0$). This suggests that the households that receive remittance can finance consumption with reduced labor supply.

The complete derivation can be found in Appendix A. In Eq.(7), we see that permanent changes in capital, labor effort, aggregate productivity, and remittance can affect output in the long run. Now, if remittances finance investment, affect labor and/or alter aggregate productivity in recipient countries, then for $d \ln Rem \neq 0$, we can divide the Eq.(7) by $d \ln Rem$ to obtain,

$$\frac{d \ln y}{d \ln Rem} = \underbrace{\lambda_k \alpha^k + \lambda_l \alpha^l + \lambda_a \alpha^A + \mu_m}_{\kappa \equiv \text{total long-run effect}} \tag{8}$$

where $\alpha^j = \frac{d \ln j}{d \ln Rem_t}$ is the elasticity of variable $j \in \{k, l, A\}$ with respect to remittances.

Remark The expression in Eq. (8) captures the total long-run effect of remittance on real GDP, which we designate as κ. This total effect can be positive, negative or zero. Specifically, the first three terms in Eq.(8) capture the effect of remittance on capital (α^k), labor (α^l), and total factor productivity (α^A), respectively. Notice that if a fraction of remittance finances investment so that $\alpha^k > 0$, then remittance has a positive effect on output through investment. At the same time because remittance can reduce labor supply by substituting for labor income, it is possible to have $\alpha^l < 0$ in which case remittance impacts output negatively via an offsetting effect on labor supply (Amuedo-Dorantes, 2014; Barajas et al., 2009; Fullenkamp et al., 2008; Shapiro and Mandelman, 2016). Additionally, the term α^A shows how remittance can affect output through components of TFP such as institutions and human capital formation. The sign of α^A is ambiguous as it can be positive or negative.[12] Finally, $\mu_m > 0$ captures the direct effect of remittance on aggregate demand. It is therefore clear that the sign and size of the total effect of remittance on output, κ, depends on the size of these competing effects.[13] Rewriting Eq. (8) as $d \ln y = \kappa \cdot d \ln Rem$ and integrating yields,

$$\ln y = \gamma + \kappa \ln Rem \tag{9}$$

[12] For instance, Ambler et al. (2015) find substantial "crowd-in" of educational investments such that for each \$1 received by beneficiaries, educational expenditures increase by \$3.72. This suggests that remittance can induce human capital formation; hence, impacting productivity positively. In contrast, studies like Abdih et al. (2012) find strong evidence that remittances negatively affect institutions in recipient countries.

[13] See, Amuedo-Dorantes (2014) for a succinct discussion on the pros and cons of remittances at both the micro- and macro-level.

where γ is a constant. Eq. (9) serves as a guide and structural equation for the empirical study that follows. In the empirical part of the paper, we make the data speak for itself in determining the sign and size of κ.

3 Evidence

The theoretical model in the previous section has provided us with an estimable model. In panel form, we can write Eq.(9) as

$$Y_{it} = \alpha_i + \beta Rem_{it} + \delta_i t + \varepsilon_{it} \tag{10}$$

where Y_{it} is defined as the natural logarithm of real GDP in country $i = 1, 2, \ldots, N$ at time t. Rem_{it} is the natural logarithm of real remittance. The parameter of interest β captures the average impact of remittance on output. The remittance-output coefficient is estimated for each country, and is heterogeneous across countries in the panel estimate. We discuss this in detail in section 4. The parameters a_i and δ_i represent the constant and linear time trends associated with each country i, respectively. Finally, we assume the error term ε_{it} to be stationary. This assumption is important because if we have omitted a non-stationary variable, which forms part of the potential cointegration relation in Eq. (10), then the error term will exhibit non-stationary properties in which case cointegration in Eq. (10) would fail to hold. We present formal residual-based cointegration tests for this stationarity assumption in the section 3.1.2.

3.1 Data and Pre-testing Annual data on GDP and remittance come from the World Development Indicators 2019 database.[14] A well-known challenge with utilizing remittance data is the issue of uneven reporting across countries, which imposes large missing values in the dataset (Abdih et al., 2012). While we start our analysis with 137 developing countries, several of the countries were missing data for many periods. In fact, preliminary organization of the data shows that over the period 1970-2017, only four countries, Algeria, Colombia, the Dominican Republic and South Africa, had complete data on remittances. Moreover, allowing for balanced data, which

[14]Data on remittances is available at the World Bank's Migration and Remittances Data here: https://www.worldbank.org/en/topic/migrationremittancesdiasporaissues/brief/migration-remittances-data. We employed the most recent version of the data, which at the time of writing this paper was the Annual Remittance Data, updated as of December 2018.

will be ideal, induces a tradeoff in the number of time periods and countries that we can include in the data. A compromise here is therefore to employ an unbalanced panel data, which in itself poses some challenges. Specifically, the number of periods T required to carry out the pre-testing exercises require T to be greater than or equal to a minimum value for a given number of lags. For instance, with 3 lags as well as constant and trend terms, at least 12 observations are required for each cross-sectional unit to successfully conduct the Pesaran (2007) unit root test. Finally, while the unit roots tests employed in the paper can be applied to unbalanced panel data, they do not permit for gaps in the data.[15] Addressing all of these issues with respect to the data, we arrive at an unbalanced panel (without gaps) with a sample of 80 countries representing approximately 58% of all developing countries for the period 1970-2014.[16]

Now, we turn our focus to the time series properties of the data in question. Specifically, since our focus is on the long run impact of remittance on output, steady state (permanent) changes in remittance are associated with permanent changes in real GDP. Consequently, we test for: (a) the presence of unit root in the individual time series, $\ln(Y_{it})$ and $\ln(Rem_{it})$, and (b) the existence of a cointegration relation between $\ln(Y_{it})$ and $\ln(Rem_{it})$.

3.1.1 Unit Root Tests

To test for the presence of unit root in the data, we employ the panel unit root test of Im, Pesaran, and Shin (2003, henceforth IPS), which is based on the Augmented Dickey-Fuller (ADF) regression for the individual cross-section unit in the panel. However, given the likelihood of common shocks or spillovers across countries, the error terms ε_{it} may not be independent. In this scenario of potential cross-sectional dependence, the IPS test can lead to spurious inferences. We therefore consider the cross-sectionally augmented IPS (CIPS) test proposed by Pesaran (2007). The CIPS filters out any cross-section dependency by augmenting the ADF regression with the cross-section averages of lagged levels and first-differences of the individual series (See for example Baltagi and Pesaran, 2007; Herzer and Grimm, 2012, for a discussion on second generation unit root tests).

[15] See Martins (2011) for a neat summary of the characteristics of unit root tests with respect to unbalanced data.

[16] There is growth in the use of cointegration techniques for unbalanced panels. See, Rajbhandari and Zhang (2018) and Eberhardt and Teal (2019) for DOLS and FMOLS applications, respectively. The list of countries and additional information on the data are available in Appendix B.Additionally, we report the country-by-country summary statistics for GDP and remittances in Appendix C

Table 1: Panel Unit Root Tests

	Deterministic trend	IPS statistics	CIPS statistics (Zt-bar)
Level Data			
$\ln(Y_{it})$	c, t	0.0703	4.138
$\ln(Rem_{it})$	c, t	-1.4057	1.065
First-Differenced Data			
$\Delta\ln(Y_{it})$	c	-10.0676^{***}	-3.249^{***}
$\Delta\ln(Rem_{it})$	c	-12.5166^{***}	-8.205^{***}

Notes: *** indicates significance at the 1 percent level. For the level data, we allow for both individual country effects (c) and country-specific time trends (t). In the case of the first-differenced data, we allow for individual country effects (c). Four lags were selected to adjust for autocorrelation. The IPS statistic is distributed as $N(0,1)$. For CIPS under unbalanced panel, only standardized Zt-bar statistic can be calculated. The CIPS statistic assumes cross-sectional dependence in data.

As can be seen from Table 1, both the IPS and CIPS fail to reject the unit-root null hypothesis for the level data, however, they strongly reject the null for the first differenced series. These findings suggest that the individual series in Eq. (10) are non-stationary I(1) processes.

3.1.2 Cointegration Tests

As shown in section 3, our simple model proposes a potential long-run relationship between remittances and output. Thus, before proceeding to estimate the long-run impact of remittances on output it is important to check if there exists an empirical long-run relationship between the two variables. To do this, we test for the presence of cointegration in Eq. (10). We employ four standard panel and group test statistics suggested by Pedroni (1999). The standard Pedroni tests, however, do not account for potential cross-sectional dependence. In the presence of cross-sectional dependence that may arise from multiple unobserved common factors, an assumption of cross-sectional independence can lead to biased inference (Baltagi and Pesaran, 2007; Herzer and Morrissey, 2013). To account for cross-sectional dependence, we utilize the four standard Pedroni test but include common time dummies to address cross-sectional dependency in the manner of Neal (2014). This strategy involves time demeaning of the data for each cross-sectional unit and variable (See, Neal, 2014, for the theory and implementation details). To highlight the relevance of accounting for cross-sectional dependence in the data, we report test results in which we assume cross sectional independence.

Notice that the Pedroni tests are residual based; hence, they allow us to formally test whether our stationarity assumption of the error term in Eq. (10) indeed holds. The null hypothesis of the

Pedroni tests is no cointegration, meaning the error term is not stationary. This also implies that if the test results reveal a failure to reject the null hypothesis, then our specification of a bivariate relationship between output and remittances is incorrect. This may be due to an omission of a non-stationary variable, which should be part of the cointegration system. On the other hand, a rejection of the null hypothesis of no cointegration for the residual based tests is a validation of our simple bivariate specification, which also suggests that issues of omitted variables and measurement errors, to a large extent, are not problematic.

To complement the residual-based tests, we utilize the approach of Larsson, Lyhagen, and Löthgren (2001), which is based on Johansen's (1988) maximum likelihood estimation procedure to test for cointegration among the variables in Eq. (10). The test allows us to confirm the presence of one cointegrating vector in Eq. (10). It is important to note that although the Larsson et al. panel test does not account for potential cross-sectional dependence in the data, it treats all variables as potentially endogenous. It therefore avoids the normalization issues inherent in residual-based cointegration tests. The null hypothesis for Larsson et al. panel test is that all countries have the same number of cointegrating vectors denoted r_i among the p variables, in our case two variables as in Eq. (10). More precisely, $H_0 : rank(\Pi_i) = r_i \leq r$ and the alternative hypothesis is $H_1 : rank(\Pi_i) = p$, for all $i = 1, ..., N$ where Π_i is the long-run matrix of order $p \times p$. For completeness we also report the Fisher statistic proposed by Maddala and Wu (1999). Computational details as well as theory related to this test are laid out in Larsson et al. (2001) and in the appendix of Herzer and Morrissey (2013) for example.

Table 2 presents the test results. In Panel A, it is clear that under the assumption of cross-sectional dependence all the tests decisively reject the null hypothesis of no cointegration at the 5 percent level or better. In contrast, only the Group ADF statistic rejects the null of no cointegration when cross sectional independence is assumed. This highlights the relevance of explicitly accounting for cross sectional dependence, which is often the rule rather than the exception in panel data analysis. Moreover, as shown in Panel B, both the standardized trace and Fisher statistics support the presence of one cointegration vector in the case of Eq. (10). Together these results validate our bivariate empirical specification.

Table 2: Panel Cointegration Tests

	Panel A: Pedroni Residual-Based Tests	
Statistics	Cross-sectional dependence	Cross-sectional independence
Panel PP statistic	-2.750^{***}	-0.438
Panel ADF statistic	-2.043^{***}	-1.259
Group PP statistic	-3.454^{***}	-0.729
Group ADF statistic	-2.818^{***}	-2.053^{***}
	Panel B: Cointegration Rank Tests	
	$r = 0$	$r = 1$
Panel standardized trace statistic	17.60^{***}	0.621
Fisher statistic	787.9^{***}	166.2

Notes: *** denote a rejection of the null hypothesis of no cointegration at the 1% levels. ADF stands for *augmented Dickey Fuller* and PP stands for *Phillips-Perron*. For the Pedroni tests the number of lags was determined by the Schwarz criterion with a maximum of three lags. All test statistics are distributed N(0,1), under a null of no cointegration. For the cointegration rank test the Schwarz criterion suggests two lags.

4 Estimation and Results

We now turn our focus to uncovering the long-run impact of remittances on output. Specifically, following the strong evidence of unit roots in the two variables of interest, and cointegration between output and remittances, we can consistently estimate the long-run relationship in Eq. (10) using recently developed cointegration techniques. We employ the between-dimension group-mean panel dynamic ordinary least squares (DOLS) estimator of Pedroni (2001b). The panel DOLS regression is given by[17]

$$Y_{it} = \beta_i Rem_{it} + \sum_{j=-p_i}^{p_i} \Psi_{1ij} \Delta Rem_{it-j} + \alpha_i + \delta_i t + \varepsilon_{it}, \tag{11}$$

where Ψ_{1ij} are coefficients of lead and lag differences which account for potential serial correlation and endogeneity of the regressors. The DOLS estimator produces unbiased estimates for variables

[17]It is important to note that an alternative estimator to DOLS is the fully-modified OLS (FMOLS) estimator proposed by Pedroni (2001a). As Pedroni (2001a) discusses, the FMOLS requires fewer assumptions and tends to be more robust. Moreover, because DOLS involves adding lead and lagged difference terms of the independent variables, in cases in which there are several independent variables and limited time observations, the DOLS estimator can result in severe loss in degrees of freedom (Liddle, 2012). However, our specification is parsimonuous and is unlikely to suffer from the latter. More importantly, Kao and Chiang (2000) illustrate that for the case of a single regressor, the DOLS estimator has a smaller bias than FMOLS. Consequently, the DOLS is our preferred estimator, however, we also report the results from FMOLS estimation.

that are cointegrated even in the presence of endogenous regressors. This feature is important in our case because as previously discussed, remittances are more likely to be endogenous than exogenous. Furthermore, the group-mean panel DOLS estimator is super consistent under cointegration and robust to any omitted variables suggesting that the use of instrumental variables to address any omitted variable problem is not required. Recall that the parameter of interest is β and under the group-mean DOLS estimator is computed as

$$\hat{\beta} = \frac{1}{N} \sum_{i=1}^{N} \hat{\beta}_i, \tag{12}$$

where $\hat{\beta}_i$ is the conventional time-series DOLS estimator applied to the ith cross sectional unit (i.e., country) of the panel.

Recently, there has been strong arguments that interdependencies due to common shocks or global spillovers among countries at the same time are likely to be the norm in panel data (Baltagi and Pesaran, 2007; Neal, 2014). Indeed, our results from the cointegration tests suggest that accounting for these potential cross-sectional dependence is required. While there are a number of ways to account for these cross- sectional-dependencies, we apply the DOLS procedure to demeaned data in the manner of Herzer and Morrissey (2013) and Francois and Keinsley (2019), among others.[18] More precisely, in place of Y_{it} and Rem_{it} in the baseline equation in Eq. (11), we utilize $\widetilde{Y}_{it}$ and $\widetilde{Rem}_{it}$ where

$$\widetilde{Y}_{it} = Y_{it} - \overline{Y}_t, \qquad \text{where } \overline{Y}_t = \frac{1}{N} \sum_{i=1}^{N} Y_{it},$$

and

$$\widetilde{Rem}_{it} = Rem_{it} - \overline{Rem}_t, \qquad \text{where } \overline{Rem}_t = \frac{1}{N} \sum_{i=1}^{N} Rem_{it},$$

For completeness, we report the results for both the data in which we assume cross-sectional dependence and independence. However, we place more weight on the results from the model in

[18] This strategy of demeaning the data avoids overparamerterization as it preserves the number of regressors in the specification. However, alternative strategies such as the Pesaran (2006) common correlated effects (CCE) approach where observed regressors are augmented by cross-sectional averages of the dependent variable and the individual specific regressors increase the number of regressors. Specifically, if we utilize this approach, we have to include $\overline{Y}_t$ and $\overline{Rem}_t$ and their respective leads and lags in our specification, which will increase the number of parameters to estimate and likely weaken the power of the DOLS estimator due to overparameterization. Although we do not report the results in the paper, the estimated of β using this augmentation option to control for cross sectional dependence is 0.045 and 0.014 for the DOLS and FMOLS, respectively. We also present results from the Pesaran (2006) CCE and augmented mean group by Eberhardt (2012) estimator by in section 5.5.

which we account for cross sectional dependence as the latter is likely to be the rule in panel data. Additionally, we report results from the fully modified OLS estimators.

Table 3: Estimated long-run relationship between remittances and output

Estimator	Data Treatment	
	C-S Dependence	C-S Independence
DOLS	0.0664***	0.0407***
	(6.0365)	(4.3050)
FMOLS	0.0638***	0.0277***
	(8.1009)	(4.2465)

Notes: The dependent variable is the natural log of GDP. *** indicates significance at the 1 percent level. C-S is cross-sectional. t-statistics in parentheses. The number of leads and lags in the individual DOLS regressions was fixed to 1 lag. The model allows for individual and time fixed effects.

Table 3 reports the baseline results from the cointegration regressions. The coefficient of remittance β is consistently positive, statistically significant, and more importantly, economically large across all four regressions in our baseline case. It is however clear that estimates of β from the demeaned data, which accounts for common shocks and spillovers, are generally larger than the results from the data in which cross sectional independence is assumed. As mentioned earlier, we place more emphasis on the results from the demeaned data. Consequently, the result from the DOLS regression suggests that a 1 percent increase in remittances will, on average, generate an increase of 0.066 percent in real GDP in the long run. Recall from the theoretical model that β captures the total effect of remittances on output; hence, we can interpret this observed positive effect as the overall long-run impact of remittances on output. From the economic sense, this means that in the long-run, the positive effects of remittances on output through the channels discussed in section 2 outweighs any potential negative effect. Our result is in sharp contrast to studies such as Barajas et al. (2009) who find that, at best, workers' remittances have no impact on economic growth and Jahjah et al. (2003), who find negative effect of workers remittance on growth. Moreover, Herzer and Morrissey (2013) find a negative long-run relationship between foreign aid and output.[19] The results in this paper therefore suggest that remittances are not simply outgrowing

[19]We must add that Herzer and Morrissey (2013) find that conditional on aid financing investment, aid has an overall positive effect on output in the long-run. Nonetheless, this conditional positive effect is still smaller than our

aid in terms of size, but they may be an important driver of long-term output than foreign aid in developing countries.

5 Robustness

In this section, we conduct a series of robustness exercises to ensure that our baseline positive remittance-output estimate is a consistent one. We begin by first splitting our sample into two income groups, low- and lower-middle income and upper-middle income groups. We then conduct the same estimation as in the baseline case to check if the effect of remittances on output varies across these income groups. Second, we conduct sensitivity analysis to confirm that our baseline results are not driven by a single outlying country or group of countries. Third, we estimate Eq. (10) for the period 1990-2014. This period generally is likely to be characterized by better measurement of remittances. We therefore employ this period to control for quality of data. Fourth, we employ per capita measures of output and remittances as alternative measures to our baseline measures, and re-estimate Eq. (10).

5.1 Income Groups A natural question that arise in our study is: Is the long run impact of remittance on output different across income groups? The rationale here is that countries in different income groups have differential characteristics, and more importantly, are at different stages of development. It is therefore important to investigate whether the positive long-run remittances-output effect is not driven by a particular income group; hence, development level. Our sample comprises 47 low and lower-middle income and 33 upper-middle income countries. We re-estimate the DOLS and FMOLS regressions for these two income groups. In both cases, we account for potential cross-sectional dependence in the data.

Table 4 presents the results. It is clear that regardless of the income group, the effect of remittance on output is positive and statistically significant at the conventional levels. There is however differences in the size of this long run effect. More precisely, the results from the DOLS estimation shows that while a 1 percent increase in remittance increases output by 0.12 percent in upper-middle income countries, low and lower-middle income countries miss about 0.044 percentage points of this impact. This suggests that on average, remittances are likely to have bigger positive long-run effect in upper-middle income countries than in low and lower-middle income countries.

estimated remittance-output impact.

Table 4: Estimated long-run relationship between remittances and output by income level

	Income Group	
Estimator	Upper-Middle Income	Low and Lower-Middle Income
DOLS	0.1167^{***}	0.0759^{***}
	(4.5904)	(8.1487)
FMOLS	0.1067^{***}	0.0833^{***}
	(6.0334)	(9.9746)

Notes: The dependent variable is the natural log of GDP. *** indicates significance at the 1 percent level. Upper middle income countries consists of 33 countries. Low- and lower-middle income countries comprises 47. t-statistics in parentheses. The number of leads and lags in the individual DOLS regressions was fixed to 1 lag. The model allows for individual and time fixed effects. The regressions account for cross-sectional dependence.

5.2 Sensitivity analysis We conduct regional and country sensitivity analysis in the manner of Herzer and Morrissey (2013) to ensure that our positive remittance-output relationship is not driven by outliers. This is important because our parameter of interest β is an average of individual coefficient for each country in our sample. Hence, if a single country or group of countries in a particular region have a positive and large estimate of β, then this will likely drive the observed average positive effect of remittance on output. Additionally, country and regional heterogeneity exist in terms of remittance inflows. For instance, remittance inflows ranged from approximately 7 percent of GDP in East Asia and the Pacific to 12 percent in South Asia in 2018. It is therefore important to account for possible outlier effects that may arise from these differences.

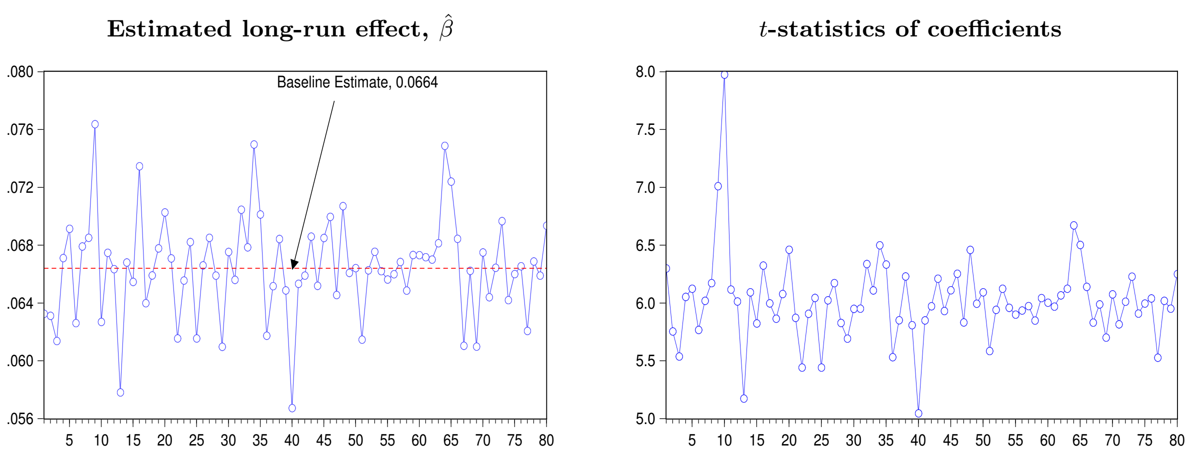

Figure 1: Sensitivity Analysis, DOLS estimation with single country excluded from the sample. The y-axis is the estimated β. The horizontal axis is the ith country left out during the estimation. Specifically, one country is excluded from the panel at each round of estimation. Number of cross-sectional units is therefore 79 for each estimation.

Against this backdrop, we begin our sensitivity analysis by re-estimating our baseline DOLS regression by excluding one country at a time from the full sample. Figure 1 shows the estimates of β in the left panel and their corresponding t-statistics in the right panel. Evidently, the estimated long-run effect of remittances on output is consistently positive and ranges between 0.057 and 0.076, values close to the baseline esitmate, 0.066, which is given as the red dashed line in the figure. All of the estimates are statistically significant at the 5 percent significant level or better.

We now turn our attention to conducting a similar sensitivity analysis at the regional level. We employ the DOLS model in which we account for cross sectional dependence in the data. We also report the estimates from the FMOLS estimator. Table 5 presents the results from the regional sensitivity analysis.

Table 5: Estimated long-run relationship between remittances and output, regional sensitivity analysis

Excluded Region	DOLS	FMOLS	No. of countries in Panel
East Asia & Pacific (EAP)	0.0779***	0.0744***	70
	(5.99)	(7.94)	
Europe and Central Asia (ECA)	0.0749***	0.0739***	66
	(6.52)	(8.33)	
Middle East and North Africa (MENA)	0.0576***	0.0559***	72
	(5.11)	(7.08)	
Latin America and Caribbean (LAC)	0.0581***	0.0612***	62
	(5.05)	(6.91)	
South Asia	0.0693***	0.0681***	75
	(6.04)	(8.18)	
Sub-Sahara Africa (SSA)	0.0822***	0.0714***	55
	(5.04)	(6.53)	

Notes: *** indicates significance at the 1 percent level and t-statistics are presented in parentheses. The dependent variable is the demeaned real GDP, $\bar{Y}_{i,t}$. The number of leads and lags in the individual DOLS regressions was fixed to one lag and one lead.

The first column in the table shows the region that was excluded from the estimation. Here, we focus on the result from the DOLS estimates. It is clear that the long-run impact of remittances on real GDP ranges from 0.058 when we preclude MENA or LAC from the sample to about 0.082 when SSA is excluded from the full sample. All of the estimates are statistically significant at the 1 percent level and are in the neighborhood of our baseline estimate of 0.066. The results from both the country and regional sensitivity analysis show that while minor differences may exist in the size of remittance-output effect, the sign of the effect remains consistently positive. These findings strongly suggest that the postive long-run impact of remittance on output is not driven by possible outlier either at the country or regional level. This conclusion holds true for the results from the FMOLS estimations.

5.3 The 1990's and 2000's It is well-known that prior to 1990, remittance data coverage and perhaps, its measurement is poor (See for instance, Clemens and McKenzie, 2018). The 1990s and 2000s were periods of rapid technological advancement in many areas of development. Additionally, these periods witnessed the commercialization of the Internet, which has led to an increased expansion to better and quality data. Hence, one would generally expect better coverage, as well as, measurement of remittance data. In this exercise, we drop the period leading up to 1990 and conduct our empirical analysis for the sub-period 1990 to 2014 in an attempt to capture the potential role of "quality" remittance data. It is however important to note that restricting the analysis to this period comes at a cost as we have fewer time periods, which can impact the detection of a long-run relationship. We acknowledge this potential issue and proceed with the analysis.

Table 6: Estimated long-run relationship between remittances and output, 1990-2014

	Model Assumption for Data	
Estimator	C-S Dependence	C-S Independence
DOLS	0.0199*	0.0269***
	(1.7366)	(2.8570)
FMOLS	0.0217***	0.0170***
	(3.3194)	(2.7832)

Notes: The dependent variable is natural log of GDP. *** indicates statistical significance at the 1 percent level, while * indicates significance at the 10 percent level. C-S is cross-sectional. t-statistics in parentheses. The number of leads and lags in the individual DOLS regressions was fixed to 1 lag. The model allows for individual and time fixed effects.

Results from the sub-period analysis are presented in Table 6. As can be seen from the table, the effect of remittance on output is consistently positive and significant at conventional levels. Specifically, focusing on the DOLS estimate in which cross sectional dependence is accounted for in the data, we find that a percent increase in remittance will induce a 0.02 percent increase in real output. Although, this effect is non-trivial, the estimated impact from the sub-period analysis is generally smaller than the effect in the baseline scenario. This can simply be attributed to the fact that fewer time periods were utilized in the long run analysis, the series in question are likely to show lower persistence; hence, weaker long-run relationship.

5.4 Per capita measures Finally, we employ an alternative measure of remittance and overall economic outcome. More precisely, we consider the per capita measure of remittance and output as the regressor and regressand, respectively. Table 7 presents the results. It is clear that remittance per capita has a positive long run impact on GDP per capita. More specifically, the results from the DOLS regression reveal that on average a 1 percent increase in remittance per capita raises GDP per capita by approximately 0.048 percent in the long run.

Table 7: Estimated long-run relationship between remittances and output, Per Capita Measure

	Model Assumption for Data	
Estimator	C-S Dependence	C-S Independence
DOLS	0.0481***	0.0362***
	(5.0935)	(3.9566)
FMOLS	0.0402***	0.0218***
	(6.0392)	(3.4028)

Notes: The dependent variable is natural log of per capita GDP. *** indicates significance at the 1 percent level. C-S is cross-sectional. t-statistics in parentheses. The number of leads and lags in the individual DOLS regressions was fixed to 1 lag. The model allows for individual and time fixed effects.

5.5 Alternative estimators As discussed earlier, cross-sectional dependence arising from global shocks and economic spillovers can lead to inaccurate inference. In section 4, we attempt to account for cross-sectional dependence by employing cross-sectionally demeaned data for the DOLS estimation. However, while the DOLS addresses the primary issues associated with endogeneity, measurement errors, lack of power and heterogeneity, it may not fully address the case where cross-sectional dependence is strong or complex. More precisely, our baseline strategy of cross-sectionally demeaning the data prior to estimation assumes that cross-section correlation is of a nature equivalent to common shocks with identical impact across countries, which is a strong assumption. Here, we relax this assumption and present results from the augmented mean group (AMG) estimator introduced by Eberhardt and Teal (2010) and the Pesaran (2006) common correlated effects mean group (CCEMG) estimator, both of which are designed to address more complex cross-sectional dependenence. For instance, the empirical strategy employed by the CCEMG naturally generates cross-section dependence, time-variant unobservables with heterogeneous impact across panel members, and problems of identification (see, Eberhardt, 2012, for detailed discussion). The CCEMG solves this problem with a simple but powerful augmentation of the group-specific regression equation. That is, apart from the standard regressors in our specification in Eq. (10), we now include the cross-section averages of the dependent and independent variables, $\bar{Y}$ and $\overline{Rem}_{it}$, respectively, as additional regressors.

There is an important distinction between the CCEMG and the AMG estimator. The CCEMG treats the set of unobservable common factors as a nuisance, with no economic interpretation. The AMG estimator on the other hand captures these unobservables as components of total factor productivity. This distinction is particularly important because in our cross-country study we model the production function (with TFP) to be an integral channel through which remittance can impact output.[20] Hence, in addition to the CCEMG, we employ the AMG estimator, which was developed as an alternative to the CCEMG with production function estimation in mind (Eberhardt and Teal, 2010).

As described in Eberhardt (2012) the AMG procedure is implemented in three steps: First, a pooled regression model augmented with year dummies is estimated by first-difference ordinary least squares, and the coefficients on the (differenced) year dummies are collected. They represent an estimated cross-group average of the evolution of unobservable TFP over time. This is referred to as "common dynamic process". Second, the group-specific regression model is then augmented with this estimated TFP process: either (a) as an explicit variable or (b) imposed on each group member with unit coefficient by subtracting the estimated process from the dependent variable. To ensure that the positive relationship between output and remittances is not affected by how we treat cross-sectional dependence, we present results from both strategies given in (a) and (b). The regression model includes an intercept, which captures time-invariant fixed effects (TFP levels). Third, similar to the grouped-mean DOLS, FMOLS, and CCEMG estimators, the group-specific model parameters are then averaged across the panel.

To this end, consider the following bivariate model: for $i = 1, ..., N$ (countries) and $t = 1, ..., T$ (years),

[20] While we allow the observable, remittances, to affect TFP, there are several unobsevable factors that represent other components of TFP.

$$Y_{it} = \beta_i Rem_{it} + \varepsilon_{it} \tag{13}$$

$$\varepsilon_{it} = \alpha_{1i} + \lambda_i f_t + u_{it} \tag{14}$$

$$Rem_{it} = \alpha_{2i} + \lambda_i f_t + \gamma_i g_t + \epsilon_{it}, \tag{15}$$

where Rem_{it} and Y_{it} are the observables remittance and output, respectively. β_i is the country-specific slope on the observable regressors, and u_{it} contains the unobservables and the error terms ϵ_{it}. The unobservables in Eq. (14) are made up of standard group-specific fixed effects α_{1i}, which capture time-invariant heterogeneity across groups, as well as an unobserved common factor f_t with heterogeneous factor loadings λ_i, which can capture time-variant heterogeneity and cross-section dependence. u_{it} and ϵ_{it} are assumed white noise. The factors f_t and g_t are not limited to linear evolution over time; they can be nonlinear and nonstationary. As one can see, this has clear and immediate implications for cointegration. Moreover, problems arise if the regressors are driven by some of the same common factors as the observables. Specifically, the presence of f_t in equations Eq. (14) and Eq. (15) induces endogeneity in the estimation equation (see, Coakley et al., 2006; Eberhardt and Teal, 2011, for detailed discussion). Both the CCEMG and AMG are designed to deal with the aforementioned issues.

Table 8: Estimated long-run relationship between remittances and output, alternative estimators

Estimator	Unweighted	Weighted
CCEMG	0.0161*	0.0099*
	(0.0088)	(0.0053)
AMG	0.0217**	0.0110*
	(0.009)	(0.0057)

Notes: The dependent variable is the natural logarithm of GDP. ** and * indicate significance at the 5 and 10 percent levels. Standard errors in parentheses.

Table 8 presents the results. The second column does not account for outlier effects whereas the third column does. The results clearly support our baseline conclusion as all estimates are positive and statistically significant at conventional levels.

5.6 Density Estimates Finally, following Eberhardt and Teal (2010), we investigate the density estimates for the estimated country-specific remittance-output coefficients from our baseline results in Table 3. The density estimates serves as a diagnostic testing and allows us to formally check whether any significant outlier is driving our baseline results, thereby complementing our findings in section 5.2. Additionally, it permits us to observe first hand the distribution of the estimated country-specific remittance-output coefficient, highlighting the variation of the remittance-output relationship across countries.

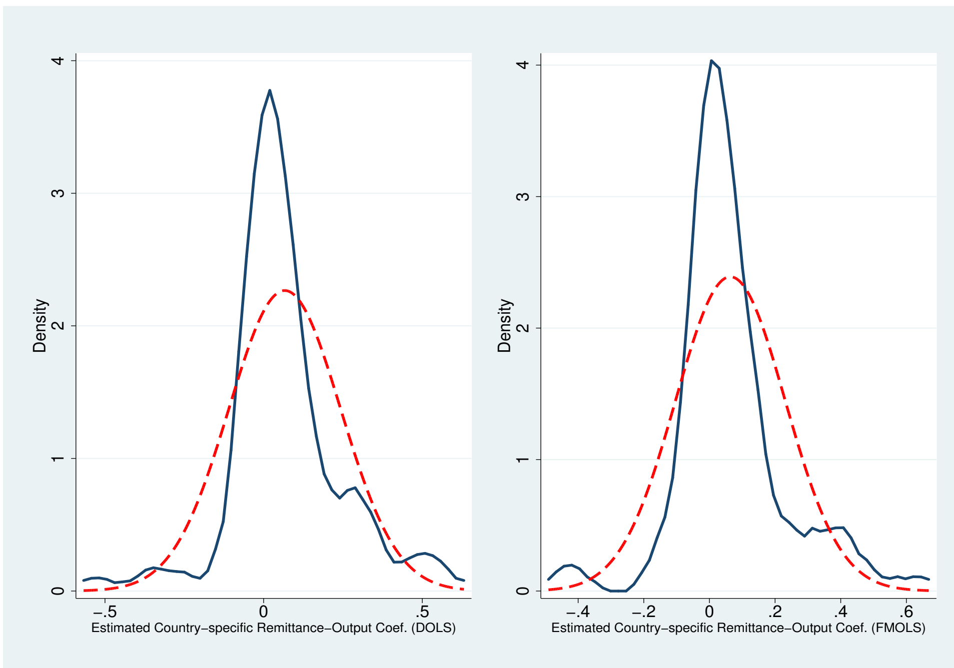

Figure 2: In each case, the kernel is the epanechnikov with automatic bandwidth selection. For the FMOLS the bandwidth is 0.0374 and the DOLS it is 0.0415. The red dashed line is the normal distribution and the blue thick line is the estimated Kernel Density. Recall that the estimated mean for the DOLS was 0.0664 and that of the FMOLS is 0.0638.

Figure 2 reports the kernel density estimates for the country-by-country DOLS and FMOLS estimates in Table 3. Evidently, both panels in the figure show that the distribution of the remittance-output coefficients are symmetric around their means of 0.0664 (DOLS) and 0.0638 (FMOLS), and approximately Gaussian. This further confirms our earlier conclusion that no significant outliers drive our resutls. Moreover, it is clear from the figure that the estimated remittance-output coefficients vary across countries. This implies that an assumption of a homogenous relationship between remittances and output across all countries is a strong one as it may not accurately capture the relevance of a heterogenous relationship.

6 Establishing a causal relationship

Our econometric approach in the previous section uncovers an important long-run economic relationship between remittances and output. Moreover, it implies long-run causality in at least one direction. Nonetheless, it does not show the direction of the long run causality. Indeed, assessing long-run association between remittance and real GDP without any insight into the potential causal link between these two variable does not inform policy strategies and implications. More precisely, the positive relationship between remittance and output could also suggest that robust aggregate economic activity in recipient countries induces higher remittances. For instance, a number of studies including Freund and Spatafora (2005) and Sayan (2006) report that higher output lead to higher remittance inflows. Hence, to examine whether there is a potential causal relationship, we utilize a causality test by Dumitrescu and Hurlin (2012, , henceforth DH). Unlike the standard Granger causality test, the DH- test allows for unbalanced data and considers two dimensions of heterogeneity— i.e., the heterogeneity of the regression model used to test the Granger causality, and the heterogeneity of the causal relationship. For a given pair of economic variables, X and Y, the null hypothesis of the DH-test is that X does not homogenously cause Y.

Table 9: Causality Tests

Null Hypothesis	Zbar-Stat
Remittances does not homogenously cause Output	2.109^{**}
Output does not homogenously cause Remittances	2.813^{**}

Notes: ** indicates rejection of the null hypothesis that the variable X does not homogenously cause the economic variable Y. The number of lags in the individual regressions was set to 1 lag as guided by the Akaike information criteria and Hannan-Quinn information criteria. We employ the cross-sectionally demeaned data, which we tested to be stationary.

Table 9 presents the results from the test. The evidence from the table shows the rejection of the null hypothesis. This suggests that there exists a long-run bi-directional causal relationship between remittance and output such that a rise in remittance increases output and that, in turn, higher output induces an increase in remmittance inflows. As we have discussed earlier, it is clear how, and why remittance can induce an increase in output. However, an important question the results in table 9 is: *Why will a rise in the recipient country's GDP increase remittance inflows?* One possible explanation is investment motives of remitters. Specifically, as discussed in De et al.

(2019) investment motive suggest that families send migrants to increase the family's income. Here, on can rationalize remittances as a return on the deployment of human capital. To this end, family members then act as agents managing the funds on behalf of the remitter. Thus, if investment is the motive, robust economic activity in the recipient country would increase remittances. Another competing argument is inheritance. In this case, potential inheritance can serve as an enforcement device to encourage migrants to send higher amounts of remittance in the hope of receiving a favourable share of the bequest (Hoddinott, 1994). Hence, one would expect that higher output in the recipient country will increase the value of the bequest, which will in turn lead to more remittances.[21]

7 Concluding Remarks

There is evidence that remittances are associated with accelerated poverty reduction, improved access to education and health services, and enhanced financial development (e.g., Acosta et al., 2008; Adams Jr and Page, 2005; Aggarwal et al., 2011; Fromentin, 2017). However, the aggregate impact of remittance on output remain ambiguous. This paper contributes to the growing and ongoing discussion on the aggregate economic effects of remittances by investigating the long-run relationship between remittances and output in developing countries. Our empirical approach differs from previous studies in that we address issues related to endogeneity, measurement errors, heterogeneity, and cross-sectional dependence due to unobserved common factors and spillovers. Our results uncover a consistent positive long-run association between remittance and output. More precisely, baseline results show that on average, a 1 percent increase in remittance induces approximately 0.07 percent increase in output in the long run. In general, this positive long-run remittance-output relationship is robust to different estimators, sub-groups, sub-period, data treatment, and sensitivity checks. We also find that the size of the positive impact of remittances on output varies across income groups. In particular, the results reveal that on average an increase in remittances are likely to raise output by 0.12 percent in upper-middle income countries whereas a similar increase in remittances would raise output by 0.076 percent in low- and lower-middle income countries.

[21] It also important to mention that our results runs counter to studies that find that remittances increase when economic activity is not robust (e.g., Frankel, 2011).

From a policy perspective, our results imply that the implementation of polices that ease the impedements of migrant remittances to developing economies would result in permanent increase of real GDP. Specifically, the cost of remittance, although falling, is still high at a global average of about 7 percent, and it is yet to reach the targeted 5 percent level. A number of studies find that high transfer costs reduce recorded remittance, and that these costs have a direct negative impact on the amount received, as well as the volume of remittance flows. For instance, Freund and Spatafora (2008) find that a 1 percentage point reduction in transaction costs raises recorded remittances by 14–23 percent.[22] Consequently, a counterfactual analysis suggests that if policymakers are successful in meeting the goal of 5 percent cost of remittance (a 2 percentage points reduction in transaction cost), then this will increase remittances by 28 – 46 percent per Freund and Spatafora (2008). Our estimates suggest that such a rise in remittances would induce an increase of 1.86 – 3.1 percent in output in developing countries. The finding is particularly important because it suggests that making remittances easier and cheaper to send can induce a sustained and permanent increase in the output in these recipient economies.

This paper has uncovered an important relationship between remittances and output. We, however, do not examine the individual factors that drive this relationship. This is because we focus on quantifying the effect of remittance on output and do not distinguish between the individual determinants of the observed positive long run impact of remittance on real GDP. Specifically, the remittance-output coefficient captures the association between remittance and determinants of output including multi-factor productivity and investment. Going forward, it is important that newer studies investigate the determinants of this positive long-run effect of remittance on output. Moreover, since our study permits heterogenous effect of remittance on output in individual countries, future studies can systematically search for country-specific factors that explain cross-country variation in the remittance-output relationship in the manner of Herzer and Morrissey (2013). Additionally, an understanding of factors that drive the heterogeneity in the size of this positive effect between income groups will be useful in streamlining policies that can interact with remittance flows to influence development. These, in general, should comprise the object of future research.

[22] Moreover, evidence from micro studies also confirms the negative effects of costs for remittance flows (see for instance, Ambler et al., 2015; Ashraf et al., 2011; Gibson et al., 2006)

APPENDICES

A Model steady state systemt

Given the model in section 2, we have the follow steady state system,

Intratemporal Euler Equation:

$$l^{\phi} = \frac{w}{c} \tag{A.1}$$

Intertemporal Euler Equation:

$$1 = \beta(1 - \delta + r) \tag{A.2}$$

Investment:

$$\delta k = i \tag{A.3}$$

Firm FOC labor:

$$(1 - \alpha)\frac{y}{l} = w \tag{A.4}$$

Firm FOC capital:

$$\alpha\frac{y}{k} = r \tag{A.5}$$

Production:

$$y = Ak^{\alpha}l^{1-\alpha} \tag{A.6}$$

Aggregate resource constraint:

$$y_t = c + i - Rem \tag{A.7}$$

Combining Eq. (A.1) and Eq. (A.4) and log differentiating yields,

$$d\ln(1 - \alpha) + d\ln y = d\ln c + (1 + \phi)\ln l \tag{A.8}$$

Substituting Eq. (A.2) and Eq. (A.5) and log differentiating we obtain,

$$d\ln \alpha + d\ln y = d\ln(1/\beta - 1 + \delta) + d\ln k \tag{A.9}$$

Totally differentiating the resource contraint in Eq. A.7 and with some algebra we obtain

$$d\ln y = \varepsilon_c d\ln c + \varepsilon_i d\ln i + \varepsilon_m d\ln m \tag{A.10}$$

where $\varepsilon_c = \frac{\partial y}{\partial c}\frac{c}{y} > 0, \varepsilon_i = \frac{\partial y}{\partial i}\frac{i}{y} > 0$ and $\varepsilon_m = -\frac{\partial y}{\partial Rem}\frac{Rem}{y} < 0$ are elasticities. Notice from the aggregate resource constraint that $\frac{\partial y}{\partial c} = \frac{\partial y}{\partial i} = \frac{\partial y}{\partial Rem} = 1$

Combining Eq.(A.8) and (A.9) and setting the terms $d\ln\alpha$ and $d\ln(1/\beta - 1 + \delta)$ to zero, we arrive at the system,

$$2d\ln y = d\ln c + (1+\phi)d\ln l + d\ln k \tag{A.11}$$

$$d\ln y = d\ln A + \alpha d\ln k + (1-\alpha)d\ln l \tag{A.12}$$

$$d\ln y = \varepsilon_c d\ln c + \varepsilon_i d\ln i + \varepsilon_m d\ln Rem \tag{A.13}$$

We can further obtain a single equation by eliminating c from Eq. (A.11) and (A.13), and solve for the permanent effect of Rem on y to obtain:

$$d\ln y = (\lambda_k\alpha^k + \lambda_l\alpha^l + \lambda_a\alpha^A + \mu_m)\cdot d\ln Rem \tag{A.14}$$

where $\alpha^j = \frac{d\ln j}{d\ln m}$ is the elasticity of variable $j \in \{k, l, A\}$ with respect to remittances, $\lambda_l = \frac{2+\phi-\alpha}{3\varepsilon_c - 1}$, $\lambda_a = \frac{\varepsilon_c}{3\varepsilon_c - 1}$, $\lambda_k = \frac{(1+\alpha)\varepsilon_c - \varepsilon_k}{3\varepsilon_c - 1}$, and $\mu_m = -\frac{\varepsilon_m}{3\varepsilon_c - 1}$ are scaling parameters. We can integrate Eq.(A.14) to obtain Eq. (9).

B Countries employed in the empircal study and number of observations

Table B.1: Countries included in the panel

Country	$t = 1$	$t = T$	Observations	Country	$t = 1$	$t = T$	Observations
Albania	1992	2014	23	Lesotho	1975	2014	40
Algeria	1970	2014	45	Macedonia, FYR	1996	2014	19
Armenia	1995	2014	20	Madagascar	1974	2014	41
Bangladesh	1976	2014	39	Malawi	1994	2014	21
Belarus	1993	2014	22	Mali	1975	2014	40
Belize	1984	2014	31	Mauritania	1975	1998	24
Benin	1974	2014	41	Mauritius	1994	2014	21
Bolivia	1976	2014	39	Mexico	1979	2014	36
Bosnia and Herze	1998	2014	17	Moldova	1995	2014	20
Botswana	1975	2014	40	Mongolia	1998	2014	17
Brazil	1975	2014	40	Morocco	1975	2014	40
Bulgaria	1996	2014	19	Mozambique	1980	2014	35
Cabo Verde	1980	2014	35	Myanmar	2000	2014	15
Cambodia	1993	2014	22	Namibia	1990	2014	25
Cameroon	1979	2014	36	Nepal	1993	2014	22
China	1982	2014	33	Nicaragua	1992	2014	23
Colombia	1970	2014	45	Niger	1974	2014	41
Congo, Dem. Rep.	2000	2014	15	Nigeria	1977	2014	38
Costa Rica	1977	2014	38	Pakistan	1976	2014	39
Dominica	1977	2014	38	Paraguay	1975	2014	40
Dominican Republ	1970	2014	45	Peru	1990	2014	25
Egypt, Arab Rep.	1977	2014	38	Philippines	1977	2014	38
El Salvador	1976	2014	39	Romania	1994	2014	21
Eswatini	1974	2014	41	Russian Federati	1994	2014	21
Ethiopia	1981	2014	34	Sao Tome and Pri	2001	2014	14
Fiji	1979	2014	36	Senegal	1974	2014	41
Georgia	1997	2014	18	South Africa	1970	2014	45
Ghana	1979	2014	36	Sri Lanka	1975	2014	40
Grenada	1986	2014	29	St. Vincent and	1986	2014	29
Guatemala	1977	2014	38	Sudan	1977	2014	38
Haiti	1998	2014	17	Tanzania	1995	2014	20
Honduras	1974	2014	41	Thailand	1975	2014	40
India	1975	2014	40	Togo	1974	2014	41
Indonesia	1983	2014	32	Tunisia	1976	2014	39
Iran, Islamic Re	1993	2014	22	Turkey	1974	2014	41
Jamaica	1976	2014	39	Uganda	1999	2014	16
Jordan	1975	2014	40	Ukraine	1996	2014	19
Kazakhstan	1995	2014	20	Vietnam	2000	2014	15
Kyrgyz Republic	1993	2014	22	West Bank and Ga	1995	2014	20
Lao PDR	1984	2014	31	Yemen, Rep.	1990	2014	25

C Summary Statistics

Table C.2: Summary Statistics by Country, GDP (in natural log)

Country	Mean	Min	Max	Std. Dev.	**Country**	Mean	Min	Max	Std. Dev.
Albania	22.83	22.15	23.27	0.36	Lesotho	20.98	19.94	21.77	0.49
Algeria	25.25	24.27	25.93	0.42	Macedonia, FYR	22.79	22.54	23.05	0.17
Armenia	22.60	21.93	23.13	0.43	Madagascar	22.55	22.29	22.99	0.23
Bangladesh	24.74	23.93	25.71	0.53	Malawi	22.35	21.85	22.84	0.28
Belarus	24.33	23.75	24.87	0.39	Mali	22.39	21.65	23.21	0.48
Belize	20.53	19.62	21.16	0.49	Mauritania	21.40	21.15	21.66	0.15
Benin	22.04	21.32	22.87	0.47	Mauritius	22.75	22.29	23.17	0.28
Bolivia	23.22	22.82	23.92	0.33	Mexico	27.38	26.92	27.80	0.27
Bosnia and Herze	23.40	23.00	23.60	0.20	Moldova	22.28	21.96	22.68	0.23
Botswana	22.42	20.79	23.52	0.79	Mongolia	22.49	22.03	23.16	0.37
Brazil	27.94	27.32	28.52	0.33	Morocco	24.61	23.76	25.41	0.48
Bulgaria	24.45	24.15	24.69	0.21	Mozambique	22.13	21.26	23.32	0.67
Cabo Verde	20.27	19.08	21.30	0.78	Myanmar	24.27	23.49	24.91	0.46
Cambodia	22.68	21.92	23.42	0.48	Namibia	22.81	22.33	23.36	0.31
Cameroon	23.63	23.16	24.18	0.27	Nepal	23.23	22.76	23.67	0.27
China	28.26	26.69	29.75	0.92	Nicaragua	22.68	22.27	23.11	0.25
Colombia	25.74	24.83	26.58	0.48	Niger	22.01	21.60	22.73	0.30
Congo, Dem. Rep.	23.65	23.32	24.10	0.25	Nigeria	25.89	25.34	26.84	0.45
Costa Rica	23.73	23.08	24.49	0.46	Pakistan	25.25	24.24	26.05	0.53
Dominica	19.63	18.94	20.04	0.31	Paraguay	23.20	22.23	23.93	0.43
Dominican Republ	23.88	22.76	24.89	0.58	Peru	25.31	24.79	25.92	0.35
Egypt, Arab Rep.	25.42	24.48	26.20	0.51	Philippines	25.48	24.95	26.25	0.37
El Salvador	23.37	23.02	23.75	0.23	Romania	25.65	25.37	25.94	0.21
Eswatini	21.51	20.41	22.36	0.62	Russian Federati	27.81	27.42	28.17	0.27
Ethiopia	23.36	22.77	24.51	0.51	Sao Tome and Pri	18.95	18.62	19.29	0.22
Fiji	21.62	21.30	22.01	0.22	Senegal	22.75	22.20	23.42	0.36
Georgia	22.94	22.49	23.39	0.31	South Africa	26.19	25.65	26.75	0.31
Ghana	23.54	22.84	24.52	0.49	Sri Lanka	24.00	23.08	25.01	0.56
Grenada	20.21	19.75	20.55	0.26	St. Vincent and	20.06	19.56	20.39	0.27
Guatemala	23.97	23.49	24.59	0.35	Sudan	24.11	23.45	24.96	0.52
Haiti	22.63	22.56	22.77	0.06	Tanzania	23.84	23.32	24.43	0.36
Honduras	22.92	22.15	23.62	0.42	Thailand	25.79	24.54	26.67	0.66
India	27.15	26.17	28.39	0.68	Togo	21.52	21.09	22.07	0.27
Indonesia	26.83	26.06	27.57	0.43	Tunisia	23.86	23.05	24.59	0.47
Iran, Islamic Re	26.63	26.31	26.94	0.22	Turkey	26.75	25.93	27.66	0.49
Jamaica	23.12	22.80	23.37	0.20	Uganda	23.47	22.99	23.94	0.33
Jordan	23.22	21.96	24.11	0.56	Ukraine	25.49	25.16	25.76	0.22
Kazakhstan	25.34	24.80	25.94	0.41	Vietnam	25.28	24.84	25.70	0.28
Kyrgyz Republic	22.04	21.62	22.49	0.26	West Bank and Ga	22.67	22.29	23.11	0.27
Lao PDR	21.97	21.14	22.99	0.57	Yemen, Rep.	23.76	23.19	24.15	0.30

Table C.3: Summary Statistics by Country, Remittances (in natural log)

Country	Mean	Min	Max	Std. Dev.	**Country**	Mean	Min	Max	Std. Dev.
Albania	20.93	20.36	21.22	0.25	Lesotho	20.26	19.74	20.60	0.22
Algeria	21.02	19.99	22.08	0.59	Macedonia, FYR	19.29	18.36	19.80	0.49
Armenia	20.32	18.82	21.47	1.04	Madagascar	16.41	11.20	19.76	2.32
Bangladesh	21.37	17.64	23.35	1.30	Malawi	15.86	13.84	17.78	1.49
Belarus	19.29	13.33	20.72	2.03	Mali	19.07	17.81	20.46	0.67
Belize	17.41	16.57	18.19	0.52	Mauritania	15.60	13.74	18.11	1.06
Benin	18.69	17.05	19.41	0.46	Mauritius	19.27	18.88	19.59	0.18
Bolivia	17.75	14.56	21.05	2.21	Mexico	23.00	20.28	24.05	0.81
Bosnia and Herze	21.68	21.32	22.30	0.29	Moldova	20.35	14.66	21.34	1.55
Botswana	18.17	16.67	19.12	0.64	Mongolia	18.93	16.71	20.02	0.97
Brazil	21.10	18.56	22.94	1.41	Morocco	21.82	20.94	22.76	0.58
Bulgaria	20.64	18.39	21.84	1.25	Mozambique	17.85	16.59	18.75	0.51
Cabo Verde	18.33	17.37	19.05	0.55	Myanmar	19.30	18.02	21.35	0.96
Cambodia	18.45	16.32	19.63	1.13	Namibia	17.16	16.65	18.34	0.59
Cameroon	17.76	15.76	19.37	0.96	Nepal	20.50	18.30	22.45	1.57
China	21.92	18.98	24.72	2.02	Nicaragua	19.75	17.09	20.77	1.06
Colombia	20.94	18.76	22.64	1.27	Niger	17.20	15.82	19.10	0.93
Congo, Dem. Rep.	16.36	13.75	18.44	1.02	Nigeria	20.72	16.23	24.34	2.90
Costa Rica	18.32	15.74	20.49	1.67	Pakistan	22.15	20.77	23.40	0.60
Dominica	16.95	16.01	17.70	0.30	Paraguay	18.95	16.79	20.09	1.07
Dominican Republ	20.68	18.12	22.27	1.24	Peru	20.93	19.08	21.73	0.75
Egypt, Arab Rep.	22.71	21.72	23.48	0.42	Philippines	22.60	20.89	23.95	1.02
El Salvador	20.86	17.85	22.09	1.11	Romania	19.78	17.10	21.91	1.41
Eswatini	18.40	16.09	19.54	0.70	Russian Federati	22.40	22.06	23.08	0.21
Ethiopia	17.72	15.27	21.08	1.67	Sao Tome and Pri	14.99	13.76	16.79	0.94
Fiji	17.84	15.71	19.14	1.00	Senegal	19.47	16.93	21.35	1.11
Georgia	20.50	19.89	21.27	0.48	South Africa	19.46	18.23	20.80	0.91
Ghana	17.55	13.84	21.56	2.13	Sri Lanka	20.96	16.99	22.59	1.31
Grenada	17.42	16.36	18.27	0.44	St. Vincent and	17.00	14.91	17.57	0.56
Guatemala	19.63	12.44	22.29	2.60	Sudan	20.17	18.19	21.78	1.05
Haiti	20.98	20.14	21.30	0.32	Tanzania	17.42	14.58	19.83	1.54
Honduras	18.70	14.86	21.89	2.73	Thailand	21.14	17.84	22.54	1.07
India	23.09	20.75	25.04	1.26	Togo	17.80	16.17	19.72	1.25
Indonesia	21.25	17.06	23.11	1.56	Tunisia	20.66	19.59	21.58	0.55
Iran, Islamic Re	21.30	20.74	22.58	0.50	Turkey	22.27	20.90	23.12	0.66
Jamaica	20.51	19.10	21.57	0.86	Uganda	20.31	19.74	20.63	0.30
Jordan	21.52	19.86	22.38	0.57	Ukraine	20.63	16.30	22.75	2.32
Kazakhstan	19.26	18.59	20.35	0.53	Vietnam	22.42	21.51	22.96	0.46
Kyrgyz Republic	18.53	14.25	21.29	2.52	West Bank and Ga	20.78	20.12	21.31	0.35
Lao PDR	16.25	14.13	18.63	1.47	Yemen, Rep.	21.57	20.87	22.11	0.33

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