



HAL
open science

Informal sector, remittances, and political stability: A study of Granger-causality in four large geopolitical sets

Mamadou Lah, Hadi Salameh

► To cite this version:

Mamadou Lah, Hadi Salameh. Informal sector, remittances, and political stability: A study of Granger-causality in four large geopolitical sets. 2024. halshs-04721826

HAL Id: halshs-04721826

<https://shs.hal.science/halshs-04721826v1>

Preprint submitted on 4 Oct 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



WORKING PAPER N° 2024-40

**Informal sector, remittances, and political stability: A study of
Granger-causality in four large geopolitical sets**

**Mamadou Lah
Hadi Salameh**

JEL Codes: C32, F22, F24, O17

**Keywords: informal sector, remittances, political stability, Granger causality,
PVAR model, migration**



Informal sector, remittances, and political stability: A study of Granger-causality in four large geopolitical sets

Mamadou Lah^a, Hadi Salameh^b

^aPhD candidate at University Paris 1 Panthéon–Sorbonne

Paris – Jourdan Sciences Économiques (PJSE) UMR8545

Email address: Mamadou.Lah@univ – paris1. fr

^bPhD candidate at University Paris 2 Panthéon–Assas

Email address: Hadi.Salameh@etu. univ – paris2. fr

Abstract

This paper investigates the relationships between remittances, the informal sector, and political stability across various large geopolitical sets, including the Middle East and North Africa (MENA), Sub-Saharan Africa, Latin America, and the Organisation for Economic Co-operation and Development (OECD) countries. Employing Granger causality tests to determine the predominate direction of causality and panel vector autoregressive models, we explore the dynamics of these relationships over short, medium, and long-term periods.

Our findings reveal a significant short-term impact of remittances on the growth of the informal sector in the MENA, Sub-Saharan Africa, and Latin America, suggesting that remittances directly influence economic activities within this sector, likely due to their use in undeclared activities and the funding of informal local businesses. However, the influence of remittances wanes over time, indicating their primary role in addressing immediate economic needs rather than fostering long-term sector growth. Political stability shows minimal direct causal interaction with the informal sector, hinting at the sector's role as an adaptive mechanism in politically volatile regions.

In OECD countries, remittances maintain a persistent influence on the informal sector over longer periods, reflecting their role in more strategic economic decisions. Additionally, our study explores the complex dynamics in countries with high remittance-to-GDP ratios, identifying a strong predictive power of the informal sector size on remittance flows, which points to the sector's pivotal economic role. We have extended our analysis to OECD countries, using outward remittances as a proxy for inward migration. We found that the size of the informal sector can predict outward remittance flows and political stability, highlighting the crucial role of the informal economy in migration and political dynamics.

The results underscore the need for region-specific policy interventions and highlight the importance of understanding the temporal dynamics of remittances. This study contributes to the discourse on economic development strategies, suggesting that leveraging remittances effectively requires comprehensive policy approaches that consider their varied impacts across different regional and economic contexts.

Keywords: informal sector, remittances, political stability, Granger causality, PVAR model, migration
JEL Classification: C32, F22, F24, O17

Résumé

Cet article explore les liens entre les envois de fonds, le secteur informel et la stabilité politique dans plusieurs ensembles géopolitiques majeurs, dont le Moyen-Orient et l'Afrique du Nord (MENA), l'Afrique subsaharienne, l'Amérique latine et les pays de l'Organisation de Coopération et de Développement Économiques (OCDE). En utilisant des tests de causalité de Granger pour déterminer la direction prédominante de la causalité et des modèles autorégressifs vectoriels de panel, nous examinons la dynamique de ces relations sur des périodes courtes, moyennes et longues.

Nos résultats révèlent un impact significatif à court terme des envois de fonds sur la croissance du secteur informel dans la région MENA, l'Afrique subsaharienne et l'Amérique latine, suggérant que les envois de fonds influencent directement les activités économiques au sein de ce secteur, probablement en raison de leur utilisation dans des activités non déclarées et le financement d'entreprises locales informelles. Cependant, l'influence des envois de fonds diminue avec le temps, indiquant leur rôle principal dans la réponse aux besoins économiques immédiats plutôt que dans la promotion de la croissance à long terme du secteur. La stabilité politique montre une interaction causale directe minimale avec le secteur informel, suggérant le rôle du secteur comme mécanisme d'adaptation dans les régions politiquement instables.

Dans les pays de l'OCDE, les envois de fonds maintiennent une influence persistante sur le secteur informel sur de plus longues périodes, reflétant leur rôle dans des décisions économiques plus stratégiques. De plus, notre étude explore la dynamique complexe dans les pays ayant des ratios envois de fonds/PIB élevés, identifiant un fort pouvoir prédictif de la taille du secteur informel sur les flux de transferts de fonds, ce qui souligne le rôle économique central du secteur. Nous avons étendu notre analyse aux pays de l'OCDE, en utilisant les envois de fonds sortants comme indicateur de la migration entrante. Nous avons constaté que la taille du secteur informel peut prédire les flux de fonds sortants et la stabilité politique, soulignant le rôle crucial de l'économie informelle dans la dynamique migratoire et politique.

Les résultats soulignent la nécessité d'interventions politiques spécifiques à chaque région et l'importance de comprendre la dynamique temporelle des envois de fonds. Cette étude contribue au discours sur les stratégies de développement économique, suggérant qu'une utilisation efficace des envois de fonds nécessite des approches politiques globales qui prennent en compte leurs impacts variés selon les contextes régionaux et économiques.

Mots clés : secteur informel, envois de fonds, stabilité politique, causalité de Granger, modèle PVAR, migration
Classification JEL : C32, F22, F24, O17

Table of Contents

ABSTRACT	I
RESUME	I
TABLE OF CONTENTS	II
LIST OF TABLES	III
LIST OF FIGURES	V
1. INTRODUCTION	1
2. LITERATURE REVIEW	3
3. DATA AND METHODOLOGY	5
4. RESULTS:	11
CONCLUSION	22
REFERENCES	24
APPENDIX 1: TABLE OF CORRELATION AND CAUSALITY	26
APPENDIX 2: PHILOSOPHY OF DATABASE CONSTRUCTION, VARIABLES DEFINITIONS, DATA SOURCES AND SAMPLE OF COUNTRIES	61
APPENDIX 3: OPTIMAL LAG ANALYSIS	67
APPENDIX 4: STATIONARITY TEST: EIGENVALUE STABILITY CONDITION	76
APPENDIX 5: COLLINEARITY DIAGNOSTICS	88
APPENDIX 6: FORECAST-ERROR VARIANCE DECOMPOSITION (FEVD)	97
APPENDIX 7: IMPULSE RESPONSE FACTOR (IRF) ANALYSIS	111

List of Tables

TABLE 1 CORRELATION AND CAUSALITY IN MENA REGION AND SUB-SAHARAN AFRICA (LAG 1)	26
TABLE 2 CORRELATION AND CAUSALITY IN MENA REGION AND SUB-SAHARAN AFRICA (LAG 2)	29
TABLE 3 CORRELATION AND CAUSALITY IN MENA REGION AND SUB-SAHARAN AFRICA (LAG 3)	31
TABLE 4 CORRELATION AND CAUSALITY IN LATIN AMERICA REGION (LAG 1)	33
TABLE 5 CORRELATION AND CAUSALITY IN LATIN AMERICA REGION (LAG 2)	35
TABLE 6 CORRELATION AND CAUSALITY IN LATIN AMERICA REGION (LAG 3)	37
TABLE 7 CORRELATION AND CAUSALITY IN OECD COUNTRIES (LAG 1)	39
TABLE 8 CORRELATION AND CAUSALITY IN OECD COUNTRIES (LAG 2)	41
TABLE 9 CORRELATION AND CAUSALITY IN OECD COUNTRIES (LAG 3)	43
TABLE 10 CORRELATION AND CAUSALITY IN OECD COUNTRIES (LAG 1): REMITTANCES PAID	45
TABLE 11 CORRELATION AND CAUSALITY IN OECD COUNTRIES (LAG 2): REMITTANCES PAID	47
TABLE 12 CORRELATION AND CAUSALITY IN OECD COUNTRIES (LAG 3): REMITTANCES PAID	49
TABLE 13 CORRELATION AND CAUSALITY IN OECD COUNTRIES (LAG 4): REMITTANCES PAID	51
TABLE 14 CORRELATION AND CAUSALITY IN OECD COUNTRIES (LAG 5): REMITTANCES PAID	53
TABLE 15 CORRELATION AND CAUSALITY IN IN HIGH REMITTANCE-TO-GDP RATIO COUNTRIES (LAG 1) <i>RemGDP > 0.84%</i> .	55
TABLE 16 CORRELATION AND CAUSALITY IN IN HIGH REMITTANCE-TO-GDP RATIO COUNTRIES (LAG 2) <i>RemGDP > 0.84%</i>	57
TABLE 17 CORRELATION AND CAUSALITY IN IN HIGH REMITTANCE-TO-GDP RATIO COUNTRIES (LAG 3) <i>RemGDP > 0.84%</i>	59
TABLE 18: LIST OF COUNTRIES	64
TABLE 19: VARIABLES DEFINITIONS AND SOURCES	65
TABLE 20 : OPTIMAL LAG, SUB-SAHARAN AFRICA AND MENA REGION	68

TABLE 21 : OPTIMAL LAG, LATIN AMERICA REGION	70
TABLE 22: OPTIMAL LAG, OECD REGION	71
TABLE 23: OPTIMAL LAG, OECD REGION, REMITTANCES PAID	72
TABLE 24: OPTIMAL LAG, HIGH REMITTANCE-TO-GDP RATIO COUNTRIES (RemGDP > 0.84%)	74
TABLE 25: STATIONARITY TEST: EIGENVALUE STABILITY CONDITION, SUB-SAHARAN AFRICA AND MENA REGION	77
TABLE 26 : STATIONARITY TEST: EIGENVALUE STABILITY CONDITION, LATIN AMERICA REGION	79
TABLE 27: STATIONARITY TEST: EIGENVALUE STABILITY CONDITION, OECD REGION	81
TABLE 28: STATIONARITY TEST: EIGENVALUE STABILITY CONDITION, OECD REGION, REMITTANCES PAID	83
TABLE 29: STATIONARITY TEST: EIGENVALUE STABILITY CONDITION, HIGH REMITTANCE-TO-GDP RATIO COUNTRIES (RemGDP > 0.84%)	86
TABLE 30 : <i>COLLINEARITY DIAGNOSTICS (SSA AND MENA REGION)</i>	89
TABLE 31 : COLLINEARITY DIAGNOSTICS (LATIN AMERICA REGION)	91
TABLE 32 : COLLINEARITY DIAGNOSTICS (OECD COUNTRIES)	93
TABLE 33 : COLLINEARITY DIAGNOSTICS (OECD COUNTRIES),), REMITTANCES PAID	94
TABLE 34: COLLINEARITY DIAGNOSTICS, HIGH REMITTANCE-TO-GDP RATIO COUNTRIES (RemGDP > 0.84%)	95
TABLE 35: FORECAST-ERROR VARIANCE DECOMPOSITION (FEVD), SUB-SAHARAN AFRICA AND MENA REGION	97
TABLE 36 : FORECAST-ERROR VARIANCE DECOMPOSITION (FEVD), LATIN AMERICA REGION	100
TABLE 37: FORECAST-ERROR VARIANCE DECOMPOSITION (FEVD), OECD REGION	103
TABLE 38: FORECAST-ERROR VARIANCE DECOMPOSITION (FEVD), OECD REGION, REMITTANCES PAID	105
TABLE 39: FORECAST-ERROR VARIANCE DECOMPOSITION (FEVD), HIGH REMITTANCE-TO-GDP RATIO COUNTRIES (RemGDP > 0.84%)	108

List of Figures

FIGURE 1 CAUSAL INTERACTIONS: INFORMAL SECTOR, REMITTANCES AND POLITICAL STABILITY IN MENA AND SUB-SAHARAN AFRICA (LAG 1).	13
FIGURE 2 CAUSAL INTERACTIONS: INFORMAL SECTOR, REMITTANCES AND POLITICAL STABILITY IN LATIN AMERICA (LAG 1)	15
FIGURE 3 CAUSAL INTERACTIONS: INFORMAL SECTOR, REMITTANCES, AND POLITICAL STABILITY IN OECD COUNTRIES (LAG 2)	18
FIGURE 4: CARTOGRAPHY OF SAMPLE COUNTRIES	63
FIGURE 5 : EIGENVALUE STABILITY CONDITION, SUB-SAHARAN AFRICA AND MENA REGION	77
FIGURE 6 : EIGENVALUE STABILITY CONDITION, LATIN AMERICA REGION	80
FIGURE 7: EIGENVALUE STABILITY CONDITION, OECD REGION	82
FIGURE 8: EIGENVALUE STABILITY CONDITION, OECD REGION, REMITTANCES PAID	83
FIGURE 9: EIGENVALUE STABILITY CONDITION, HIGH REMITTANCE-TO-GDP RATIO COUNTRIES (<i>RemGDP</i> > 0.84%)	86
FIGURE 10 : IMPULSE RESPONSE FACTOR (IRF), SUB-SAHARAN AFRICA AND MENA REGION	111
FIGURE 11 : IMPULSE RESPONSE FACTOR (IRF), LATIN AMERICA REGION	114
FIGURE 12: IMPULSE RESPONSE FACTOR (IRF), OECD REGION	122
FIGURE 13: IMPULSE RESPONSE FACTOR (IRF), OECD REGION, REMITTANCES PAID	124
FIGURE 14: IMPULSE RESPONSE FACTOR (IRF), HIGH REMITTANCE-TO-GDP RATIO COUNTRIES (<i>RemGDP</i> > 0.84%)	126

1. Introduction

All economies worldwide have to deal with the more or less significant presence of the informal economy. In some regions, it may represent up to 70% of the global economy. Several factors are associated with this sector, including political stability, taxation, economic growth, and remittances. In this article, we explore the subtle link between the informal economy, political stability, and remittances through a comparative study of four large geopolitical sets: the Middle East/North Africa (MENA), Sub-Saharan Africa (SSA), the Organisation for Economic Co-operation and Development (OECD) countries and Latin America.

Most articles on the informal economy focus on the determinants of the size of the informal economy and on estimating its size (Amaral & Quintin, 2006; Dabla-Norris et al., 2008; Ihrig & Moe, 2004; Loayza, 1996; Schneider & Enste, 2000, 2010, 2017; Tanzi, 1983, 1999). Our approach is empirical and focused on the panel vector autoregressive model (PVAR) and Granger causality test.

Many papers have studied the link between political stability and remittances (Abbas et al., 2017; Aydas et al., 2005; Catrinescu et al., 2009, among others), but very few have been interested in the informal economy at the same time, and few have conducted a comparative study between MENA and SSA, Latin America and OECD regions. These regions differ in their political systems, the level of remittances as a percentage of GDP and the size of the informal sector.

Depending on the perspective, the informal economy can both weaken and support political stability. On the one hand, in times of political stability, it can stimulate the growth of the informal economy by building confidence and reducing disruption. On the other hand, during periods of political instability, it can undermine informal activity through increased repression, erosion of trust and economic uncertainty. The informal economy can also have both positive and negative effects on political stability through (a) the provision of jobs and livelihoods to a significant proportion of the population, thereby reducing poverty and strengthening political stability, and (b) tax evasion, corruption and a lack of social protection.

In many economies around the world, the informal economy is often the foundation of family support, while remittances are the link that strengthens that foundation. Indeed, remittances directly impact the informal economy by (a) providing financial support to small, informal

businesses and (b) stimulating consumption and local demand, targeting both formal and informal businesses.

To determine which direction of causality prevails, we conducted a Granger causality test. In the four large geopolitical sets, examining the short-term impacts (lag 1), the results show a positive correlation between remittances and the size of the informal sector. We found that remittances Granger-cause the size of the informal sector. Political stability as a separate variable had no causal relationship with the informal sector, but remittances and political stability together Granger cause an informal sector. However, we did not find a significant result when we ran our test in the medium to long run for Latin America, SSA and MENA. Therefore, we conclude that the effect of these two variables in these regions is only short-term. This could mean remittances are invested in primary needs rather than formal or informal investments.

However, In OECD countries, medium to long-term tests yielded significant results, matching those of the short term. Nevertheless, we found that political stability Granger causes remittances on the one hand, and the informal sector and remittances Granger cause political stability both together and separately on the other hand.

Additionally, in an increasingly globalized world, the flow of remittances and migration has significant economic and social impacts, particularly within OECD countries which are characterized by complex interdependencies between developed and developing economies. This paper also explores the intricacies of outward remittances used as a proxy for inward migration, examining their relationships with the informal sector and political stability in regions like the USA/Canada and EU/UK. We found that the size of the informal sector predicts outward remittances (as a proxy for inward migration) and political stability, but remittances do not significantly influence the informal sector or political stability. More precisely, in the short-term dynamics (Lag 1), the immediate effects of remittances on the informal sector and political stability are minimal or delayed. In the medium to long-term dynamics (Lags 2 to 5), the size of the informal sector predicts outward remittances and political stability, but remittances do not significantly influence the informal sector or political stability.

Finally, to examine how dependency on remittances might affect the relationships between remittances, political stability, and the informal sector, we analyze the impact of remittances on the informal sector and political stability in countries with high remittance dependence (defined as a remittance-to-GDP ratio exceeding the OECD average of 0.84% and the median

of our sample evaluated to 1.45%). We found a strong link between remittances and the informal sector. However, these economic factors do not directly translate into political changes.

Further, this paper is structured as follows: The second section briefly reviews the existing literature. The third section describes the model, methodology, data and research techniques. The fourth section analyses the empirical results, and the final section provides concluding remarks.

2. Literature review

Many articles have examined the link between political stability and remittances, such as Catrinescu et al. (2009), Abbas et al. (2017) and Aydas et al. (2005). These papers analyse this relationship in terms of several factors in remittance-receiving countries. We contribute to this literature by focusing on the informal economy at the same time. In addition, we examine this link through a comparative study between four large political sets (MENA, SSA, OECD and Latin America). According to the World Bank dataset, these regions and countries exhibit different levels of political stability. We used the panel vector autoregressive model (PVAR), GMM estimation and Granger causality test.

Catrinescu et al. (2009) used dynamic panel data analysis to investigate the relationship between remittances and growth, concluding that remittances were more likely to contribute to longer-term growth in countries with higher-quality political and economic policies and institutions.

Abbas et al. (2017) employed the GMM method to examine the impact of macroeconomic, financial and political factors on remittances to Pakistan using data from 1972–2012. The authors found a positive correlation between remittances and institutional quality.

Aydas et al. (2005) used ordinary least squares to examine the effect of various macroeconomic variables on remittance flows in Turkey for the period 1965–1993. They found a positive and significant effect on growth, indicating the importance of sound exchange rate policies and economic and political stability in attracting remittance flows. These results are consistent with our findings, but only for the OECD countries. In these countries, we conclude that political stability Granger causes remittances in the short run. We do not find a causal relationship for

the SSA-MENA region and the Latin America region for the same run. However, the informal sector and political stability jointly Granger cause remittances for the Latin America region on short run.

Elbahnasawi and Ellis (2016) studied the informal sector and political instability. They found that political instability, social polarisation along ethnic and religious lines, and autocratic patterns of authority were associated with larger informal economies.

By regressing the size of the informal economy on six indicators of world governance and across 149 countries over six years, Friedman (2014) found that in a country where citizens perceive the current government as unstable, think the quality of regulations is poor, and feel that corruption is not being tackled, there is a correlation with a larger informal economy. The stability of a political system may be a prerequisite for the growth of a formal economy. Entrepreneurs need to be confident that business regulations are reasonably stable and that contracts signed now will be valid in the future to transition from the informal to the formal economy. Countries must develop regulations that motivate individuals to move into the formal economy. Policies encouraging private sector growth, such as access to capital, favourable interest rates and the lure of foreign investment, are examples of such initiatives. The results of our paper are consistent with these considerations, showing that political stability as a separate variable does not Granger cause the informal sector in our studied four geopolitical sets. However, for the OECD countries, we found that the informal sector does Granger cause political stability in medium-long run.

Chatterjee and Turnovsky (2018) analysed the impact of remittances on the informal sector by developing a general equilibrium framework to better understand the dynamic absorption of remittances in a two-sector, small, open economy. The researchers determined that the impact of remittances depends critically on how they affect the recipient economy.

Njangang et al. (2018) analysed this link for 30 SSA countries over the period 1991–2015 and showed that remittances significantly increase the size of the informal economy. They used OLS and GMM as empirical strategies. These results are in line with our findings. We found that remittances Granger-cause the informal sector in MENA, SSA and Latin America in short run. We also found that remittances and political stability jointly Granger-cause the informal sector in these regions in short run. In the OECD countries, the same outcomes are seen in the short, medium and long runs.

3. Data¹ and methodology

3.1. Informal sector

The informal sector is an unobservable phenomenon. Therefore, estimation methods are needed. Although this estimation can be a challenging task due to the clandestine nature of the informal economy, economists and researchers have developed several methods and indicators that can provide rough estimates of the shadow economy.

Here are some commonly used approaches:

- National accounts discrepancy method: This method compares the reported national income, as measured by official statistics, with the total expenditure in the economy. The discrepancy between these two figures can be attributed to unreported or underreported economic activities that are part of the shadow economy. By analysing this gap, researchers can estimate the size of the shadow economy relative to the official economy.
- Currency demand method: The currency demand method focuses on estimating the amount of cash in circulation used for transactions in the shadow economy. Researchers examine the velocity of money (how often it changes hands) and the ratio of currency to GDP. Analysts can infer the size of the shadow economy by comparing the observed amount of cash in circulation with the expected amount based on legitimate transactions.
- Labour market indicators: The shadow economy often involves unreported employment and undeclared wages. Researchers analyse labour market indicators, such as the difference between official and actual employment figures, the number of workers without social security coverage, and discrepancies in tax declarations. These indicators can provide insights into the extent of informal employment and economic activity.
- Indirect approaches: Several indirect methods are used to estimate the shadow economy. These include analysing electricity consumption patterns, analysing discrepancies in trade data, studying the sales of certain commodities (e.g. tobacco or alcohol) often associated with underground activities, and conducting surveys or interviews to capture individuals' self-reported participation in the shadow economy.

¹ The philosophy of database construction is provided in Appendix 2.

- Multiple indicators: Estimating the shadow economy is complex, and no single method can provide a definitive measurement. Researchers often use a combination of the above approaches and indicators to obtain a more comprehensive estimate. By triangulating different data sources and methodologies, they can minimise bias and arrive at a reasonable approximation.

This paper uses the method of multiple indicators and causes (MIMIC) referred to Medina and Schneider (2017). This method is among the best known and widely used in the literature.

MIMIC

The MIMIC approach is to estimate the size of the informal economy. Unlike other methods that rely on a single indicator, the MIMIC model considers the multiple causes and effects of the informal economy. This method exploits the interactions between the observable causes and effects of the informal economy itself. Formally, the MIMIC model consists of two components: the structural model and the measurement model. The structural model describes how a set of exogenous causal variables influence the latent variable (in this case, the size of the informal economy).

Model: Mathematically, the structural model can be expressed as follows:

$$I = \beta X + \varepsilon$$

Where:

I represents the latent variable (the size of the informal economy).

X stands for the exogenous causal variables.

β represents the coefficients or weights determining the relationship between the causal variables (X) and the latent variable (I).

ε stands for the error term or the unobserved factors affecting the latent variable.

The equation states that the size of the informal economy (I) is determined linearly by the exogenous causal variables (X) with coefficients β . The error term (ε) captures any unobserved or unaccounted-for factors that affect the size of the informal economy but are not directly accounted for by the exogenous variables.

In the MIMIC model, the exogenous causal variables (X) may include factors such as income inequality, unemployment rates, tax burden, regulatory burden, institutional quality, size of the

agricultural sector, self-employment and other relevant indicators associated with the informal economy.

The structural model provides the basis for understanding how the causal variables influence the latent variable (the size of the informal economy), but it does not directly measure the latent variable itself. This is where the measurement model comes in.

The measurement model in the MIMIC approach links the latent variable (the size of the informal economy) to a set of selected indicators. It determines how these observable indicators relate to the unobserved informal economy.

Mathematically, the measurement model can be expressed as follows:

$$Y = \gamma I + \mu$$

Where:

Y represents the observed indicators (e.g. electricity consumption, money demand, labour force participation, real GDP, etc.).

γ is the factor loadings or weights that determine the relationship between the latent variable (I) and the observed indicators (Y).

I represents the latent variable (the size of the informal economy).

μ stands for the measurement error or unobserved factors that affect the observed indicators but are not directly accounted for by the latent variable.

The equation states that the observed indicators (Y) are linearly related to the latent variable (I) with factor loadings γ . The measurement error term (μ) captures any unobserved or unaccounted-for factors that affect the observed indicators but are not directly attributable to the latent variable.

Within the context of the MIMIC model for estimating the size of the informal economy, the observed indicators (Y) can be selected on the basis of their relevance and association with the informal economy. These indicators should capture different manifestations or symptoms of the informal economy, such as electricity consumption, money demand and other relevant variables.

3.2. Panel Vector Autoregression (PVAR) and Granger causality test

We also used the PVAR model and the Granger causality test. To answer the above questions, we created three panels' data from 1996 to 2017 for the following geopolitical sets: The MENA

and SSA (25 countries), Latin America (22 countries) and OECD countries (38 countries). We collected our data from the World Bank's database (Databank).

Our variables used are personal remittances, GDP and political stability, in addition to the informal sector. In our database, we tried to harmonise our data to obtain clearer results. As a first step, we normalized the data by using logarithmic values of remittances and the informal economy. Furthermore, it seemed that our model might suffer from causality problems, so we used the vector autoregressive (VAR) model, more specifically, the PVAR model, which is well-suited to our dataset given the repeated time values. The PVAR model seems to be particularly well suited to address issues that are currently at the centre of academic and policy discussion, as it can (a) capture both static and dynamic interdependencies, (b) treat the links between units in an unrestricted manner, (c) easily incorporate time variation in the coefficients and in the variance of the shocks, and (d) account for cross-sectional dynamic heterogeneities.

The PVAR model was run using the generalised method of moments, which exploits all the orthogonality conditions between the dependent lagged variables and the error term.

Hypothesis 1: The informal sector and remittances vary in the same direction.

Hypothesis 2: Political stability and remittances vary in the same direction.

Hypothesis 3: Remittances and political stability are dynamically correlated with the informal sector.

The preliminary results of our PVAR model showed that our variables might be correlated with each other, as well as the possibility that they might be correlated with their own lagged values.

To address this issue, we used the Granger causality test to better identify, understand and define the causality issues. Introduced by Clive Granger in the 1960s, this method focuses on improving forecasts, aligning perfectly with our primary objective: to evaluate whether the information contained in one time series (e.g., remittances) can better predict the evolution of another series (e.g., the size of the informal sector). Granger developed these causality models in response to criticisms of the structural equations in macroeconomics, where the pure exogeneity or endogeneity of variables was often inadequately ensured.

Granger causality presents several advantages that justify our choice. Firstly, it is conceptually simpler and easier to interpret than other approaches, such as the Sims causality proposed in the 1970s. The Sims method, based on impulse response analysis, is more complex and requires

stronger assumptions about the model structure, which can be difficult to justify in our context where relationships between variables are complex and potentially nonlinear.

Secondly, Granger causality requires fewer data and a priori assumptions, making it more suitable for situations where data are limited or incomplete, as is often the case in developing countries where the informal sector is predominant. Finally, it has been widely used and accepted in econometric literature since its introduction, facilitating the comparison of our results with those of previous studies and enhancing the validity of our conclusions.

Although Granger causality has certain limitations, particularly in terms of strict causal interpretation (since it does not establish causality in the strict sense, but rather temporal precedence), it remains a valuable tool for analyzing temporal relationships between economic and financial variables. In the context of our study, its historical and practical advantages, as well as its ability to capture dynamic relationships between variables, outweigh its drawbacks, justifying our methodological choice.

The bivariate Granger causality test in two variables is carried out by predicting a specific index using its own past values (m -lag) and the past values (m -lag) of another reference index.

$$Y_t = \sum Y_{t-i} + \sum X_{t-i}$$

$$X_t = \sum X_{t-i} + \sum Y_{t-i}$$

$$Y_{i,t} = \alpha_{0,i} + \alpha_{1,1}Y_{i,t-1} + \dots + \alpha_{1,i}Y_{1,t-1} + \beta_{1,i}X_{i,t-1} + \dots + \beta_{1,i}X_{1,-1} + \dots + \varepsilon_{i,t},$$

$$X_{i,t} = \alpha_{0,i} + \alpha_{1,1}X_{i,t-1} + \dots + \alpha_{1,i}X_{1,t-1} + \beta_{1,i}Y_{i,t-1} + \dots + \beta_{1,i}Y_{1,-1} + \dots + \varepsilon_{i,t},$$

The null hypothesis, which states that the reference index does not influence the selected index according to Granger causality, is accepted if none of the lagged values of the reference index are included in the regression. An F -test was then performed to check whether all coefficients of the m -lagged values of the reference index were simultaneously zero. The p -values for each F -test are presented in a table.

$$\begin{aligned} Informal S_t = & \alpha_0 + \alpha_1 Informal S_{t-1} + \dots + \alpha_{1,2} Informal S_{t-n} + \alpha_2 PS_{t-1} + \dots \\ & + \alpha_{2,1} PS_{t-n} + \alpha_3 Rem_{t-1} + \alpha_{3,1} Rem_{t-n} + \gamma_4 C_t \end{aligned}$$

$$\begin{aligned} Rem_t = & \alpha_0 + \alpha_1 Rem S_{t-1} + \dots + \alpha_{1,2} Rem S_{t-n} + \alpha_2 PS_{t-1} + \dots + \alpha_{2,1} PS_{t-n} + \alpha_3 Informal S_{t-1} \\ & + \alpha_{3,1} Informal S_{t-n} + \gamma_4 C_t \end{aligned}$$

$$PS_t = \alpha_0 + \alpha_1 PS_{t-1} + \dots + \alpha_{1,2} PS_{t-n} + \alpha_2 Informal S_{t-1} + \dots + \alpha_{2,1} Informal S_{t-n} \\ + \alpha_3 Rem_{t-1} + \alpha_{3,1} Rem_{t-n} + \gamma_4 C_t$$

Where *Informal S* stands for the informal sector, *Rem* represents remittances, *PS* stands for political stability, and *C* is the exogenous control variable; $\alpha_{1..4}$, $\beta_{1..4}$, $\gamma_{1..4}$ are the coefficients, α_0 , β_0 , γ_0 are the constants.

To give more consistency to our work, we also conducted collinearity tests and stationarity tests. These tests are crucial for ensuring the reliability of our time series data. Collinearity tests are necessary to detect multicollinearity issues that could distort our regression estimates and undermine the validity of the causal relationships. Stationarity tests confirm that the statistical properties of the series do not change over time, which is a key assumption for Granger causality analysis. Details and analysis of these tests can be found in Appendix 4 and 5.

Additionally, we conducted impulse response function (IRF) and forecast error variance decomposition (FEVD) analyses, with a detailed analysis provided in the appendix. The coherence between Granger causality, IRF, and FEVD results enhances the robustness of the findings. The detailed analyses of IRF and FEVD can be found in Appendix 6 and 7.

Moreover, it is important to use a lagged value for the different variables to see causality issues more clearly. Therefore, we searched for the optimal lag value for our model. Our results show that the optimal lag for our model is the lag of one year with the smallest MBIC, MAIC and MQIC, as it minimises Hansen's J (*p*-value) for SSA and MENA and Latin America geopolitical sets, while the optimal lag is lag 2 for OCDE set². We refer here to Andrews and Lu's (2001) selection criteria. Many other results are significant when we use lag 2 and lag 3. We will delve deeper into these findings in the following sections.

² Economic and statistical considerations lead us to choose the optimal lag. The details of this choice are provided in Appendix 3.

4. Results:

In the present study, we observe a significant correlation between the variables that form its core subject. As mentioned at the outset, we have analysed the correlation and causality between the indicators and variables used.

4.1. MENA and Sub-Saharan Africa

4.1.1. Short-term impact

In the short term, there is a notable positive correlation between remittances and the size of the informal sector within MENA and Sub-Saharan Africa. It appears that remittances Granger-cause growth in the informal sector, likely because these funds are often channelled into undeclared activities, as indicated in Table 1 and Figure 1. This trend suggests that an increase in remittances could expand the informal sector, possibly due to the funding of informal businesses or increased demand for informal goods and services.

Separately, political stability does not exhibit a direct causal link with the informal sector, which may reflect the region's adaptation to enduring political instability.

Furthermore, the combined influence of remittances and political stability on the informal sector size indicates a complex interaction, suggesting that both elements contribute to shaping the informal sector dynamics in the short term.

4.1.2. Medium-term and long-term dynamics

Expanding the analysis to include medium-term effects (lag 2), remittances continue to Granger-cause the informal sector size. However, the joint impact of remittances and political stability on the informal sector becomes statistically insignificant with an extended lag. This diminishing influence after two periods suggests that remittances and political stability have a more pronounced short-term effect, potentially indicating that remittances in the medium term primarily address basic needs rather than fostering investments in formal or informal businesses.

4.1.3. Implications

The findings from this analysis predominantly pertain to the unique context of MENA and Sub-Saharan Africa and should be interpreted with regional specifics in mind.

- Remittances and the informal sector in MENA and Sub-Saharan Africa

Firstly, the robust positive correlation between remittances and informal sector size in the short term suggests that remittances significantly bolster the informal sector in these regions. This support may stem from factors like limited access to formal financial services and heightened demand for informal goods and services, which promotes the sector's growth. Additionally, in the short term, remittances are typically used to meet basic needs, thus further driving demand for informal sector services.

Secondly, the lack of a causal link beyond two periods might explain why remittance flows are predominantly spent in undeclared activities. This indicates a short-lived effect where remittances are used for immediate needs, with minimal long-term investment in formalizing or expanding informal businesses.

However, other factors potentially influencing undeclared remittance spending include limited access to formal services, high formalization costs, and bureaucratic inefficiencies.

- Political stability and the informal sector

The absence of a direct causal relationship between political stability and the informal sector in the short term may be due to the regional adaptation to political instability, where the informal sector serves as a coping mechanism during fluctuating political conditions.

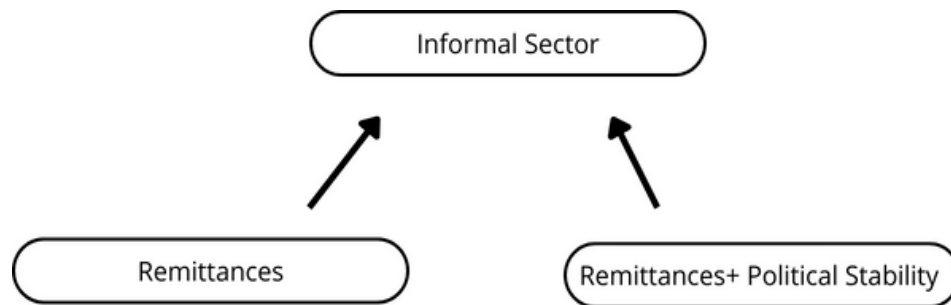
- Medium-term and long-term dynamics

In the medium to long term, the influence of remittances and political stability on the informal sector wanes, potentially due to diversification of investments into more formal sectors and improvements in institutional frameworks that encourage formalization.

Understanding the intricate dynamics between remittances, the informal sector size, and political stability in MENA and Sub-Saharan Africa is essential for policymakers and development practitioners aiming to foster sustainable economic growth and inclusive development in these regions.

Figure 1

Causal interactions: Informal sector, remittances and political stability in MENA and Sub-Saharan Africa (lag 1).



4.2. Latin America

4.2.1. Short-term analysis of remittances and the informal sector

Our analysis of the Latin America region reveals a clear positive correlation between remittances and the size of the informal sector. This correlation suggests that increases in remittances lead to a corresponding increase in the informal sector. The data indicates that remittances not only Granger-cause the informal sector, suggesting a predictive relationship from past remittance values to future informal sector size, but also show reverse causality. This reverse causality means that changes in the informal sector size can predict future remittance values, highlighting a complex, bidirectional relationship between these variables.

Moreover, while political stability alone does not show a causal relationship with the informal sector, it appears jointly with the informal sector to Granger cause remittances, as demonstrated in Table 4 and Figure 2.

4.2.2. Causal relationships beyond a one-period lag

The analysis suggests no significant causal links among remittances, the informal sector, and political stability beyond a one-period lag. This observation points to the predominance of short-term interactions between these variables, with minimal long-term influences detectable with the current data and modelling approach.

4.2.3. Implications for policy and research

Given the predominantly short-term causal relationships identified, policymakers and development agencies might need to focus on immediate interventions that address the impacts of remittances and the informal sector. It is crucial to continue research to unearth the long-term drivers influencing these variables in Latin America, which might include factors like global economic trends, technological advances, and changes in migration patterns.

4.2.4. Recommendations for further research and policy formulation

- **Model and data enhancements:** Employ alternative model specifications and expand lag structures to verify the robustness of these findings. Including more comprehensive variables could provide a deeper understanding of long-term influences.
- **Qualitative insights:** Augment quantitative analyses with qualitative research to explore the mechanisms underlying these relationships more thoroughly.
- **Regional and contextual considerations:** Recognize the potential for significant regional variations within Latin America, which could impact the generalizability of findings and necessitate tailored policy responses.

4.2.5. Understanding reverse causality

The observed reverse causality between the informal sector size and remittances is intriguing but must be interpreted with caution due to the limitations inherent in Granger causality tests, such as the potential for omitted variable bias. This might imply other underlying factors, such as economic conditions, that simultaneously affect both the informal sector and remittance flows.

4.2.6. Exploratory recommendations

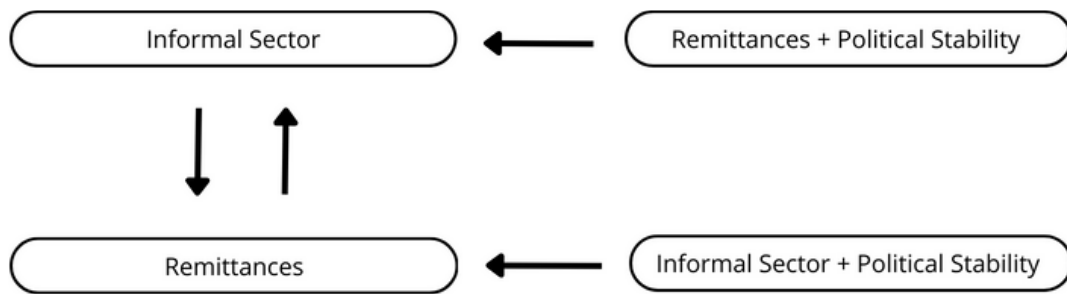
- **Theoretical development:** Craft a theoretical framework to explain potential mechanisms by which a larger informal sector could lead to increased remittances.
- **Control for confounders:** Integrate additional controls in the analytical models to address potential confounding variables that could influence both the informal sector and remittances.

The findings underscore the dynamic and interwoven relationship between remittances and the informal sector in Latin America, necessitating nuanced analyses and targeted policy interventions to harness these interactions for regional economic development. Further investigations are needed to fully understand the complexities of these relationships and to

design effective development strategies tailored to the unique contexts of Latin American countries.

Figure 2

Causal interactions: Informal sector, remittances and political stability in Latin America (lag 1)



4.3. Analysis of remittances, informal sector, and political stability in OECD countries

This section systematically examines the relationship between remittances, the informal sector, and political stability within the context of Organisation for Economic Co-operation and Development (OECD) countries. Utilizing Granger causality tests over multiple time frames—short, medium, and long-term—this analysis reveals consistent positive correlations and dynamic interplays that suggest nuanced policy implications.

The role of remittances in economic development has been extensively studied, yet its impact within developed economies, particularly in relation to the informal sector and political stability, requires deeper investigation. OECD countries, characterized by higher levels of economic development and political stability, offer a unique setting to explore these dynamics.

Granger causality tests were applied to a longitudinal data set to explore the relationships between remittances received, the informal sector, and political stability across different lags. The analysis was segmented into short-term (1 year), medium-term (2-3 years), and long-term (5 years) effects to distinguish immediate from delayed impacts.

4.3.1. Short-term and medium-term findings

- Remittances and informal sector: There is a consistent positive correlation where remittances Granger-cause changes in the informal sector's size.
- Political stability dynamics: Political stability interacts with remittances to jointly Granger-cause the informal sector. Additionally, there is a reciprocal causality between remittances and political stability, indicating a mutual influence within the economic-political nexus.

4.3.2. Long-term analysis

- Persistence of remittance effects: The influence of remittances on the informal sector remains robust even in the long term.
- Diminishing influence of political stability: Over extended periods, political stability's direct influence on remittances dissipates, underscoring possible adaptation or equilibration effects within political systems.

4.3.3. Discussion

The findings suggest that remittances contribute to the size and dynamics of the informal sector in OECD countries. Unlike in developing countries, where the informal sector often arises from necessity, in OECD countries, it may reflect strategic economic choices influenced by remittance inflows. Moreover, the reciprocal relationship between remittances and political stability highlights the economic contributions to political conditions.

4.3.4. Contextual factors in OECD countries:

The data provided is specifically for OECD countries. This context is important when interpreting the results because:

- **OECD countries** tend to have more developed economies compared to the global average. This can influence the nature of the informal sector and the role of remittances. The informal sector in OECD countries might be more involved in services or niche goods production, rather than basic needs as in developing countries. Remittances in OECD countries might be used for different purposes compared to developing countries, potentially including investment in established businesses, or supporting family members pursuing education or starting businesses within the informal sector.
- **Political stability** is generally higher in OECD countries on average. This can affect the relationship between political stability and the informal sector. A more stable political environment might lead to a smaller informal sector as businesses are incentivized to formalize. However, even in stable OECD countries, political changes

or specific policies might still influence the size and characteristics of the informal sector.

4.3.5. Implications for policy and research

- Policy directions:

Sector-specific strategies: Policies aimed at managing the informal sector must consider its unique characteristics in OECD contexts, potentially focusing on formalization incentives and regulatory adjustments.

Remittance management: Understanding the cyclical nature of remittances and their impact on both the economy and political stability can help in crafting balanced fiscal and monetary policies.

- Research recommendations:

Further Causal Analysis: Additional studies should aim to unpack the underlying mechanisms of these relationships, perhaps through mixed methods approaches that incorporate qualitative data.

Comparative Studies: Examining these dynamics across different OECD sub-regions could illuminate diverse economic behaviours and policy outcomes.

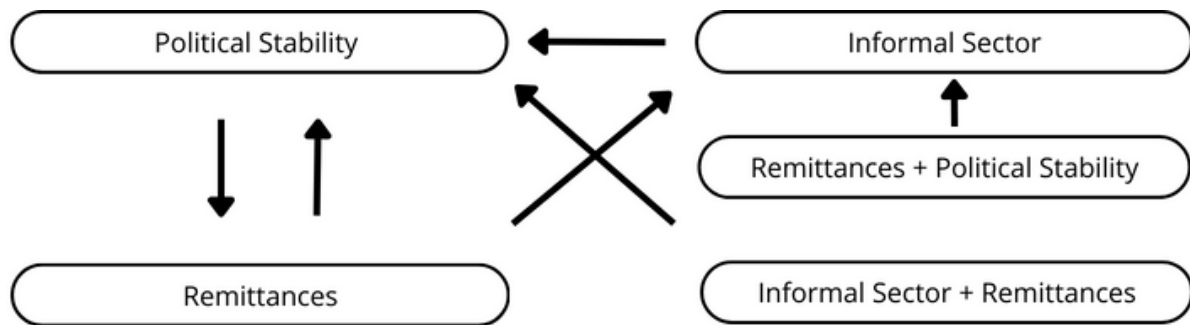
In addition, variations within OECD countries: There might be significant variations within the OECD group. Economic development levels, political systems, and cultural factors can all influence the relationships between remittances, political stability, and the informal sector.

Direction of causality: While the Granger causality test suggests remittances influence the informal sector, it's important to remember that causality can run in both directions. A larger informal sector might also attract more migrant workers who send remittances back home. While a majority of OECD countries are net recipients of migrants, they are also net senders of remittances. To explore this aspect, we have collected data on outward remittances from OECD countries. We have used these outward remittances as a proxy for inward migration. These results are provided and discuss in the next section.

This comprehensive analysis underscores the significant yet complex roles that remittances play in shaping the informal sector and influencing political stability within OECD countries. The insights garnered here should inform both scholarly discourse and policy debates, aiming to harness the potential benefits of remittances while mitigating associated risks. Further

research is crucial to refine our understanding and to substantiate these findings across broader contexts and extended time frames.

Figure 3 Causal interactions: Informal sector, remittances, and political stability in OECD countries (lag 2)



4.4. Remittances paid and migration dynamics in OECD countries: An in-depth analysis

In an increasingly globalized world, the flow of remittances and migration has significant economic and social impacts, particularly within OECD countries which are characterized by complex interdependencies between developed and developing economies. This section explores the intricacies of outward remittances used as a proxy for inward migration, examining their relationships with the informal sector and political stability in regions like the USA/Canada and EU/UK.

Data on outward remittances was collected from world bank database. Granger causality tests were applied to assess the predictive power of one variable over another across multiple time lags.

The specific lags considered ranged from 1 to 5 years, providing insights into both immediate and delayed effects (Table 10 to 14).

4.4.1. Short-term dynamics (Lag 1):

The analysis at this stage did not reveal any significant causal relationships among the variables, indicating that the immediate effects of remittances on the informal sector and political stability are minimal or delayed.

4.4.2. Medium to long-term dynamics (Lags 2 to 5)

- Informal sector influence on remittances and political stability: The size of the informal sector consistently predicts outward remittances and political stability, with p-values indicating strong statistical significance (0.003 and 0.001 at lag 2, respectively).

These results suggest that a larger informal sector, possibly indicative of economic underdevelopment or regulatory gaps, drives higher remittance outflows. This could be due to increased economic pressures or as a coping mechanism for economic disparities.

- Lack of reciprocal causality between migration and political stability: No evidence was found that outward remittances influence the informal sector size or political stability, suggesting that the causal pathway is predominantly one-directional from the informal sector. This one-way relationship highlights the potential of the informal sector as a precursor to changes in migration patterns and political dynamics rather than a consequence of these factors.

4.4.3. Interpretation and policy implications

- Economic and social impacts of the informal sector: The findings that the informal sector drives remittance flows suggest that individuals might be relying on informal employment to meet financial obligations, both domestically and abroad. A significant informal sector might also reflect social inequities or inadequate economic integration, which could fuel political discontent or instability.
- Policy recommendations: Policies aimed at reducing the size of the informal sector through formalization could also decrease outward remittances—used as a proxy for inward migration—and enhance economic stability. Given the lack of direct impact of migration on political stability, economic policies should aim at broader socio-economic reforms to address underlying issues of inequality and economic disparity. While controlling migration flows alone may not influence political stability directly, well-rounded migration policies that include economic integration for migrants could indirectly stabilize political environments by reducing the reliance on the informal sector.

The complex interplay between outward remittances, the informal sector, and political stability in OECD countries underscores the need for comprehensive and integrated policy approaches that consider economic, social, and political factors. The Granger causality results point towards the informal sector as a key element in understanding and managing the dynamics of migration and political stability. Further research is essential to unravel the underlying

mechanisms and to ensure that policies are effectively tailored to the unique challenges and opportunities within OECD countries.

4.5. Analysis of remittance dependence and economic dynamics in high remittance-to-GDP ratio countries

There might be significant variations within each large geopolitical set. Remittance dependence³ can influence the relationships between remittances, political stability, and the informal sector. To address this possibility, this section analyzes the influence of remittances on the informal sector and political stability in countries with a remittance-to-GDP ratio exceeding the OECD average of 0.84%⁴. By utilizing a panel VAR-Granger causality model, we assess the dynamics among remittances, the informal sector size, and political stability, focusing on countries heavily dependent on remittances.

Countries with a remittance-to-GDP ratio above 0.84% were selected to highlight the impact of high remittance inflows. A panel VAR-Granger causality test was employed to determine the predictive relationships among the variables over selected time lags.

4.5.1. Results and analysis

- Remittances and economic activity: There is a strong Granger-causal relationship from the size of the informal sector in the past (\log_{inf}) to current remittances (p-value = 0.000), indicating a significant predictive power of past informal sector activities on current remittance volumes. Political stability shows a weaker influence on remittances (p-value = 0.168), suggesting potential, albeit non-significant, causal effects at the 5% level.
- Impact on the informal sector: Past remittances significantly Granger-cause the size of the informal sector (p-value = 0.019), implying that fluctuations in remittances can predict changes in the informal sector size. No significant causal influence from political stability to the informal sector was detected (p-value = 0.380).

³ Economic development levels, political systems, and cultural factors can all influence the relationships between remittances, political stability, and the informal sector.

⁴ We analyze the impact of remittances on the informal sector and political stability in countries with high remittance dependence defined as a remittance-to-GDP ratio exceeding the OECD average of 0.84% and the median of our sample evaluated to 1.45%. We found the same results.

- **Political Stability Dynamics:** Neither remittances nor the informal sector size show significant Granger-causal effects on political stability (both p-values above 0.48), indicating that these economic variables do not predict changes in political conditions.

4.5.2. Interpretation and Contextualization

The results underscore a strong linkage between remittances and the informal sector in countries with high remittance dependence. This suggests that remittances are a pivotal factor in driving economic activities, particularly within the informal sector, which might include activities from self-employment to small-scale enterprises that do not formally register their economic contributions.

The lack of significant causal links from remittances or the informal sector to political stability suggests that while economic factors are crucial, they do not directly translate into political changes in these contexts. This may indicate that political dynamics are influenced by other structural or external factors.

Given the significant role of remittances in supporting the informal sector, policies aimed at enhancing the productive use of remittances could foster more sustainable economic development. This could involve measures to facilitate greater financial inclusion, improve investment opportunities for remittance funds, or provide better support systems for small and informal businesses.

The potential, albeit weak, influence of political stability on remittances highlights the need for stable governance structures that can enhance economic confidence and possibly influence economic behaviors related to remittance flows.

The weak link between political stability and remittances requires additional exploration to fully understand the nuances of this relationship. Further studies could also assess the impact of different model specifications, lag structures, and include more nuanced socio-economic variables to broaden the understanding of these dynamics.

The analysis provides crucial insights into the dynamics of remittances, the informal sector, and political stability in countries heavily dependent on remittances. The findings highlight the importance of remittances in shaping economic conditions, particularly within the informal sector, and indicate that political factors may not directly influence these economic outcomes. Continued research is essential to delve deeper into these relationships and to guide effective

policy-making that leverages remittances for economic development while ensuring political stability.

Conclusion

This study used the PVAR model and the Granger causality test to analyse the subtle relationship between the informal sector, political stability, and remittances in four large geopolitical sets (MENA and SSA, Latin America and OECD countries) using data from 1996 to 2017.

The findings offer a compelling overview of the dynamics between remittances, the informal sector, and political stability across these regions. Specifically, the study shows how remittances significantly boost the informal sector's size in the short term, particularly in the MENA, Sub-Saharan Africa, and Latin America. This relationship, characterized by Granger causality, indicates that remittances are a predictive factor for changes in the informal sector, often reflecting the sector's expansion due to funding of informal activities and increased demand for goods and services. Notably, the impact of political stability on the informal sector appears negligible, suggesting that remittances play a more decisive role in the immediate economic adjustments within these regions.

In MENA and Sub-Saharan Africa, the influence of remittances on the informal sector diminishes over time, revealing that their immediate effect primarily addresses on basic needs rather than long-term business investment. The absence of a strong causal relationship between political stability and the informal sector highlights the region's resilience to political fluctuations, with the informal sector as an adaptive mechanism.

Latin America presents a unique case with a bidirectional relationship between remittances and the informal sector, suggesting a complex, interdependent interaction. However, like in other regions, this influence wanes beyond the short term, underscoring the transient nature of remittances' impact.

The OECD countries show a sustained influence of remittances on the informal sector over longer periods, unlike the developing regions. This persistence may reflect the different roles remittances play in more developed economies, potentially influencing more strategic economic decisions rather than mere survival strategies.

This comprehensive analysis highlights the need for tailored policy responses that consider the temporal and regional dynamics of remittances and their broader economic implications. Future research should focus on further exploring the underlying mechanisms of these relationship, employing both qualitative and quantitative methods to gain a deeper understanding of how remittances can be leveraged for sustainable economic development and stability in diverse geopolitical contexts.

Synthetic Table of Identified Causalities by Region

Causality	MENA and SSA	Latin America	OECD	OECD Remittances Paid (Migration)	Remittances/GDP > 0.84%
Remittances → Informal Sector	YES	YES	YES	NO	YES
Informal Sector → Remittances	NO	YES	NO	YES	YES
Political Stability → Remittances	NO	NO	YES	NO	NO
Remittances + Political Stability → Informal Sector	YES	YES	YES	NO	YES
Political Stability → Informal Sector	NO	NO	NO	NO	NO
Remittances → Political Stability	NO	NO	YES	NO	NO
Informal Sector → Political Stability	NO	NO	YES	YES	NO

Legend :

- *YES: Causality identified in the study.*
- *NO: No causality identified in the study.*

References

- Abbas, F., Masood, A., & Sakhawat, A. (2017). What determine remittances to Pakistan? The role of macroeconomic, political and financial factors. *Journal of Policy Modeling*, 39(3), 519–531.
- Amaral, P. S., & Quintin, E. (2006). A competitive model of the informal sector. *Journal of Monetary Economics*, 53, 1541–1553. <https://doi.org/10.1016/j.jmoneco.2005.07.016>
- Aydas, O. T., Metin-Ozcan, K., & Neyapti, B. (2005). Determinants of workers' remittances: The case of Turkey. *Emerging Markets Finance and Trade*, 41(3), 53–69. <https://doi.org/10.1080/1540496X.2005.11052609>
- Catrinescu, N., Leon-Ledesma, M., Piracha, M., & Quillin, B. (2009). Remittances, institutions, and economic growth. *World Development*, 37(1), 81–92.
- Centeno, M. A., & Portes, A. (2006). The informal economy in the shadow of the state. *Out of the shadows: Political action and the informal economy in Latin America* (23–48).
- Chatterjee, S., & Turnovsky, S. J. (2018). Remittances and the informal economy. *Journal of Development Economics*, 133, 66–83.
- Dabla-Norris, E., Gradstein, M., & Inchauste, G. (2008). What causes firms to hide output? The determinants of informality. *Journal of Development Economics*, 85(1–2), 1–27.
- Elbahnasawy, N. G., Ellis, M. A., & Adom, A. D. (2016). Political instability and the informal economy. *World Development*, 85, 31–42. <https://doi.org/10.1016/j.worlddev.2016.04.009>
- Friedman, B. A., & Hall, R. (2014). The relationship between effective governance and the informal economy. *International Journal of Business and Social Science*, 5(9), 51–58.
- Ihrig J., & Moe. K. (2004). Lurking in the shadows: The informal sector and government policy. *Journal of Development Economics*, 73.
- Loayza N. V. (1996). The economics of the informal sector: A simple model and some empirical evidence from Latin America. *Carnegie-Rochester Conference Series on Public Policy*, 45, 129–162.

- Medina, L., & Schneider, F. (2019, December). *Shedding light on the shadow economy: A global database and the interaction with the official one* (CESifo Working Paper Series No.).
- Njangang, H., Noubissi, E., & Nkengfack, H. (2018). Do remittances increase the size of the informal economy in Sub-Saharan African countries? *Economics Bulletin*, 38(4), 1997–2007.
- Schneider F., & Enste, D. H. (2000), Shadow economies: Size, causes and consequences. *Journal of Economic Literature*, 38, 77–114.
- Tanzi, V. (1983). The underground economy in the United States: Annual estimates, 1930–80. *Staff Papers (International Monetary Fund)*, 30(2), 283–305.
- Tanzi, V. (1999). Uses and abuses of estimates of the underground economy. *The Economic Journal*, 109(456), F338–F347.
- Akaike, H. (1969). Fitting autoregressive models for prediction. *Annals of the Institute of Statistical Mathematics*, 21, 243-247.
- Akaike, H. (1977). On entropy maximization principle. In: Krishnaiah, P.R. (Ed.), *Applications of Statistics*. Amsterdam: North-Holland.
- Andrews, D.W.K. and B. Lu (2001). Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics*, 101(1), 123- 164.
- Granger, C.W.J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37(3), 424-438.
- Lutkepohl, H. (1993). *Introduction to Multiple Time Series Analysis*, 2nd Ed. New York: Springer.
- Lutkepohl, H. (2005). *New Introduction to Multiple Time Series Analysis*. New York: Springer.
- Sims, C.A. (1980). Macroeconomics and reality. *Econometrica*, 48(1), 1-48.

Appendix 1: Table of correlation and causality

Table 1

Correlation and causality in MENA Region and Sub-Saharan Africa (Lag 1)

Number Of observations: 409

Number of panels: 23

Ave. No. Of T: 17.783

LogInformal			
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.8453803	0.0601146	-0.1124868
Std. Err.	0.053754	0.0243894	0.0629
z	15.78***(0.000)	2.46*(0.014)	-1.79 (0.074)
95% Conf.	0.7403744	0.123123	-0.2357685
Interval	0.9503861	0.107917	0.107949

LogRem			
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.338493	0.9679429	0.0366235
Std. Err.	0.1811349	0.924027	0.1697083
z	0.19(0.852)	10.48***(0.000)	0.22(0.829)
95% Conf.	-0.3211687	0.786837	0.2959987
Interval	0.3888672	1.149049	0.3692457

PS			
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.0535468	-0.0366996	0.9963843
Std. Err.	0.0873081	0.0346203	0.0752386
z	0.61(0.540)	-1.06(0.289)	13.24***(0.000)
95% Conf.	-0.1175739	-0.1045541	0.8489193
Interval	0.2246675	0.0311548	1.143849

Granger test:

Equation \ Excluded	LogInformal			LogRem			PS		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	6.075	3.198	6.140	0.035	0.047	0.047	0.376	1.124	2.317
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.014	0.074	0.046	0.852	0.829	0.977	0.540	0.289	0.314

Panel VAR (p-VAR)

- **GMM Estimation:** This indicates that the model was estimated using the Generalized Method of Moments (GMM), a technique commonly used in panel data analysis to address potential endogeneity and correlation issues.
- **LogInformal, LogRem, ps:** These are the variables included in the p-VAR model. The "L1." in front of them means they are lagged by one period.
- **Coefficients and Standard Errors:** The coefficients show the estimated relationships between the variables. For example, a one-unit increase in lagged LogInformal is associated with an 0.845 increase in current LogInformal. The standard errors measure the uncertainty around these estimates.
- **z and P>z:** These are the z-statistics and p-values for the coefficients. They test whether the coefficients are statistically significant (i.e., different from zero). In this case, most lagged coefficients are significant, indicating that the variables are likely to influence each other over time.

Granger Causality Tests

- **Ho and Ha:** The null hypothesis (Ho) is that the excluded variable does not Granger-cause the equation variable. The alternative hypothesis (Ha) is that it does.
- **chi2, df, Prob > chi2:** These are the chi-squared statistic, degrees of freedom, and p-value for the Granger causality test. The p-value indicates the probability of observing a test statistic as extreme as or more extreme than the one calculated, assuming the null hypothesis is true.

Interpretation of Granger Causality Results

- **LogRem Granger-causes LogInformal:** The p-value (0.014) is less than the conventional significance level of 0.05, so we reject the null hypothesis and conclude that LogRem Granger-causes LogInformal. This means that past values of LogRem help predict current values of LogInformal.
- **ps Granger-causes LogInformal:** The p-value (0.074) is slightly above 0.05, so we fail to reject the null hypothesis at the 5% level. However, it is close to being significant, suggesting a potential weak Granger causal relationship.
- **No other significant Granger causal relationships:** The other p-values are all above 0.05, so we fail to reject the null hypothesis for these pairs of variables.

Table 2*Correlation and causality in MENA Region and Sub-Saharan Africa (Lag 2)*

Number Of observations: 385

Number of panels: 22

Ave. No. Of T: 17.500

LogInformal						
LogInformal		LogRem		PS		
Lag1	Lag2	Lag1	Lag2	Lag1	Lag2	
Coef.	0.7396507	0.0944383	0.736987	-0.127218	-0.1156011	0.0011914
Std. Err.	0.1518668	0.1356557	0.0302511	0.0148645	0.0651644	0.0353576
z	4.87***(0.000)	0.70(0.486)	2.44***(0.015)	-0.86(0.392)	-1.77(0.076)	0.03(0.973)
95% Conf.	0.4419072	-0.1714419	0.0144077	-0.0418556	-2.43321	-0.0681083
Interval	1.037214	0.3603185	0.1329898	0.0164121	0.0121188	0.0704911

LogRem						
LogInformal		LogRem		PS		
Lag1	Lag2	Lag1	Lag2	Lag1	Lag2	
Coef.	0.326672	-0.2203865	0.9503132	-0.0204795	-0.219315	0.1270841
Std. Err.	0.3448019	0.2667508	0.1149867	0.1003069	0.2238874	0.1931651
z	0.95(0.343)	-0.83(0.409)	8.26***(0.000)	-0.21(0.837)	-0.10(0.922)	0.66(0.511)
95% Conf.	-0.3491273	-0.7432085	0.7249435	0.2171773	-0.4607427	-0.2515126
Interval	1.002471	0.3024355	1.175683	0.1760183	0.4168798	0.5056809

PS						
LogInformal		LogRem		PS		
Lag1	Lag2	Lag1	Lag2	Lag1	Lag2	
Coef.	0.644087	-0.036196	-0.0326188	0.0079643	0.9969981	-0.0472671
Std. Err.	0.1181979	0.0864544	0.0386419	0.0256022	0.1012987	0.888518
z	0.54(0.586)	-0.42(0.675)	-0.84(0.399)	0.31(0.756)	9.84***(0.000)	-0.53(0.595)
95% Conf.	-0.167255	-0.2056436	-0.1083555	-0.0422151	0.7984564	-0.2214133
Interval	0.2960724	0.1332516	0.0431179	0.0581437	1.19554	0.1268792

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	6.068	3.164	6.247	0.912	0.579	1.493	0.305	0.713	2.079
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.048	0.206	0.181	0.634	0.749	0.828	0.859	0.700	0.721

Table 3
Correlation and causality in MENA Region and Sub-Saharan Africa (Lag 3)

Number Of observations: 362

Number of panels: 22

Ave. No. Of T: 16.455

LogInformal									
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.7951596	0.1694154	-0.1180774	0.0594186	-0.0080147	-0.0022929	-0.1038448	-0.0019902	0.0038996
Std. Err.	0.1558166	0.1555772	-0.054191	0.0282964	0.0187167	0.0105527	0.0693117	0.0409488	0.036066
z	5.10***(0.000)	1.09(0.276)	-2.18(0.029)	2.10*(0.036)	-0.43(0.668)	-0.22(0.828)	-1.50(0.134)	-0.05(0.961)	0.11(0.914)
95% Conf.	0.4897646	-0.1355102	-0.2242899	0.0039587	-0.0446988	-0.229758	-0.2396933	-0.0822485	0.0667884
Interval	1.100555	0.4743411	-0.0118649	0.1148785	0.0286694	0.0183901	0.0320036	0.078268	0.0745876

LogRem									
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.3866773	-1.1797432	-0.0789417	0.938758	0.0348156	-0.610517	-0.0185637	0.1480924	-0.0271387
Std. Err.	0.3575031	0.2853772	0.1888534	0.119741	0.1289606	0.0840281	0.2455316	0.2436163	0.1584798
z	1.08(0.279)	-	-0.42(0.676)	7.84***(0.000)	0.27(0.787)	-0.73(0.467)	-0.08(0.940)	0.61(0.543)	-0.17(0.864)
95% Conf.	-0.3140159	-0.7390722	-0.4490876	0.7040699	-0.2179425	-0.2257437	-0.4997967	-0.3293868	-0.3377533
Interval	1.08737	0.3795859	0.0745876	1.173446	0.2875737	0.1036403	0.4626693	0.6255717	0.283476

PS									
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.0875825	-0.0010517	-0.0478968	-0.0399565	0.0178049	-0.007493	0.9594889	-0.068963	0.053058
Std. Err.	0.1213867	0.1109015	0.0872313	0.403466	0.027942	0.0251451	0.106301	0.0841605	0.0482764
z	0.72(0.471)	-	-0.55(0.583)	-0.99(0.322)	0.64(0.524)	-0.30(0.766)	9.03***(0.000)	-0.82(0.413)	1.10(0.272)
95% Conf.	-0.1503312	-0.2184146	-0.2188671	-0.1190344	-0.0369604	-0.0567798	0.7511428	-0.2339146	-0.0415619
Interval	0.3254961	0.2163111	0.1230735	0.0391215	0.0725703	0.0417872	1.167835	0.0959886	0.14678

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	4.588	2.636	4.837	1.220	0.594	2.041	0.749	1.153	3.128
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.205	0.451	0.565	0.748	0.898	0.916	0.862	0.764	0.793

Table 4
Correlation and causality in Latin America Region (Lag 1)

Number Of observations: 399

Number of panels: 21

Ave. No. Of T: 19.000

	LogInformal		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.8392321	0.1006696	-0.0185053
Std. Err.	0.0622309	0.0439035	0.0395146
z	13.49***(0.000)	2.29*(0.022)	-0.47(0.640)
95% Conf.	0.7172618	0.0146203	-0.0959525
Interval	0.9612024	0.1867189	0.058942

	LogRem		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.8546292	0.282111	0.641814
Std. Err.	0.2416439	0.1731138	0.1671121
z	3.54***(0.000)	1.63(0.103)	0.38(0.701)
95% Conf.	0.3810335	-0.0571858	-0.2633522
Interval	1.328225	0.6214077	0.391715

	ps		
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.0607033	-0.0054925	0.8505773
Std. Err.	0.0882709	0.053449	0.1102841
z	0.69(0.492)	-0.10(0.918)	7.71***(0.000)
95% Conf.	-0.1123046	-0.1102507	0.6344244
Interval	0.2337111	0.992657	1.06673

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInforml	LogRem	ALL
chi2	5.258	0.219	6.364	12.509	0.148	15.432	0.473	0.011	2.827
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.022	0.640	0.042	0.000	0.701	0.000	0.492	0.918	0.243

Table 5
Correlation and causality in Latin America Region (Lag 2)

Number Of observations: 376
 Number of panels: 21
 Ave. No. Of T: 17.905

LogInformal						
LogInformal		LogRem		PS		
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.5189676	-0.0020748	0.3389896	0.0234207	0.0089076	-0.0864376
Std. Err.	0.4199867	0.1215327	0.2324969	0.0195498	0.0555605	0.0603564
z	1.24(0.217)	-0.02(0.986)	1.46(0.145)	1.20(0.231)	0.16(0.873)	-1.43(0.152)
95% Conf.	-0.3041912	-0.2402744	-0.1166959	-0.0148962	-0.99989	-0.204734
Interval	1.342126	0.2361249	0.794675	0.0617376	0.1178041	0.0318588

LogRem						
LogInformal		LogRem		PS		
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.2495699	0.0402886	0.7392583	-0.0415592	-0.0612996	0.0410912
Std. Err.	0.7517265	0.1548751	0.5107101	0.196723	0.0741749	0.053868
z	0.33(0.740)	0.26(0.759)	1.45(0.148)	-2.11(0.035)	-0.83(0.409)	0.76(0.446)
95% Conf.	-1.223787	-0.263261	-0.2617151	-0.0801162	-0.2066797	-0.064488
Interval	1.722927	0.3438383	1.740232	-0.0030023	0.0840804	0.1466705

PS						
LogInformal		LogRem		PS		
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.0596969	0.0188725	0.0451681	0.0301917	0.827837	0.0920784
Std. Err.	0.530627	0.1564046	0.3119626	0.0209521	0.1063846	0.1152653
z	-0.115(0.910)	0.12(0.904)	0.14(0.885)	1.44(0.150)	7.78***(0.000)	0.80(0.424)
95% Conf.	-1.099707	-0.2876749	-0.5662673	-0.0108736	0.6193036	-0.1338374
Interval	0.980313	0.3254199	0.6566035	0.071257	1.036324	0.3179942

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInforml	ps	ALL	LogInformal	LogRem	ALL
chi2	2.542	0.086	4.520	0.546	1.061	1.264	0.015	2.253	8.753
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.281	0.352	0.340	0.761	0.588	0.867	0.992	0.324	0.068

Table 6
Correlation and causality in Latin America Region (Lag 3)

Number Of observations: 354

Number of panels: 21

Ave. No. Of T: 16.857

LogInformal									
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.1713452	0.1768504	-0.0269669	0.4086816	0.0943397	0.0299244	-0.0350999	0.0203511	-0.119838
Std. Err.	1.093487	0.3322144	0.0831168	0.4369983	0.1635226	0.0540839	0.0863595	0.1141009	0.1226621
z	0.16(0.875)	0.53(0.594)	-0.32(0.746)	0.94(0.350)	0.58(0.564)	0.55(0.580)	-0.41(0.684)	0.18(0.858)	-0.98(0.329)
95% Conf.	-1.97185	-0.4742779	-0.1898728	-0.4478193	-0.2261587	-0.076078	-0.2043614	-0.2032826	-0.3602513
Interval	2.31454	0.8279787	0.135939	1.265183	0.4148382	0.1359268	0.1341616	0.2439848	0.1205753

LogRem									
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.826089	-0.1128749	-0.0627139	0.607746	-0.1520875	-0.0472742	-0.25463	-0.0767457	0.1265292
Std. Err.	1.786664	0.4683733	0.1362355	0.7961304	0.2089404	0.0850593	0.1047115	0.1814431	0.233297
z	0.46(0.644)	-0.24(0.810)	-0.46(0.645)	0.79(0.429)	0.73(0.467)	-0.56(0.578)	-0.24(0.808)	0.42(0.672)	0.54(0.588)
95% Conf.	-2.675587	-1.03087	-0.3291306	-0.8997632	-0.5616032	-0.2139873	-0.2306937	-0.4323677	-0.3307245
Interval	4.328005	0.80512	0.2043028	2.115172	0.2574282	0.1194389	0.1797676	0.2788763	0.5837829

PS									
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-0.5138577	0.1999311	-0.048549	0.1309883	0.1790267	0.0278241	0.7512232	0.164115	-0.0116789
Std. Err.	1.19056	0.3212893	0.1235548	0.4813578	0.1592799	0.0623832	0.1129051	0.1534169	0.120615
z	-0.43(0.666)	0.62(0.534)	-0.39(0.694)	0.27(0.786)	1.12(0.261)	0.45(0.656)	6.65***(0.000)	1.07(0.285)	-0.10(0.923)
95% Conf.	-2.847313	-0.4297843	-0.2907119	-0.8124558	-0.1331563	-0.0944447	0.5299332	-0.1365766	-0.24808801
Interval	1.819597	0.8296465	0.1936139	1.074432	0.4912096	0.1500929	0.9725132	0.4648065	0.2247222

Granger test:

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInforml	ps	ALL	LogInforml	LogRem	ALL
chi2	1.259	1.736	2.093	0.413	0.613	0.724	0.544	2.635	11.126
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.739	0.629	0.911	0.938	0.894	0.994	0.909	0.451	0.085

Table 7
Correlation and causality in OECD Countries (Lag 1)

Number Of observations: 565

Number of panels: 38

Ave. No. Of T: 14.868

LogInformal			
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.8953818	0.0692069	0.0486066
Std. Err.	0.0257093	0.0203035	0.0593826
z	34.83***(0.000)	3.41**(0.001)	0.82(0.413)
95% Conf.	0.8449925	0.0294128	-0.0677811
Interval	0.9457711	0.109001	0.1649944

LogRem			
	LogInformal	LogRem	ps
	Lag1	Lag1	Lag1
Coef.	-0.0462552	0.9196654	0.1940397
Std. Err.	0.0698064	0.07842264	0.1179327
z	-0.66(0.508)	11.73***(0.000)	1.65(0.100)
95% Conf.	-0.1830733	0.7659525	-0.0371042
Interval	0.0905629	1.073378	0.4251835

ps			
	LogInformal	LogRem	PS
	Lag1	Lag1	Lag1
Coef.	0.0389493	-0.0470712	0.8327858
Std. Err.	0.0521309	0.0465519	0.1037744
z	0.75(0.455)	-1.01(0.312)	8.02***(0.000)
95% Conf.	-0.0622254	-1.383113	0.6293918
Interval	0.1411241	0.0441689	1.03618

Granger test :

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInforml	ps	ALL	LogInforml	LogRem	ALL
chi2	11.619	0.670	12.873	0.439	2.707	3.266	0.588	1.022	1.051
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.001	0.413	0.002	0.508	0.100	0.195	0.455	0.312	0.591

Number Of observations: 526

Number of panels: 38

Ave. No. Of T: 13.842

Table 8 *Correlation and causality in OECD Countries (Lag 2)*

LogInformal						
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	1.167744	-0.2832315	0.0457344	0.03476	0.1100709	-0.0018152
Std. Err.	0.0641595	0.0501351	0.351472	0.160856	0.0550295	0.0296677
z	18.20***(0.000)	-5.65***(0.000)	1.30(0.193)	2.13*(0.033)	2.00*(0.045)	-0.06(0.951)
95% Conf.	1.041993	-0.3814946	-0.0231528	0.0027488	0.0022151	-0.0599627
Interval	1.293494	-0.1849685	0.1146215	0.0658033	0.2179268	0.0563324

LogRem						
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.0383938	0.0443598	0.909262	-0.01065172	0.1656521	-0.1128504
Std. Err.	0.1329821	0.1145663	0.1224874	0.0506786	0.1003116	0.0618005
z	-0.29(0.773)	0.39(0.699)	7.42***(0.000)	-2.10 (0.036)	1.65*(0.099)	-1.83*(0.068)
95% Conf.	-0.200034	-0.180186	0.669191	-0.2058454	-0.0309549	-0.2339773
Interval	0.2222463	0.2689055	1.149333	-0.0071889	0.3622591	0.0082764

PS						
	LogInformal		LogRem		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.3016356	0.2791754	-0.1445049	0.1021394	0.9312334	-0.1523752
Std. Err.	0.1125404	0.885264	0.0751706	0.0353762	0.0978688	0.0580343
z	-2.68***(0.007)	3.15***(0.002)	-1.92*(0.055)	2.89***(0.004)	9.52***(0.000)	-2.63***(0.009)
95% Conf.	-0.5222109	0.1056669	-0.2918365	0.0328034	0.739414	-0.2661204
Interval	-0.0810604	0.4526839	0.0028266	0.1714754	1.123053	-0.03863

Granger test :

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	17.474	4.815	22.016	0.159	6.617	7.258	9.965	8.405	22.502
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.000	0.090	0.000	0.924	0.037	0.123	0.007	0.015	0.000

Table 9
Correlation and causality in OECD Countries (Lag 3)

Number Of observations: 487

Number of panels: 38

Ave. No. Of T: 12.816

LogInformal									
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	1.136251	-0.2982462	0.0247549	0.115877	-0.0099529	0.0240281	0.1351462	-0.0285333	0.0464022
Std. Err.	0.0697511	0.072963	0.0470291	0.0582035	0.0221935	0.0177107	0.709566	0.0315618	0.0424375
z	16.29***(0.000)	-4.09***(0.000)	0.53(0.599)	1.99*(0.046)	-0.45(0.654)	1.36(0.175)	1.90*(0.057)	-0.90(0.366)	1.09(0.274)
95% Conf.	0.9995607	-0.4412511	-0.0674204	0.0018002	-0.0534514	-.0106843	-0.0039262	-0.0903933	-0.0367737
Interval	1.272941	-0.1552412	0.1169302	0.2299538	0.0335456	0.0587405	0.2742186	0.0333267	0.1295781

LogRem									
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.0527431	-0.158474	0.0793508	0.8967679	-0.0711191	-0.0257777	0.0441247	-0.1040292	-0.0215873
Std. Err.	0.1287574	0.1558165	0.1003682	0.11663246	0.0547125	0.0427281	0.1012991	0.0547334	0.0645955
z	0.41(0.682)	-1.02(0.309)	0.79(0.429)	7.69***(0.000)	-1.30(0.194)	-0.60(0.546)	0.44(0.663)	-1.90*(0.057)	-0.33(0.738)
95% Conf.	-0.1996168	-0.4638687	-0.1173673	0.6681683	-0.1783537	-0.1095232	-0.1544179	-0.2113047	-0.1481922
Interval	0.305103	0.1469208	0.276088	1.125368	0.0361155	0.0579678	0.2426672	0.0032464	0.1050176

PS									
	LogInformal			LogRem			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-0.2697594	0.3540739	-0.0640324	-0.2214773	0.1349376	-0.116693	0.9211429	-0.1847498	0.0821311
Std. Err.	0.1192152	0.1223949	0.0908496	0.1153001	0.0521231	0.0469624	0.1240155	0.0687993	0.0720053
z	-2.26*(0.024)	2.89***(0.004)	-0.70(0.481)	-1.92*(0.055)	2.59*(0.010)	-0.25(0.804)	7.43***(0.000)	-2.69***(0.007)	1.14(0.254)
95% Conf.	-0.503417	0.1141843	-0.2420943	-0.4474614	0.0327782	-0.103714	0.6780769	-0.3195939	-0.0589967
Interval	-0.0361019	0.5939635	0.1140295	0.0045068	0.237097	0.0803754	1.164209	-0.0499056	0.2232589

Granger test :

Equation \ Excluded	LogInformal			LogRem			ps		
	LogRem	ps	ALL	LogInformal	ps	ALL	LogInformal	LogRem	ALL
chi2	22.744	4.098	28.767	1.248	5.601	6.383	11.732	11.470	26.537
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.000	0.251	0.000	0.742	0.133	0.382	0.008	0.009	0.000

Table 10*Correlation and causality in OECD Countries (Lag 1): remittances paid*

Number Of observations: 732

Number of panels: 38

Ave. No. Of T: 19.263

	LogInformal		
	LogInformal	LogRemPaid	PS
	Lag1	Lag1	Lag1
Coef.	0.9580286	-0.0059135	0.0007373
Std. Err.	0.0567127	0.0174086	0.0341418
z	16.89***(0.000)	-0.34(0.743)	0.02(0.983)
95% Conf.	0.8468737	-0.0400338	-0.0661794
Interval	1.069183	0.0282068	0.067654

	LogRemPaid		
	LogInformal	LogRemPaid	PS
	Lag1	Lag1	Lag1
Coef.	0.2069279	0.8769278	-0.1369653
Std. Err.	0.2321372	0.0908481	0.140922
z	0.89(0.373)	9.65***(0.000)	-0.97(0.331)
95% Conf.	-2.2480525	0.6988689	-0.4131672
Interval	0.6619084	1.054987	0.1392367

	PS		
	LogInformal	LogRemPaid	PS
	Lag1	Lag1	Lag1
Coef.	0.0795029	-0.154484	0.9874803
Std. Err.	0.1489162	0.441194	0.0736594
z	0.53(0.593)	-0.35(0.726)	13.41***(0.000)
95% Conf.	-0.2123675	-0.1019208	0.8431105
Interval	0.3713732	0.071024	1.13185

Granger test:

Equation \ Excluded	LogInformal			LogRemPaid			PS		
	LogRemPaid	PS	ALL	LogInformal	PS	ALL	LogInformal	LogRemPaid	ALL
chi2	0.115	0.000	0.117	0.795	0.945	1.568	0.285	0.123	0.574
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.734	0.983	0.943	0.373	0.331	0.456	0.593	0.726	0.750

Number Of observations: 693

Number of panels: 38

Ave. No. Of T: 18.23

Table 11
Correlation and causality in OECD Countries (Lag 2): remittances paid

LogInformal						
	LogInformal		LogRemPaid		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	1.360466	-0.3840207	-0.0065308	0.002945	0.0583471	-0.0193248
Std. Err.	0.073654	0.0481134	0.160094	0.114866	0.036415	0.0229302
z	18.47***(0.000)	-7.98***(0.000)	-0.41(0.683)	0.26(0.798)	1.60(0.109)	-0.84(0.399)
95% Conf. Interval	1.216107	-0.4783212	-0.0379087	-0.195684	-0.013025	-0.0642671
	1.504825	-2.2897202	0.248471	0.0254584	0.1297192	0.0256175

LogRemPaid						
	LogInformal		LogRemPaid		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.9924805	-0.6764348	0.9617891	-0.0874437	-1.1046627	0.0476408
Std. Err.	0.3131534	0.2367045	0.0845231	0.0368543	0.1426004	0.1299767
z	3.17**(0.002)	-2.86**(0.004)	11.83***(0.000)	-2.37*(0.018)	-0.73(0.463)	0.37(0.714)
95% Conf. Interval	0.378112	-1.140367	0.7961268	-0.1596767	-0.3841544	-0.2071088
	1.60625	-0.2125025	1.127451	-0.0152107	0.174829	0.3023905

PS						
	LogInformal		LogRemPaid		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.3035668	0.3629499	0.0068936	-0.0327596	1.021767	-0.0914943
Std. Err.	0.14883	0.1026519	0.0389419	0.204105	0.0814005	0.0557938
z	-2.04*(0.041)	0.354***(0.000)	0.18(0.859)	-1.61(0.108)	12.55***(0.000)	-1.64(0.101)
95% Conf. Interval	-5.5952683	0.1617559	-0.064311	-0.0727635	0.862225	-0.2008482
	-0.118654	0.5641439	0.832182	0.0072444	1.181309	0.0178596

Granger test:

Equation Excluded \	LogInformal			LogRemPaid			PS		
	LogRemPaid	PS	ALL	LogInformal	PS	ALL	LogInformal	LogRemPaid	ALL
chi2	0.197	2.897	2.982	11.410	0.557	12.668	13.365	2.723	14.591
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.906	0.235	0.561	0.003	0.757	0.013	0.001	0.256	0.006

Number Of observations: 655

Number of panels: 38

Ave. No. Of T: 17.237

Table 12

Correlation and causality in OECD Countries (Lag 3): remittances paid

LogInformal									
	LogInformal			LogRemPaid			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	1.325388	-0.3951468	0.0058838	0.0013966	0.0042726	0.0015986	0.0483507	-0.0127384	0.0005039
Std. Err.	0.0757871	0.0697635	0.0472766	0.0156652	0.0122517	0.0080384	0.382625	0.0228755	0.0225063
z	17.49***(0.000)	5.66***(0.000)	0.12(0.901)	0.09(0.929)	0.35(0.727)	0.20(0.842)	1.26(0.206)	-0.56(0.578)	0.02(0.982)
95% Conf.	1.176848	0.5318808	-0.0867765	-0.0293066	-0.197402	-0.014564	-0.0266424	-0.0575737	-0.0436077
Interval	1.473928	-0.2584128	0.0985442	0.0320998	0.0282855	0.0173536	0.1233438	0.0320968	0.0446155

LogRemPaid									
	LogInformal			LogRemPaid			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	1.04929	-0.4397908	-0.2387666	0.9472194	-1.176453	0.0943482	-0.0279132	-0.123861	0.1550785
Std. Err.	0.3389495	0.2950484	0.2144998	0.902345	0.1095718	0.1199293	0.1479484	0.1368853	0.121102
z	3.10**(0.002)	-1.49(0.136)	-1.11(0.266)	10.50***(0.000)	-1.61(0.107)	0.79(0.431)	-0.19(0.850)	-0.90(0.366)	1.28(0.200)
95% Conf.	0.3849615	-1.018075	-0.6591785	0.7703614	-0.3912098	-0.1407088	-0.3178867	-0.3921513	-0.082277
Interval	1.713619	0.1384933	1.1816454	1.124078	0.0383039	0.3294052	0.2620603	0.1444293	0.392434

PS									
	LogInformal			LogRemPaid			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-0.2925123	0.3831569	0.0161488	-0.0023633	-0.0225452	-0.0162553	1.013667	-0.1938092	0.1450766
Std. Err.	0.1603349	0.1320686	0.1144485	-0.0404404	0.0288827	0.0265107	0.0856549	0.0643041	0.0571436
z	-1.82*(0.068)	2.90**(0.004)	0.14(0.888)	-0.06(0.953)	-0.78(0.435)	-0.61(0.540)	11.83***(0.000)	-3.01**(0.003)	2.54*(0.011)
95% Conf.	-0.6067629	0.1243072	-0.2081662	-0.0816249	-0.0791542	-0.682154	0.8457862	-0.3198428	0.330771
Interval	0.0217383	0.6420065	0.2404638	0.0768984	0.0340638	0.0357048	1.181547	-0.0677755	0.257076

Granger test:

Equation \ Excluded	LogRem			LogInformal			PS		
	LogInformal	PS	ALL	LogRem	PS	ALL	LogRem	LogInformal	ALL
chi2	0.258	2.032	2.336	11.886	2.078	14.651	14.092	2.539	15.453
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.968	0.566	0.886	0.008	0.556	0.023	0.003	0.468	0.017

Number Of observations: 617

Number of panels: 37

Ave. No. Of T: 16.676

Table 13 Correlation and causality in OECD Countries (Lag 4): remittances paid

LogInformal												
LogInformal					LogRemPaid				PS			
	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4
Coef.	1.372205	-0.5160073	0.2440756	-0.1604935	-0.004512	0.004867	0.0068582	-0.0075928	0.0301961	-0.0100302	0.0278012	-0.045057
Std. Err.	0.73417	0.0659754	0.0655038	0.471395	0.0159081	0.0129691	0.0087171	0.0079789	0.0406977	0.0226054	0.0248027	0.0198689
z	18.70***(0.000)	7.82***(0.000)	3.73***(0.000)	3.40**(0.001)	-0.28(0.777)	0.38(0.707)	0.79(0.341)	-0.95(0.341)	0.74(0.458)	-0.44(0.657)	1.12(0.262)	2.27*(0.023)
95% Conf.	1.22931	-0.6453166	0.1156905	-0.2528852	-0.0356913	-0.0205518	-0.0102271	-0.0232311	-0.04957	-0.0543359	-0.0208112	-0.839994
Interval	1.517099	-0.3866979	0.3724608	-0.681017	0.0266672	0.0302859	0.0239435	0.0080455	0.1099622	0.0342755	0.0764135	-0.0061146

LogRemPaid												
LogInformal					LogRemPaid				PS			
	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4
Coef.	1.48823	-0.8511229	0.2273042	-0.2028999	0.8844218	-0.1827917	0.1597261	-0.0903786	-0.0658525	-0.1000252	0.0426899	0.00841745
Std. Err.	0.3457734	0.2954237	0.3110301	0.2347202	0.0967798	0.1079157	0.124241	0.0547876	0.1571627	0.1378448	0.1014052	0.1404585
z	4.30***(0.000)	-2.88**(0.004)	0.73(0.465)	-0.86(0.387)	9.14***(0.000)	1.69*(0.90)	1.29*(1.99)	1.65*(0.099)	-0.42(0.675)	-0.73(0.468)	0.42(0.674)	0.60(0.549)
95% Conf.	0.8105262	-1.430143	-0.3823036	-0.66243	0.6947369	-0.3943026	-0.0837818	-0.1977602	-0.3738857	-0.3701961	-0.1560606	-0.1911191
Interval	2.165933	-0.2721031	0.8369119	0.2571431	1.074107	0.0287192	0.4032341	0.0170031	0.2421807	0.1701456	0.2414404	0.3594682

PS												
LogInformal					LogRemPaid				PS			
	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4	Lag1	Lag2	Lag3	Lag4
Coef.	-0.1866167	0.3231224	0.242156	-0.2298259	-0.0069506	-0.0274914	-0.0216994	0.0212353	1.056557	-0.1708017	0.068969	0.0711855
Std. Err.	0.1853573	0.1414573	0.1483811	0.1071752	0.0441992	0.332004	0.0326128	0.0224317	0.944481	0.0684673	0.060654473	0.0587926
z	-1.01(0.314)	2.28*(0.022)	1.63(0.103)	-2.14*(0.032)	-0.16(0.875)	0.83(0.408)	0.67(0.506)	0.95(0.344)	11.19***(0.000)	2.49*(0.013)	1.05(0.292)	1.21(0.226)
95% Conf.	-0.5499104	0.0458712	-0.0486657	-0.4398854	-0.0935795	-0.092563	-0.856194	-0.02273	0.8714417	-0.3049951	-0.0593054	-0.044046
Interval	0.176677	0.6003736	0.5329776	-0.0197663	0.0796783	0.0375801	-0.0422206	0.0652007	1.241672	-0.0366082	0.1972433	0.1864169

Granger test:

Equation \ Excluded	LogInformal			LogRemPaid			PS		
	LogRemPaid	PS	ALL	LogInformal	PS	ALL	LogInformal	LogRemPaid	ALL
chi2	2.182	8.385	11.875	22.884	1.581	28.204	19.944	3.188	21.255
df	4	4	8	4	4	8	4	4	8
Prob > chi2	0.702	0.078	0.157	0.000	0.812	0.000	0.001	0.527	0.006

Table 14 Correlation and causality in OECD Countries (Lag 5): remittances paid

Number Of observations: 580

Number of panels: 37

Ave. No. Of T: 15.676

LogInformal						LogRemPaid					PS				
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5
Coef.	1.325017	-0.4754586	0.1583701	-0.0433376	-0.0542619	-0.003631	-0.0001207	0.0162637	0.0267733	0.0199812	0.0606999	-0.014885	0.0537215	-0.0822561	0.0584627
Std. Err.	0.843685	0.705436	0.0705411	0.0743664	0.0504474	0.163816	0.0114189	0.0083297	0.0087652	0.0082661	0.0419315	0.0028548	0.0245611	0.023058	0.205343
z	15.71***(0.000)	6.74***(0.000)	2.25*(0.025)	0.58(0.560)	1.08(0.282)	-0.22(0.825)	-0.01(0.992)	1.95*(0.051)	3.05***(0.002)	2.42*(0.016)	1.45(0.148)	-0.65(0.515)	2.19*(0.029)	3.57***(0.000)	2.85***(0.004)
95% Conf.	1.159658	-0.6137216	0.20112	-0.189093	-0.153137	-0.0357383	-0.0225014	-0.0000623	-0.0439527	0.0037799	-0.0214843	-0.0596796	0.0055825	-0.1274489	32161
Interval	1.490376	-0.3371956	0.2966282	0.1024178	0.446131	0.0284763	0.2226	0.0325897	-0.0095939	0.0361825	0.1428841	0.0299097	0.1018604	-0.0370632	0.0987092

LogInformal						LogRemPaid					PS				
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5
Coef.	0.8917913	-0.2062752	0.175541	-0.0735742	0.0154987	0.8917913	-0.2062752	0.1757741	-0.0735742	0.0154987	0.355483	-0.0632403	0.1150646	-0.1956125	0.3006034
Std. Err.	0.1065391	0.1122547	0.1306703	0.0566529	0.0536463	0.1065391	0.1122547	0.1306703	0.0566529	0.0536463	0.1578861	0.109164	0.1066946	0.1780972	0.123362
z	8.37***(0.000)	-1.84*(0.66)	1.35(0.179)	1.30(0.194)	0.29(0.773)	8.37***(0.000)	0.184(0.066)	1.35(0.179)	-1.30(0.194)	0.29(0.773)	0.23(0.822)	-0.58(0.562)	1.08(0.281)	-1.10(0.272)	2.44*(0.015)
95% Conf.	0.6829786	-0.4262903	-0.080335	-0.1846118	-0.0896461	0.6829786	-0.4262903	-0.080335	-0.1846118	-0.0896461	-0.2739028	-2.771979	-0.094053	-0.5446767	0.0588182
Interval	1.100604	0.0137398	0.4318832	0.0374634	0.1206436	1.100604	0.0137398	0.4318832	0.0374634	0.1206436	0.3449994	0.1507173	0.3421822	0.1534517	0.5423885

LogInformal						LogRemPaid					PS				
	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5	Lag1	Lag2	Lag3	Lag4	Lag5
Coef.	-0.0899776	0.2871059	0.2718226	-0.2488899	-0.0171771	-0.0172356	-0.0224928	0.0308241	0.0196396	0.0111194	-1.011011	-0.1206461	0.0689153	0.0095652	0.0618045
Std. Err.	0.2248752	0.1579527	0.1632081	0.1611203	0.120808	0.0513708	0.0369548	0.0349018	0.0277344	0.0244743	0.1009161	0.0719365	0.0682557	0.0675827	0.0535521
z	-0.40(0.689)	1.82*(0.69)	1.67*(0.096)	1.54(0.122)	0.14(0.887)	-0.34(0.737)	0.61(0.543)	-0.88(0.377)	0.71(0.479)	0.45(0.650)	10.02***(0.000)	1.68*(0.094)	1.01(0.313)	0.14(0.887)	1.15(0.248)
95% Conf.	-0.5307249	-0.224758	0.0480595	-0.5646798	-0.2539564	-0.1179205	-0.0949228	-0.0992305	-0.0347188	-0.0368493	0.813219	-0.2616391	-0.0648634	-0.1228945	-0.0431557
Interval	0.3507696	0.5966875	0.5917046	0.0669001	0.2196022	0.0834494	0.0499372	0.375822	0.0739979	0.0590882	1.208803	0.0203469	0.2026939	0.1420249	0.1667647

Granger test:

Equation \ Excluded	LogInformal			LogRemPaid			PS		
	LogRemPaid	PS	ALL	LogInformal	PS	ALL	LogRem	LogInformal	ALL
chi2	11.701	15.440	27.613	23.895	8.805	27.162	21.862	5.121	23.562
df	5	5	10	5	5	10	5	5	10
Prob > chi2	0.039	0.009	0.002	0.000	0.117	0.002	0.001	0.401	0.009

Number Of observations: 745

Number of panels: 54

Ave. No. Of T: 13.796

Table 15

Correlation and causality in in High Remittance-to-GDP Ratio Countries (Lag 1) $\frac{Rem}{GDP} > 0.84\%$.

LogRem			
	LogRem	LogInformal	PS
	Lag1	Lag1	Lag1
Coef.	0.4380854	0.5680695	-0.1566762
Std. Err.	0.0920708	0.1135325	0.1135211
z	4.76***(0.000)	5.00***(0.000)	-1.38 (0.168)
95% Conf.	0.2576301	0.3455499	-0.3791734
Interval	0.6185408	0.790589	0.0658211

LogInformal			
	LogRem	LogInf	PS
	Lag1	Lag1	Lag1
Coef.	0.0595111	0.0878931	-0.0257453
Std. Err.	0.254646	0.0371912	0.0293223
z	2.34* (0.019)	23.63***(0.000)	-0.88(0.380)
95% Conf.	0.0096013	0.8060376	-0.0832159
Interval	0.1094208	0.9518243	0.317253

PS			
	LogRem	LogInformal	PS
	Lag1	Lag1	Lag1
Coef.	-0.0299883	0.0435274	0.9228176
Std. Err.	0.0430991	0.0684638	0.0504262
z	-0.70(0.487)	0.64(0.525)	18.30***(0.000)
95% Conf.	-0.114461	-0.0906592	0.8239839
Interval	0.0544844	0.1777141	1.021651

Granger test:

Equation \ Excluded	LogRem			LogInformal			PS		
	LogInformal	PS	ALL	LogRem	PS	ALL	LogRem	LogInformal	ALL
chi2	25.036	1.905	25.190	5.462	0.771	6.624	0.0484	0.404	0.488
df	1	1	2	1	1	2	1	1	2
Prob > chi2	0.000	0.168	0.000	0.019	0.380	0.036	0.487	0.525	0.784

Number Of observations: 710

Number of panels: 53

Ave. No. Of T: 13.396

Table 16

Correlation and causality in in High Remittance-to-GDP Ratio Countries (Lag 2) $\frac{Rem}{GDP} > 0.84\%$

LogRem						
	LogRem		LogInformal		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.4454432	-0.0478839	0.6375815	-0.0173674	-0.1929972	-0.025104
Std. Err.	0.1099623	0.0436648	0.1699906	0.1475426	0.1227952	0.0722774
z	4.05***(0.000)	-1.10(0.237)	3.75***(0.000)	-0.12(0.906)	-1.57(0.116)	-0.35(0.728)
95% Conf.	0.2299211	-0.1334653	0.304406	-0.306547	-0.4336714	-0.1667652
Interval	0.6609652	0.0376975	0.970757	0.2718109	0.0476769	0.1165571

LogInformal						
	LogRem		LogInformal		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	0.0815659	-0.0248709	1.046848	-0.1546316	0.0033993	-0.184519
Std. Err.	0.0311212	0.0114376	0.0644362	0.0513773	0.0303271	0.0246571
z	2.62**(0.009)	-2.17*(0.030)	16.25***(0.000)	-3.01**(0.003)	0.11(0.911)	-0.75(0.454)
95% Conf.	0.0205695	-0.0472882	0.920555	-0.2553293	-0.0560408	-0.0667788
Interval	0.1425623	- 0.0024536	1.17314	- 0.053934	0.0628394	0.0298751

PS						
	LogRem		LogInformal		PS	
	Lag1	Lag2	Lag1	Lag2	Lag1	Lag2
Coef.	-0.0399399	0.126319	0.0275894	0.017858	0.9268125	-0.0125703
Std. Err.	0.049418	0.0260797	0.1135779	0.091277	0.0633693	0.0615407
z	- 0.81(0.419)	0.48(0.628)	0.24(0.808)	0.20(0.845)	14.63***(0.000)	-0.20(0.838)
95% Conf.	-0.1367975	-0.0384833	-0.1950192	-0.1610411	0.8026109	-0.1331878
Interval	0.0569177	0.0637471	0.250198	0.1967581	1.051014	0.1080471

Granger test:

Equation \ Excluded	LogRem			LogInformal			PS		
	LogInformal	PS	ALL	LogRem	PS	ALL	LogRem	LogInformal	ALL
chi2	26.518	2.882	27.147	8.116	0.574	9.083	0.719	0.382	0.865
df	2	2	4	2	2	4	2	2	4
Prob > chi2	0.000	0.327	0.000	0.017	0.750	0.059	0.698	0.826	0.930

Table 17

Correlation and causality in in High Remittance-to-GDP Ratio Countries (Lag 3) $\frac{Rem}{GDP} > 0.84\%$

Number Of observations: 653

Number of panels: 48

Ave. No. Of T: 13.604

LogRem									
	LogRem			LogInformal			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.8084272	0.131424	-0.027523	0.7467665	-0.800278	-0.0896828	0.3490726	0.0794645	0.1801469
Std. Err.	0.0928195	0.0890016	0.040625	0.3362018	0.2597197	0.1394981	0.2426767	0.2788479	0.1567275
z	8.71***(0.000)	0.15(0.883)	-0.68(0.498)	2.22*(0.026)	-0.31(0.758)	-0.64(0.520)	1.44(0.150)	0.28(0.776)	1.15(0.250)
95% Conf. Interval	0.6265044	-0.1612974	-0.1071466	0.0878231	-0.5890691	-0.363094	-0.1265649	-0.4670673	-0.1270335
Interval	0.99035	0.1875822	0.521007	1.40571	0.4290135	0.1837284	0.8247101	0.6259963	0.4873272

LogInformal									
	LogRem			LogInformal			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	0.397596	0.022725	0.0013076	0.8644136	0.1030806	-0.115889	0.0098807	0.0051194	-0.0218082
Std. Err.	0.180119	0.144479	0.0076958	0.1264271	0.1238265	0.420691	0.0612486	0.0362416	0.0453687
z	2.21*(0.027)	0.16(0.875)	0.17(0.865)	6.84***(0.000)	0.78(0.438)	2.75***(0.006)	0.16(0.872)	0.14(0.888)	-0.48(0.631)
95% Conf. Interval	0.04457	-0.0260449	-0.0137759	0.6166211	-0.1572545	-0.198343	-0.1101643	-0.659128	-0.1107291
Interval	0.750622	0.305899	0.163911	1.112206	0.3634157	-0.033435	0.1299257	-0.761515	0.0671128

PS									
	LogRem			LogInformal			PS		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Coef.	-0.0178977	-0.0261308	0.0115601	-0.0781841	0.10993	-0.0779812	0.9631396	-0.1410037	0.0560198
Std. Err.	0.0288337	0.23060645	0.0146139	0.1085855	0.0948731	0.06612	0.0936306	0.0739742	0.0513676
z	-0.62(0.535)	1.13(0.257)	0.79(0.429)	-0.72(0.472)	1.16(0.247)	-0.18(0.238)	10.29***(0.000)	-1.91*(0.057)	1.09(0.275)
95% Conf. Interval	-0.0744106	-0.190748	-0.0170827	-0.2910077	-0.0760179	-0.2075739	0.7796271	-0.2859906	-0.0446589
Interval	0.0386153	0.0713363	0.0402029	0.1346395	0.2958779	0.0516115	1.146652	0.0039831	0.1566985

Granger test:

Equation \ Excluded	LogRem			LogInformal			PS		
	LogInformal	PS	ALL	LogRem	PS	ALL	LogRem	LogInformal	ALL
chi2	8.900	10.411	14.393	9.234	0.280	11.335	3.335	2.467	5.753
df	3	3	6	3	3	6	3	3	6
Prob > chi2	0.031	0.015	0.026	0.026	0.964	0.079	0.343	0.481	0.451

Appendix 2: Philosophy of database construction, variables definitions, data sources and sample of countries

The Philosophy of Database Construction

In our research, we constructed a panel dataset encompassing four geopolitical clusters: MENA (Middle East and North Africa), SSA (Sub-Saharan Africa), Latin America, and OECD (Organisation for Economic Co-operation and Development) countries. This task was inherently complex, requiring the identification of consistent variables and datasets across these diverse regions.

The selected observation period spans from 1996 to 2017. This period was chosen for several reasons. First, data on remittances, the informal sector, and political stability are more complete and consistent from 1996 onwards. Second, this period covers significant phases of globalization, economic crises, and political changes that strongly influence the dynamics studied. Finally, a period of more than 20 years allows for capturing long-term trends and economic and political dynamics that are not visible over shorter periods.

The database comprises 1373 observations spread over 82 panels, with an average of 17.217 observations per panel. The main variables used include remittances (logarithmic), the informal sector (logarithmic), and political stability. The data have been normalized to ensure comparability and robust analysis.

We used data on remittances, political stability, and GDP from the World Bank. For information on the informal sector, we drew inspiration from the work of Medina and Schneider (2019), who developed a database covering 157 countries from 1991 to 2017. To harmonize these data with other variables in our study, we selected data starting from 1996, due to incomplete data on political stability from 1991 to 1995. This approach allowed us to compile a balanced panel database integrating all variables from various sources for the period between 1996 and 2017.

The data from Medina and Schneider on the informal sector, expressed as percentages, were recalculated in our study for better clarity. We multiplied this percentage of the informal sector by GDP (in US dollars) as reported by the World Bank, applying the logarithm of this ratio, along with the log of remittances, to enhance interpretability. To verify the integrity of our dataset, we conducted several statistical tests. A collinearity assessment, based on a rule of thumb, indicated that multicollinearity does not significantly affect most of our regression models. To explore causality in the sense of Granger, we ensured our dataset's stationarity. Through a stationarity test based on eigenvalue conditions, we confirmed that our Panel Autoregressive Model meets the requisite stability conditions.

Collecting reliable and complete data on the informal sector was a major challenge due to its unreported nature. We opted for the MIMIC (Multiple Indicators, Multiple Causes) method provided by Medina and Schneider (2019) to estimate the size of the informal sector. Harmonizing data from different sources required particular attention to ensure their consistency and comparability. To overcome potential causality issues, we used the Panel

Vector Autoregressive (PVAR) model and the Granger causality test to better understand the dynamic relationships between the variables.

The database for this study was constructed with meticulous attention to the quality and consistency of the data. The methodological choices and observation periods were selected to maximize the relevance and robustness of the results. By overcoming various challenges in data collection and harmonization, this database provides a solid foundation for analyzing the dynamics between remittances, the informal sector, and political stability across different geopolitical contexts.

Figure 4: Cartography of sample countries

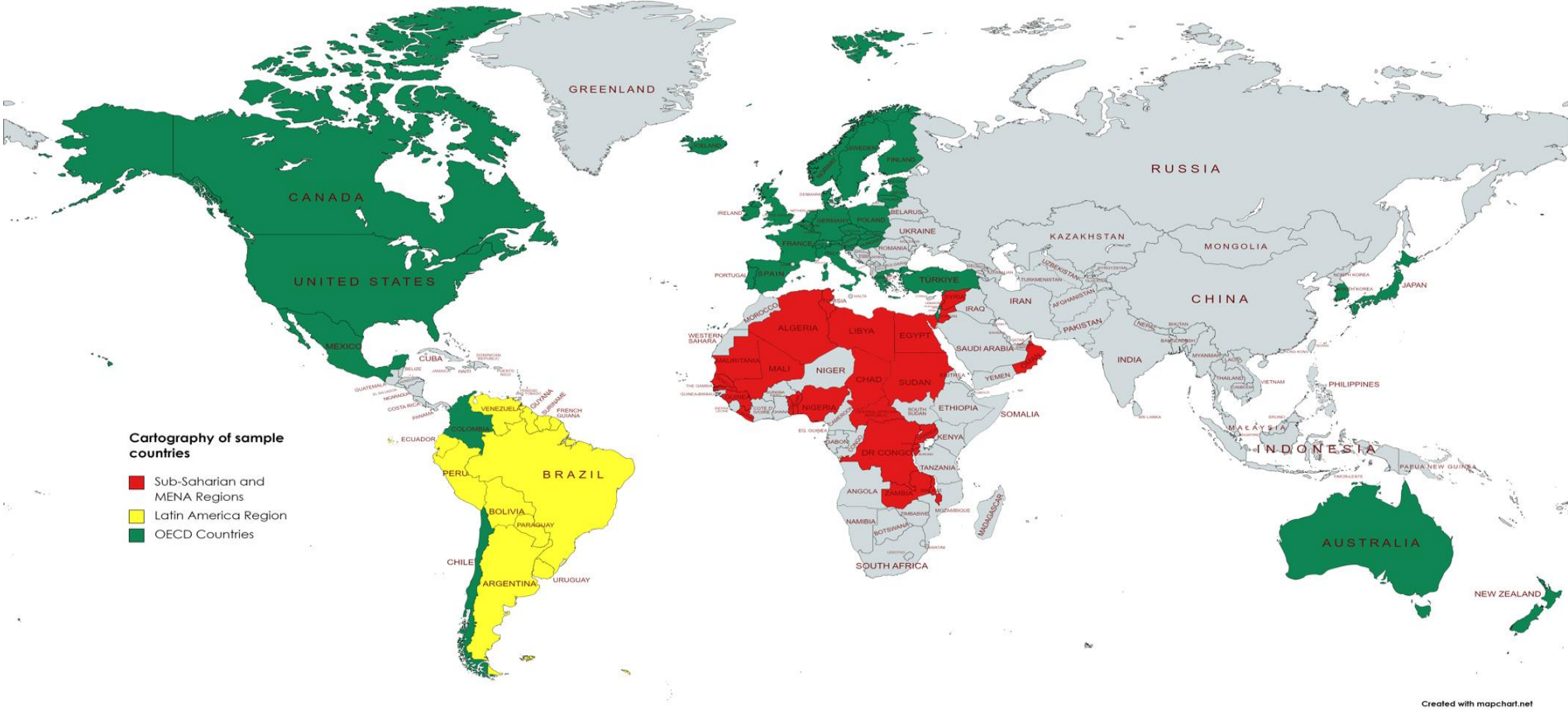


Table 18: List of countries

MENA and Sub-Saharan Africa region:

1 - Algeria	11 - LebaNO	21 – Syrian Arab Republic
2 - Benin	12 - Liberia	22 - Togo
3 - Burundi	13 - Libya	23 - Tunisia
4 - Central African Republic	14 - Malawi	24 - Uganda
5 - Chad	15 - Mali	25 - Zambia
6 - Congo. Dem. Rep.	16 - Mauritania	
7 - Egypt. Arab Rep.	17 - Nigeria	
8 - Gambia. The	18 - Oman	
9 - Guinea	19 - Rwanda	
10 - Jordan	20 - Senegal	

Latin America region:

1 - Argentina	11 - Guatemala	21 – Uruguay
2 - Bahamas	12 - Guyana	22 - Venezuela
3 - Bolivia	13 - Haiti	
4 - Brazil	14 - Honduras	
5 - Chile	15 - Jamaica	
6 - Colombia	16 - Mexico	
7 – Costa Rica	17 - Nicaragua	
8 – Dominican Republic	18 - Paraguay	
9 - Ecuador	19 - Peru	
10 – El Salvador	20 – Trinidad and Tobago	

Table 19: Variables definitions and sources

Variable	Code	Definition	Source
Personal remittances, received (current US\$)	BX.TRF.P WKR.CD.D T	<p>Personal remittances comprise personal transfers and compensation of employees. Personal transfers consist of all current transfers in cash or in kind made or received by resident households to or from NOresident households.</p> <p>Personal transfers thus include all current transfers between resident and NOresident individuals.</p> <p>Compensation of employees refers to the income of border, seasonal, and other short-term workers who are employed in an economy where they are not resident and of residents employed by NOresident entities. Data are the sum of two items defined in the sixth edition of the IMF's Balance of Payments Manual: personal transfers and compensation of employees. Data are in current U.S. dollars.</p>	World Bank staff estimates based on IMF balance of payments data.
Control of Corruption: Estimate	CC.EST	<p>Control of Corruption captures perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests.</p> <p>Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.</p>	<p>Detailed documentation of the WGI, interactive tools for exploring the data, and full access to the underlying source data available at Erreur ! Référénc de lien hypertexte non valide..</p> <p>The WGI are produced by Daniel Kaufmann (Natural Resource Governance Institute and Brookings Institution) and Aart Kraay (World Bank Development Research Group).</p>
Voice and Accountabil	VA.EST	Voice and Accountability captures perceptions of the extent to which	Detailed documentation of the WGI, interactive tools for exploring the

ity: Estimate		a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	data, and full access to the underlying source data available at Erreur ! Référence de lien hypertexte non valide..
Political Stability and Absence of Violence/Terrorism: Estimate	PV.EST	Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically-motivated violence, including terrorism. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	Detailed documentation of the WGI, interactive tools for exploring the data, and full access to the underlying source data available at Erreur ! Référence de lien hypertexte non valide..
Rule of Law: Estimate	RL.EST	Rule of Law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution, i.e. ranging from approximately -2.5 to 2.5.	Detailed documentation of the WGI, interactive tools for exploring the data, and full access to the underlying source data available at Erreur ! Référence de lien hypertexte non valide..

Appendix 3: Optimal lag analysis

Each lag indicates how far back in time the variables are being analyzed to predict future values. Here's a breakdown of the columns and what each metric represents:

Columns Explanation

- Lag: The number of time periods used to shift the data for the analysis.
- CD (Cross-correlation Decay): Indicates the degree to which correlations between variables decrease as the lag increases. Values close to 1 suggest little decay, indicating that earlier data points remain highly relevant.
- J: The test statistic value for a specific test (not specified but often related to testing for serial correlation or another time-series property).
- J pvalue: P-value associated with the J test statistic, indicating the probability of observing the test results under the null hypothesis.
- MBIC (Modified Bayesian Information Criterion): A criterion for model selection among a finite set of models; lower values indicate better models, with adjustments to penalize more complex models.
- MAIC (Modified Akaike Information Criterion): Similar to MBIC, it's another model selection criterion that penalizes less harshly for model complexity.
- MQIC (Modified Hannan-Quinn Information Criterion): Also used for model selection, providing a balance between MBIC and MAIC in terms of penalizing model complexity.

Table 20 : Optimal lag, Sub-Saharan Africa and MENA region

Number Of observations: 339

Number of panels: 22

Ave. No. Of T: 15.409

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9999647	24.58146	0.597905	-132.7205	-29.41854	-70.5844
2	0.9999646	17.52127	0.487583	-87.34674	-18.47873	-45.92264
3	0.99996	11.54558	0.2401556	-40.88842	-6.454417	-20.17637

The table 23 provides statistical metrics for selecting the optimal lag in a time-series analysis specifically for the Sub-Saharan Africa (SSA) and Middle East and North Africa (MENA) regions.

Interpretation and Selection of Optimal Lag

- CD (Cross-correlation Decay): Across all lags, the CD value is very close to 1, indicating that correlations are maintained even with increasing lags, suggesting a strong persistent relationship in the data across time periods.
- J and J p-value: Lower J values and higher p-values (as seen from lag 1 to 3) suggest decreasing statistical significance in terms of the model's ability to predict future values based on past values. This implies that as we incorporate more past data (increasing lag), it becomes less statistically significant in explaining future variations.
- Information Criteria (MBIC, MAIC, MQIC):
 - Lag 1: Offers the lowest (most negative) values for MBIC, MAIC, and MQIC, suggesting that it provides the best fit among the tested models with the least penalty for model complexity.
 - Lag 2 and 3: Show increasing values in MBIC, MAIC, and MQIC, indicating that adding more lags leads to models that fit worse, even after adjusting for complexity.

Given this data, Lag 1 is the optimal choice for analyzing time-series data in SSA and MENA for this study. It provides the best balance between model fit and complexity according to the information criteria and maintains statistical significance according to the J statistic and its associated p-value. This suggests that looking one period back provides the most relevant and significant insight into future values without unnecessarily complicating the model with data that do not add predictive value.

Given the MBIC, MAIC, and MQIC values, along with the J p-values, the choice of Lag 1 can be economically justified as it offers a balance between capturing essential economic dynamics

and maintaining model parsimony and robustness. This choice is particularly appropriate in the SSA and MENA context, where annual economic fluctuations are closely tied to national and international economic policies, and where economic modelling needs to remain adaptable and robust against frequent economic and political changes.

Table 21 : Optimal lag, Latin America region

Number Of observations: 332

Number of panels: 21

Ave. No. Of T: 15.810

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9999951	21.24601	0.7746324	-135.4926	-32.75399	-73.7261
2	0.9999945	12.18899	0.837328	-92.30344	-23.81101	-51.12575
3	0.9999933	8.435541	0.4909184	-43.81067	-9.564459	-23.22183

Analysis of Results

- Lag 1 offers the lowest MBIC, which means it is the most preferred model according to the Bayesian Information Criterion modified for panel data. It has considerably lower MBIC values compared to other lags, suggesting that including only one lag minimizes information loss while adequately capturing the data dynamics under the Bayesian framework.
- Lag 3 has the highest J p-value, which might seem to indicate a good model fit from the perspective of instrument validity, but its information criteria values are much higher (worse) than those for Lag 1.
- Lag 2 has a higher J p-value than Lag 1 but its information criteria scores are not as low as those for Lag 1.

Given the MBIC, MAIC, and MQIC values along with the J p-values, Lag 1 appears to be the optimal choice for our model. It provides a balance between model simplicity and fit, suggesting that it sufficiently captures the dynamics in the data with the least complexity, hence minimizing the risk of overfitting while maintaining robustness and validity of the instruments used in the model. This choice would generally be considered the most prudent based on these criteria, particularly noting the substantial drop in MBIC from Lag 2 to Lag 1.

Given the MBIC, MAIC, and MQIC values, along with the J p-values, the choice of Lag 1 can be economically justified as it offers a balance between capturing essential economic dynamics and maintaining model parsimony and robustness. This choice is particularly appropriate in the Latin American context, where annual economic fluctuations are closely tied to national and international economic policies, and where economic modelling needs to remain adaptable and robust against frequent economic and political changes.

Table 22: Optimal lag, OECD region

Number Of observations: 448

Number of panels: 38

Ave. No. Of T: 11.789

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9999976	72.36982	5.12e-06	-92.4596	18.36982	-25.32019
2	0.9999985	29.18498	0.461647	-80.7013	-6.815021	-35.94169
3	0.999998	20.58191	0.0146419	-34.36123	2.581911	-11.98143

Optimal Lag Selection

The results indicate varying recommendations from different criteria:

- **MBIC** suggests a more parsimonious model is better, showing its lowest value at lag 2.
- **MAIC** and **MQIC** show their lowest values at different lags, with **MQIC** also suggesting lag 2 as optimal, considering it gives a good balance between fitting complexity and maintaining parsimony.

Given these observations, **lag 2** might be considered optimal based on the MBIC and MQIC values.

Lag 2 also shows a significant improvement in the J p-value compared to lag 1, suggesting that adding the second lag helps in addressing instrument validity without overly complicating the model. Choosing lag 2 is economically justified as it likely captures the medium-term effects and cyclic dynamics inherent in OECD economies. It may reflect the different roles remittances play in more developed economies, potentially influencing more strategic economic decisions rather than mere survival strategies.

Choosing a lag of 2 is not only statistically justified based on model fit and validity criteria but also economically sensible given the typical economic behaviors, policy response times, and data characteristics in OECD countries⁵.

⁵ **Economic and policy response delays:** Economic processes and policy responses typically do not materialize instantly but rather unfold over time. A lag of 2 years can capture these delayed responses, providing a more realistic model of economic interactions and policy impacts. For example, changes in the informal sector might influence migration patterns or political stability over a period extending beyond just the immediate past year.

Business cycles: OECD countries generally experience business cycles that can last several years. Incorporating at least two lags allows the model to account for mid-cycle adjustments in the economic variables, better reflecting the cyclic nature of economic activity and its impact on variables like informal sector size, remittances, and political stability.

Table 23: Optimal lag, OECD region, Remittances Paid

Number Of observations: 617

Number of panels: 37

Ave. No. Of T: 16.676

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.9999727	109.3687	7.09e-12	-64.10281	55.36865	8.919134
2	0.9999792	34.6483	0.0104631	-80.99934	-1.3517	-32.31804
3	0.9999753	26.13722	0.00194	-31.6866	8.13722	-7.345952

Lag Order Selection:

- **Lag 1:** Shows a very low J p-value, indicating significant problems with the model/instruments at this lag.
- **Lag 2:** Significantly improved over lag 1 in terms of the J-statistic and its p-value (.0102095), indicating that instruments are more valid here. MBIC shows a considerable improvement, suggesting that adding the second lag helps in better capturing the dynamics in the data.
- **Lag 3:** Although the J-statistic continues to improve, suggesting better instrument validity, the MBIC increases compared to lag 2, indicating that the additional complexity might not be justified despite the acceptable J p-value.

Optimal Lag:

Given these results, **Lag 2** appears to be the most appropriate choice for further analysis:

- **Validity:** The significant improvement in J-statistic and its p-value at lag 2 compared to lag 1 implies that instruments are valid and the model fits the data better.
- **Information criteria:** The MBIC at lag 2 is considerably lower than at lag 1 and lag 3, suggesting an optimal balance between model complexity and fit.

Implications for Modeling:

Data collection and reporting delays: In the context of macroeconomic data, there are often delays in data collection, processing, and reporting. A lag of 2 years helps mitigate the impact of these delays on the analysis, ensuring that the effects of any late-reported changes are adequately captured.

With the chosen lag of 2, our PVAR model would appropriately balance capturing the data's dynamics without overfitting, considering the panel and temporal dimensions of our dataset. This lag structure allows for assessing the impacts of variables with up to two periods of lag, which can be critical when examining the relationships in economic data, where effects might not be immediate but occur over time. This model setup is particularly suited to further investigate how variables like the size of the informal sector, remittance flows, and political stability interact in the context of OECD countries over this period.

Table 24: Optimal lag, High Remittance-to-GDP Ratio Countries ($\frac{Rem}{GDP} > 0.84\%$)

Number Of observations: 642

Number of panels: 52

Ave. No. Of T: 12.346

Lag	CD	J	J pvalue	MBIC	MAIC	MQIC
1	0.999997	45.771	0.013464	-128.7729	-8.229004	-55.01133
2	0.9999974	28.69581	0.0522258	-87.66678	-7.304192	-38.49241
3	0.9999844	16.43617	0.0583133	-41.74512	-1.563829	-17.15794

Interpretation of Results

- Lag 1 :
 - Has the highest J statistic and the lowest J p-value, suggesting some issues with instrument validity compared to other lag choices.
 - Offers the best MBIC score, indicating it's the most parsimonious model according to this criterion.
- Lag 2 :
 - Sees a reduction in the J statistic and an increase in the J p-value, suggesting improved instrument validity.
 - The MBIC increases (less negative), indicating a less parsimonious model compared to Lag 1.
- Lag 3 :
 - Continues the trend with a further reduced J statistic and slightly better J p-value, suggesting continued improvement in instrument validity.
 - The MBIC score further reduces its negative value, suggesting increasing complexity without enough justification in data fitting or prediction improvement over Lag 1.

The choice of lag should balance model complexity with the ability to capture enough of the data dynamics and the validity of instruments. While Lag 1 provides the best MBIC and is the simplest model, it has the lowest p-value for the J statistic, suggesting possible issues with instrument validity. On the other hand, Lag 3, while offering better instrument validity, significantly increases model complexity as seen in the less favorable MBIC score.

Given this, Lag 2 might be a reasonable compromise, offering improved instrument validity over Lag 1 with a moderate increase in model complexity, and still maintaining a better balance according to the MBIC compared to Lag 3. But economics considerations lead us to choose 1.

Appendix 4: Stationarity test: Eigenvalue stability condition

The Eigenvalue stability condition in appendix 4 provide the part of the stability analysis for a Panel Vector Autoregression (PVAR) model. This analysis is crucial for assessing whether the model is dynamically stable and whether the inferences drawn from it about the long-term relationships and impacts are valid. Here is what the table means and its implications:

Understanding Eigenvalues in PVAR Stability

- **Eigenvalue:** Each eigenvalue of the model's companion matrix indicates the stability of a particular dynamic process within the PVAR system. The eigenvalue is composed of a real part and an imaginary part, with the modulus (absolute value) reflecting the distance of the eigenvalue from the origin in the complex plane.
- **Real part:** Indicates the speed of the response in the system. A real part closer to 1 indicates a slower decay of the effect of shocks.
- **Imaginary part:** Indicates the oscillatory behavior of the system. A NO-zero imaginary part suggests cyclical behavior.
- **Modulus:** The critical measure for stability. For the PVAR model to be stable, the modulus of each eigenvalue must be less than 1.

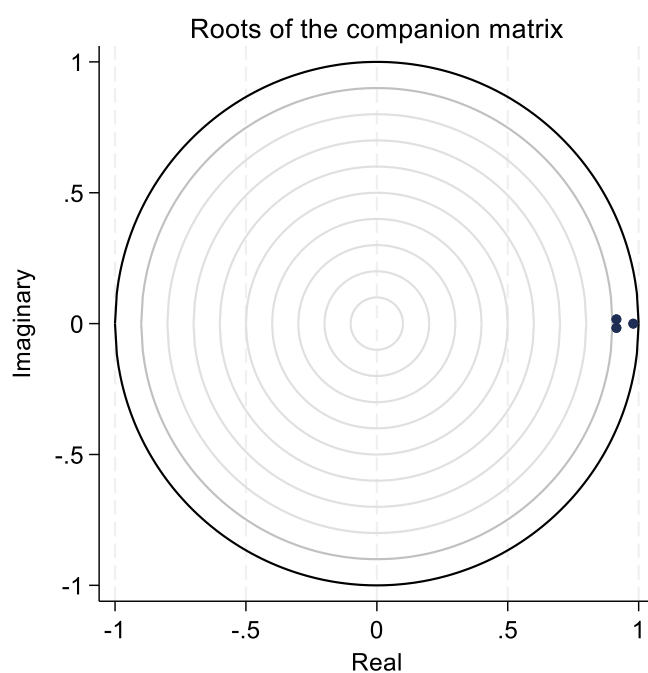
Given our model's stability, we can proceed with analyzing the dynamic responses of these variables to different shocks (e.g., through impulse response functions) or conduct scenario analyses to explore how changes in one variable might affect others over time. This kind of analysis can be particularly useful for examining the impacts of potential policy changes or external economic shocks.

Table 25: Stationarity test: Eigenvalue stability condition, Sub-Saharan Africa and MENA region

Eigenvalue		
Real	Imaginary	Modulus
0.9794008	0	0.9794008
0.9151533	0.0164215	0.9153006
0.9151533	-0.0164215	0.9153006

All the eigenvalues lie inside the unit circle.
pVAR satisfies stability condition.

Figure 5 : Eigenvalue stability condition, Sub-Saharan Africa and MENA region



Stability condition

- Eigenvalues listed:
 - The first eigenvalue has a modulus of approximately 0.979 and is real, indicating a stable, NO-oscillatory process.
 - The next two eigenvalues are complex conjugates of each other (as seen from the imaginary parts being positive and negative versions of the same number), with a modulus of about 0.915. The presence of the imaginary component suggests that

this part of the system exhibits cyclical behavior, but since the modulus is less than 1, these cycles dampen over time, contributing to overall system stability.

- Condition met: All the eigenvalues have moduli less than 1, which confirms that all dynamic responses within the PVAR system decay over time rather than exploding, ensuring the model's stability.

Implications for SSA and MENA Regions

Given that the PVAR model is stable:

- Long-term predictions: The model can reliably be used for forecasting and analyzing long-term relationships within the data. This is crucial for policy planning and economic forecasts in the SSA and MENA regions, where economic dynamics are influenced by factors like remittances, informal sector activities, and political stability.
- Dynamic responses: The model's ability to highlight the impact of a shock in one variable on others over time is validated. For instance, understanding how shocks to remittances affect political stability or the size of the informal sector can help in crafting policies that mitigate negative impacts or enhance positive ones.
- Cyclical behavior: The cyclical behavior indicated by the complex eigenvalues suggests that some economic phenomena in these regions might undergo regular ups and downs, which could influence policy timing and focus.

Overall, the stability of the PVAR model means that it provides a reliable tool for economic analysis and decision-making in regions characterized by complex interdependencies between economic factors.

Table 26 : Stationarity test: Eigenvalue stability condition, Latin America region

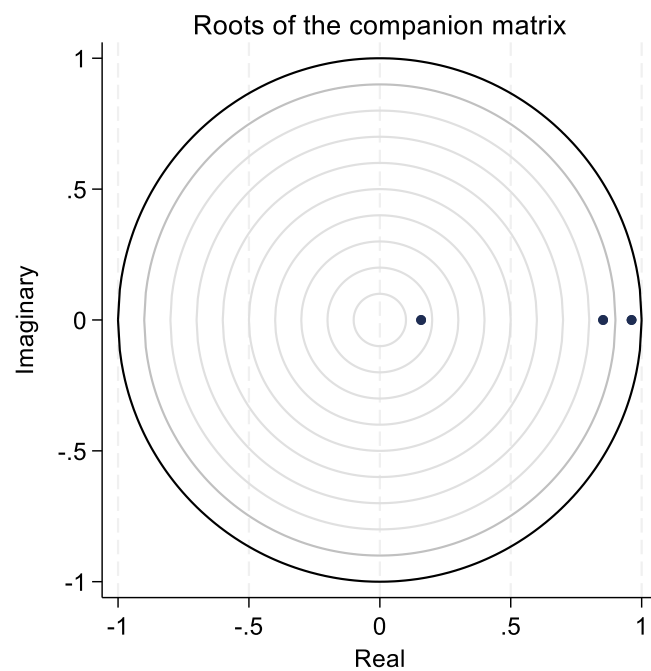
Eigenvalue		Modulus
Real	Imaginary	
0.9615227	0	0.9615227
0.8527042	0	0.8527042
0.1576935	0	0.1576935

All the eigenvalues lie inside the unit circle.
p-VAR satisfies stability condition.

Eigenvalues analysis:

- Real Part: All eigenvalues are real numbers (no imaginary part), which simplifies the interpretation. The presence of real eigenvalues implies oscillations or responses that either damp out over time or converge without oscillating.
- Modulus: Each eigenvalue's modulus (absolute value) is less than 1, which is exactly what we want for a stable VAR model. The eigenvalues reported are 0.9615227, 0.8527042, and 0.1576935.
 - The eigenvalue of 0.9615227, while close to 1, still lies within the unit circle, indicating that any impact from shocks to the system will eventually dampen rather than increase over time.
 - The lower moduli (0.8527042 and 0.1576935) suggest quicker damping of shocks to those components of the system, implying that some variables in the model respond to shocks more rapidly than others.

Figure 6 : Eigenvalue stability condition, Latin America region



Given this model's stability, we can proceed with analyzing the dynamic responses of these variables to different shocks (e.g., through impulse response functions) or conduct scenario analyses to explore how changes in one variable might affect others over time. This kind of analysis can be particularly useful for examining the impacts of potential policy changes or external economic shocks on the Latin American region.

Table 27: Stationarity test: Eigenvalue stability condition, OECD region

Eigenvalue		Modulus
Real	Imaginary	
0.8719101	0	0.8719101
0.752251	0	0.752251
0.5506327	-0.1985913	0.5853503
0.5506327	0.1985913	0.5853503
0.1414062	0.1379768	0.1975685
0.1414062	-0.1379768	0.1975685

All the eigenvalues lie inside the unit circle.
pVAR satisfies stability condition.

- Eigenvalues listed:
 - The eigenvalues we've provided all have moduli less than 1, as indicated by the highest modulus being 0.8719101. This suggests that the system is stable.
 - Real components are dominant in our eigenvalues, showing that the dynamics mainly involve growth or decay rather than oscillatory behavior.
- Complex eigenvalues:
 - The presence of complex eigenvalues (those with NO-zero imaginary parts) indicates oscillatory behavior in the dynamics of the variables. This can reflect cyclical patterns in the data, such as seasonal effects or business cycles.

The fact that all eigenvalues lie within the unit circle confirms that our PVAR model satisfies the stability condition, suggesting that the model is appropriately specified to capture the dynamics among remittances, the informal sector size, and political stability without leading to explosive or divergent behaviors. This stability is crucial for reliable simulations and forecasts based on the model, as it ensures that the dynamic responses to shocks are both realistic and bounded over time.

In practical terms, this stability allows policymakers and researchers to trust the model's predictions about how changes in one variable might impact others in the system, making it a valuable tool for economic analysis and policy planning in the context of OECD countries.

Figure 7: Eigenvalue stability condition, OECD region

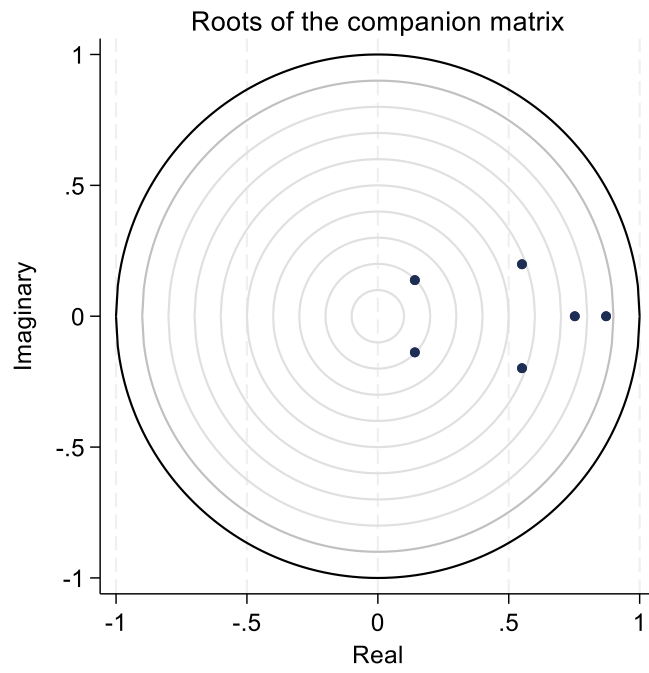
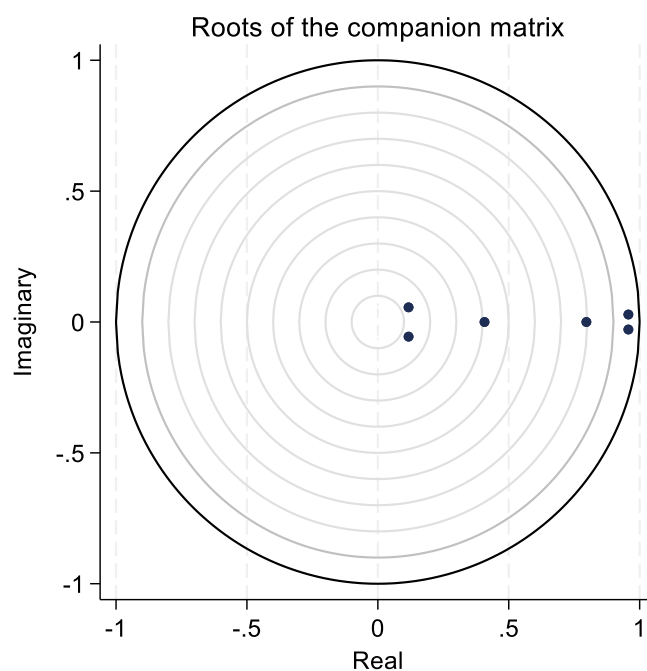


Table 28: Stationarity test: Eigenvalue stability condition, OECD region, Remittances Paid

Eigenvalue		Modulus
Real	Imaginary	
0.956965	0.0286112	0.9573927
0.956965	-0.0286112	0.9573927
0.7965988	0	0.7965988
0.4074795	0	0.4074795
0.117326	0.0559841	0.1299986
0.117326	-0.0559841	0.1299986

All the eigenvalues lie inside the unit circle.
pVAR satisfies stability condition.

Figure 8: Eigenvalue stability condition, OECD region, Remittances Paid



Eigenvalue stability condition

- **Eigenvalues and modulus:**

- The stability of a PVAR model is generally assessed by examining the eigenvalues of its associated companion matrix. The critical condition for stability is that all eigenvalues must have moduli (absolute values) less than one.

- The modulus of each eigenvalue reflects the speed at which effects from shocks to the system decay over time. A modulus less than one suggests that the effects of a shock will diminish, leading to stable dynamic responses in the model.
- **Interpretation of our results:**
 - All the eigenvalues listed have moduli less than one, as shown in the column labeled "Modulus". This indicates that over time, any perturbation to the system (e.g., a shock to one of the variables like a sudden change in remittances or political stability) will eventually die out, leading the system back to its equilibrium.
 - Eigenvalues close to one, such as .956407, suggest that some dynamic responses in our model may persist longer before they decay, indicating that shocks may have relatively enduring effects but will still stabilize over time.
 - Lower moduli, like .4077992, imply that shocks to those components of the system dissipate more quickly.
 - **Implications for economic analysis**
 - **Model reliability:** Since our PVAR model satisfies the eigenvalue stability condition, it is reliable for forecasting and impulse response analysis. This reliability is crucial for policy simulation and economic forecasting in the context of OECD countries, where accurate predictions of economic dynamics are essential for policy planning.
 - **Policy insights:** The stability of the model allows policymakers and researchers to use the model's predictions confidently, knowing that the model accurately represents the long-run behavior of the system. This is particularly useful for evaluating the impacts of potential policy changes on the informal sector, remittances, and political stability.
 - **Dynamic analysis:** With a stable model, impulse response functions (IRFs) can be meaningfully interpreted. These IRFs will show how a shock to one variable (e.g., a sudden increase in remittances) will affect other variables in the system over time, providing insights into the transmission mechanisms within the economy.

The confirmation that all eigenvalues lie inside the unit circle and that the PVAR satisfies the stability condition means that our model is well-suited for further analysis and can be reliably

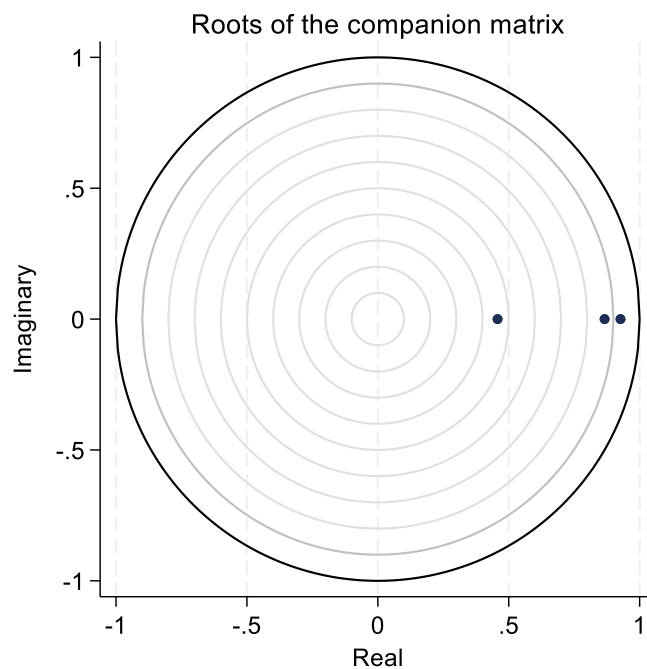
used to study dynamic interactions among the size of the informal sector, remittance flows, and political stability in OECD countries. This enables both short-term and long-term economic and policy analyses, making it a valuable tool for researchers and policymakers alike.

Table 29: Stationarity test: Eigenvalue stability condition, High Remittance-to-GDP Ratio Countries ($\frac{Rem}{GDP} > 0.84\%$)

Eigenvalue		Modulus
Real	Imaginary	
0.9354819	-0.0143186	0.9355915
0.9354819	0.0143186	0.9355915
0.3741746	0	0.3741746

All the eigenvalues lie inside the unit circle.
pVAR satisfies stability condition.

Figure 9: Eigenvalue stability condition, High Remittance-to-GDP Ratio Countries ($\frac{Rem}{GDP} > 0.84\%$)



Interpretation of Results

- The eigenvalues presented are 0.9269379, 0.8661825, and 0.4573094. All these values are less than 1.
- **Stability:** Since all eigenvalues have moduli less than 1, this indicates that the PVAR model satisfies the stability condition. This is a good sign as it implies that the impacts of shocks to the variables in the model will dissipate over time rather than increase or oscillate indefinitely.

Implications

- **Model dynamics:** The model is stable, suggesting that it appropriately captures the dynamics among the variables (log of informal sector size, log of remittances, and political stability) without leading to explosive predictions.
- **Forecasting and inference:** Stability ensures that the model can be used for forecasting and policy inference within the bounds of the data and model specifications used, without concerns about the results diverging over time.

The graphical representation of these results, usually displayed in a root locus plot, visually confirm that the eigenvalues are within the unit circle. This plot is provided in figure9.

Appendix 5: Collinearity diagnostics

The Variance inflation factors (VIF) range from 1 upwards. The numerical value for VIF tells us (in decimal form) what percentage the variance is inflated for each coefficient. For example, a VIF of 1.9 tells that the variance of a particular coefficient is 90% bigger than what we would expect if there was no multicollinearity if there was no correlation with other predictors.

A **rule of thumb** for interpreting the variance inflation factor:

- 1 = not correlated.
- Between 1 and 5 = moderately correlated.
- Greater than 5 = highly correlated.

$$VIF = \frac{1}{1 - R_i^2}$$

Table 30 : Collinearity diagnostics (SSA and MENA region)

Nb of observations : 457

Variable	VIF	SQRT VIF	Tolerance	R-Squared
PS	1.04	1.02	0.9589	0.0411
LogInformal	1.77	1.33	0.5657	0.4343
LogRem	1.72	1.31	0.5819	0.4181
Mean VIF	1.51			

	Eigenval	Cond Index
1	3.3945	1.0000
2	0.5942	2.3901
3	0.0102	18.2372
4	0.0011	54.9271
Condition Number		54.9271

Note: Eigenvalues and Cond Index computed from scaled *sscp* (w/ intercept)
Det(correlation matrix) 0.5655

Table 25 shows statistics related to multicollinearity diagnostics and condition indexes for a model involving the variables: Political Stability (PS), logarithm of informal sector size (LogInformal), and logarithm of remittances (LogRem). Here's a breakdown of these statistics and what they imply about the data model:

Multicollinearity diagnostics

Variance Inflation Factor (VIF): Measures how much the variance of a regression coefficient is inflated due to multicollinearity in the model.

- PS: VIF is 1.04, suggesting very little inflation and thus minimal multicollinearity with other variables.
- LogInformal: VIF is 1.77, indicating some moderate multicollinearity.
- LogRem: VIF is 1.72, also indicating moderate multicollinearity.
- SQRT VIF: The square root of VIF, easier to interpret directly as a factor of inflation.
- Tolerance: The inverse of VIF, representing the proportion of variance in the predictor not explained by other predictors.

- R-Squared: Proportion of variance in the predictor explained by other predictors.
 - The Mean VIF of 1.51 suggests that, on average, the variables show a low to moderate level of multicollinearity. Usually, a VIF above 5 is cause for concern, so these levels are generally acceptable.
-

Table 31 : Collinearity diagnostics (Latin America region)

Nb of observations : 443

Variable	VIF	SQRT VIF	Tolerance	R-Squared
PS	1.11	1.05	0.8992	0.1008
LogRem	1.30	1.14	0.7676	0.2324
LogInformal	1.20	1.09	0.8349	0.1651
Mean VIF	1.20			

	Eigenval	Cond Index
1	3.2953	1.0000
2	0.6992	2.1710
3	0.0039	29.0822
4	0.0016	44.7930
Condition Number		44.7930

*Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)
Det(correlation matrix) 0.7510*

Interpretation of collinearity diagnostics

- Variance Inflation Factor (VIF):
 - loginf: VIF of 1.20 suggests a low level of multicollinearity.
 - logrem: VIF of 1.30 also indicates minimal multicollinearity.
 - ps: VIF of 1.11 shows very low multicollinearity.
 - The Mean VIF across all variables is 1.20, which is well below the common threshold of 5 or 10, indicating that multicollinearity is generally not a concern for these variables.
- Tolerance:

Values are all above 0.7 (ranging from 0.7676 to 0.8992), which further confirms that multicollinearity is not severe, as lower values (below 0.1 or 0.2) would indicate potential problems.
- R-Squared:

The R-squared values are relatively low (all below 0.25), suggesting that NOe of these variables is highly predictable from the others.
- Condition Number:

The condition index of 44.7930 points to a potential issue. A rule of thumb is that condition indices above 30 may indicate multicollinearity that could be problematic, particularly with the presence of small eigenvalues (as seen here with 0.0039 and 0.0016).

The presence of a very small eigenvalue (0.0016) and a high condition index suggests that despite the low VIF and R-squared values, there might be a specific combination of linear dependencies that could potentially affect estimates or make the model sensitive to small changes in the data.

- Implications

The overall diagnostics suggest that while individual multicollinearity is not a concern, the high condition index accompanied by very small eigenvalues might indicate some deeper, less apparent collinearity issues, possibly associated with specific linear combinations of the predictors. This could be influenced by the structure of our data or the relationships among variables in Latin American economies.

Table 32 : Collinearity diagnostics (OECD countries)*Nb of observations : 642*

Variable	VIF	SQRT VIF	Tolerance	R-Squared
LogInformal	1.90	1.38	0.5266	0.4734
LogRem	1.85	1.36	0.5418	0.4582
PS	1.08	1.04	0.9264	0.0736
Mean VIF	1.61			

	Eigenval	Cond Index
1	3.5417	1.0000
2	0.4551	2.7896
3	0.0021	40.9326
4	0.0011	57.9763
Condition Number		57.9763

*Note: Eigenvalues and Cond Index computed from scaled sscp (w/ intercept)**Det(correlation matrix) 0.5028*

For OECD countries, loginf has a VIF of 1.90 and a tolerance of 0.5266, logrem has a VIF of 1.85 and a tolerance of 0.5418, and ps has a VIF of 1.08 and a tolerance of 0.9264. These values indicate a moderate level of multicollinearity for loginf and logrem, but less so for ps.

Table 33 : Collinearity diagnostics (OECD countries), Remittances Paid

Nb of observations : 809

Variable	VIF	SQRT VIF	Tolerance	R-Squared
logrempaid	1.56	1.25	0.6430	0.3570
loginf	1.61	1.27	0.6196	0.3804
ps	1.05	1.02	0.9530	0.0470
Mean VIF	1.41			

	Eigenval	Cond Index
1	3.5946	1.0000
2	0.3994	2.9999
3	0.0052	26.2582
4	0.0008	69.0915
Condition Number		69.0915

Note: Eigenvalues and Cond Index computed from scaled *sscp* (w/ intercept)

Det(correlation matrix) 0.6188

Variance Inflation Factor (VIF):

- **loginf:** VIF of 1.61 indicates a moderate level of collinearity.
 - **logrempaid:** VIF of 1.56 also indicates a moderate level.
 - **ps:** VIF of 1.05 suggests minimal collinearity with other variables.
 - **Mean VIF:** The average VIF across the variables is 1.41, which is generally considered low to moderate, suggesting that multicollinearity is not a severe concern in this model.
-

Table 34: Collinearity diagnostics, High Remittance-to-GDP Ratio Countries ($\frac{\text{Rem}}{\text{GDP}} > 0.84\%$)

Nb of observations : 847

Variable	VIF	SQRT VIF	Tolerance	R-Squared
logrem	3.31	1.82	0.3022	0.6978
loginf	3.32	1.82	0.3013	0.6987
ps	1.01	1.00	0.9948	0.0052
Mean VIF	2.54			

	Eigenval	Cond Index
1	3.0606	1.0000
2	0.9356	1.8087
3	0.0031	31.4537
4	0.0007	68.5391
Condition Number		68.5391

Note: Eigenvalues and Cond Index computed from scaled *sscp* (w/ intercept)
Det(correlation matrix) 0.3008

Table 37 provides the collinearity diagnostics in High Remittance-to-GDP Ratio Countries.

- **loginf** and **logrem** have VIFs around 3.3, which is moderately high and suggests some level of multicollinearity, although typically VIF values above 5 or 10 are considered indicative of serious multicollinearity concerns.
- **ps** has a VIF very close to 1, indicating almost no collinearity with the other variables.

The diagnostics suggest that **loginf** and **logrem** are likely to be collinear. This can impact the precision of the estimates in regression analysis, leading to wider confidence intervals and less reliable p-values. **ps** does not exhibit such issues. The relatively high mean VIF, coupled with a low determinant of the correlation matrix (0.3008), confirms that the model's predictors do not provide completely independent information about the response variable.

- **Further analysis:** It might be necessary to reconsider the model specification, perhaps by removing one of the collinear variables or using techniques such as principal component analysis (PCA) to reduce dimensionality and collinearity.
- **Model testing:** Re-estimating the model with one of the collinear variables dropped (either **loginf** or **logrem**) could help clarify the impact of multicollinearity on our results.

In the presence of moderate multicollinearity as indicated by these diagnostics, it's still technically possible to conduct Forecast-error Variance Decomposition (FEVD) and Impulse Response Functions (IRF) analyses. However, there are some important considerations and limitations to keep in mind:

Precision and stability: Multicollinearity can affect the precision of the estimated coefficients in our model. This imprecision can carry over into our FEVD and IRF analyses, potentially leading to less reliable or stable results.

Confidence intervals: The standard errors of the estimated coefficients are likely to be inflated due to multicollinearity, which might result in wider confidence intervals for the IRF estimates.

Interpretation difficulties: The interpretation of the results from FEVD and IRF analyses could be complicated by the fact that the independent variables (in our case, **loginf** and **logrem**) are not entirely independent. Changes in one variable may be indistinguishable from changes in the other, which can cloud interpretations of causal pathways and impacts.

Appendix 6: Forecast-error variance decomposition (FEVD)

Table 35: Forecast-error variance decomposition (FEVD), Sub-Saharan Africa and MENA region

		Impulse variable			
		LogRem	LogInformal	PS	
Response variable and Forecast horizon	LogRem	0	0	0	
		1	1	0	
		2	0.9998292	0.0000289	0.0001419
		3	0.9994764	0.0000895	0.000434
		4	0.9989845	0.0001752	0.0008403
		5	0.9983889	0.0002804	0.0013308
		6	0.9977189	0.0004004	0.0018807
		7	0.996999	0.0005313	0.0024698
		8	0.9962487	0.0006696	0.0030817
		9	0.9954841	0.0008127	0.0037033
	10	0.9947177	0.0009582	0.0043241	
	LogInformal	0	0	0	
		1	0.0270135	0.9729865	0
		2	0.0754016	0.9071817	0.0174167
		3	0.13863	0.8104666	0.0509034
		4	0.2067437	0.7023058	0.0909505
		5	0.2721521	0.5979086	0.1299393
		6	0.3308985	0.5054557	0.1636458
		7	0.3818425	0.4275312	0.1906264
		8	0.4253877	0.3635707	0.2110417
		9	0.4625482	0.311709	0.2257428
	10	0.4944437	0.2698015	0.2357548	
	PS	0	0	0	
		1	0.0055955	0.0130944	0.9813101
		2	0.0028248	0.0099614	0.9872138
		3	0.0034259	0.0076852	0.988889
		4	0.0066945	0.0060624	0.9872432
		5	0.012058	0.0049327	0.9830093
		6	0.0190546	0.0041712	0.9767742
		7	0.0273138	0.0036816	0.9690046
8		0.0365386	0.0033899	0.9600715	
9		0.0464902	0.0032397	0.9502701	
10	0.056976	0.0031884	0.9398355		

The table 23 shows a Forecast-error Variance Decomposition (FEVD) from a Panel Vector Autoregression (PVAR) model, analyzing the effects of shocks in one variable on the forecast error variance of other variables over different forecast horizons for the variables LogInformal, LogRem, and PS (political stability) in SSA and MENA regions. This analysis helps us understand how much of the future variation in each variable can be explained by its own shocks versus shocks to other variables in the system. Here are the findings for each response variable over different horizons:

FEVD for LogInformal

- Immediate Horizon (0): No variance is explained by any variable, which is typical at horizon 0 since no shocks have yet occurred.
- Short-term (Horizon 1): Variance in LogInformal is fully explained by its own shocks.
- Medium-term (Horizon 2-6): Gradually, shocks to LogRem and PS begin to explain more of the variance in LogInformal. The proportion explained by LogInformal's own shocks decreases over time from about 96.3% at horizon 2 to 60.6% at horizon 6.
- Long-term (Horizon 7-10): Shocks to LogRem and PS explain increasingly larger portions of the forecast error variance in LogInformal, indicating growing external influences over time. By horizon 10, LogRem and PS together explain approximately 43% of the variance in LogInformal.

FEVD for LogRem

- Immediate Horizon (0): Similar to LogInformal, no variance is explained by any variable at the immediate horizon.
- Short-term (Horizon 1): Almost all variance in LogRem is explained by its own shocks (97.3%).
- Medium to Long-term (Horizon 2-10): The influence of LogRem's own shocks remains dominant, only slightly decreasing to 95.9% by horizon 10. The contributions of shocks from LogInformal and PS remain minimal, though they slightly increase over time.

FEVD for PS

- Immediate Horizon (0): No variance is explained by any variable.
- Short-term (Horizon 1): The vast majority of variance in PS is explained by its own shocks (98.1%).

- Medium to Long-term (Horizon 2-10): Shocks to LogRem become increasingly important in explaining variance in PS, from a negligible 0.4% at horizon 2 to 5.7% at horizon 10. The variance explained by PS's own shocks gradually decreases but remains the dominant factor.

Interpretation in SSA and MENA contexts

This decomposition is crucial for understanding economic dynamics in the SSA and MENA regions:

- LogInformal: The increasing influence of LogRem and PS on LogInformal suggests that remittances and political stability are important factors in determining the size of the informal sector over time. This might reflect the dependence of informal economic activities on external financial inflows and the broader political environment.
- LogRem: The dominance of LogRem's own shocks in explaining its variance indicates that remittances are relatively stable and influenced mainly by their own past values rather than other factors like the size of the informal sector or political stability.
- PS: The decreasing influence of PS's own shocks and the increasing role of LogRem indicate that external economic factors (like remittances) gradually become more significant in influencing political stability.

These insights can guide policymakers in both regions to focus on stabilizing remittance flows and enhancing political stability as strategies to manage the informal sector and overall economic health.

Table 36 : Forecast-error variance decomposition (FEVD), Latin America region

		Impulse variable			
		LogInformal	LogRem	PS	
Response variable and Forecast horizon	LogInformal	0	0	0	0
		1	1	0	0
		2	0.934952	0.0643565	0.0006915
		3	0.8965571	0.1020866	0.0013564
		4	0.8747457	0.1232966	0.0019577
		5	0.8610588	0.1364244	0.0025168
		6	0.8516851	0.1452714	0.0030435
		7	0.8448409	0.1516184	0.0035406
		8	0.8396071	0.1563841	0.0040089
		9	0.8354657	0.160086	0.0044483
	10	0.8321028	0.1630379	0.0048593	
	LogRem	0	0	0	0
		1	0.0002306	0.9997693	0
		2	0.0582453	0.9406003	0.0011544
		3	0.1189823	0.8791379	0.0018798
		4	0.1694974	0.8283619	0.0021407
		5	0.2106487	0.7871931	0.0021582
		6	0.2445024	0.7534201	0.0020775
		7	0.2727095	0.7253146	0.0019759
		8	0.296482	0.7016271	0.0018909
		9	0.3167143	0.6814474	0.0018382
	10	0.3340793	0.6640989	0.0018218	
	PS	0	0	0	0
		1	0.0020048	0.0025549	0.9954404
		2	0.003952	0.0030837	0.9929643
		3	0.0060932	0.0029597	0.9909471
		4	0.0084838	0.0026922	0.988824
		5	0.0111225	0.0024519	0.9864256
		6	0.013979	0.0022983	0.9837227
		7	0.0170097	0.0022505	0.9807397
8		0.0201665	0.00231	0.9775235	
9		0.0234006	0.0024696	0.9741298	
10	0.0266662	0.0027176	0.9706162		

Interpretation of FEVD Results

- For logrem (Logarithm of Remittances):
 - Immediate Impact (Horizon 0): All of the forecast error variance of logrem is explained by its own shocks.
 - Short-Term (Horizon 1-2): Nearly all the variance in remittances is still explained by its own shocks, with a very small percentage explained by loginf.
 - Medium to Long-Term (Horizon 3-10): As the forecast horizon increases, the influence of loginf on logrem steadily increases, indicating that economic activities in the informal sector increasingly explain the variations in remittances over time. This could reflect a scenario where changes in the informal sector, perhaps due to economic policies or external economic conditions, start affecting the flow of remittances.

- For loginf (Logarithm of Informal Sector Size):
 - Immediate to Short-Term (Horizon 0-1): Almost all of the forecast error variance of loginf is explained by its own shocks initially.
 - Medium to Long-Term (Horizon 2-10): A gradual increase in the proportion of variance explained by logrem suggests a growing impact of remittances on the informal sector size over time. This could be due to remittances funding informal sector activities or affecting economic conditions that influence the informal sector.

- For ps (Political Stability):
 - Immediate to Short-Term (Horizon 0-1): The variance in political stability is overwhelmingly explained by its own shocks, indicating a high degree of autonomy in how political stability evolves over time.
 - Medium to Long-Term (Horizon 2-10): A gradual increase in the variance explained by loginf and logrem suggests that both the size of the informal sector and remittances start to have a more noticeable impact on political stability, albeit still small. This could be seen in how economic factors might influence political sentiments or stability indirectly.

Economic Implications for Latin America

- **Impact of Informal Sector and Remittances:** The results suggest a significant economic interplay between remittances and the informal sector in Latin America. As remittances increase, they might be boosting the informal sector, either through direct investments or by providing a financial safety net that supports informal economic activities.
 - **Political Stability Dynamics:** The relative independence of political stability from economic variables (remittances and informal sector size) in the short term indicates that other factors (like governance, external political pressures, or historical context) might be more influential. However, the gradual increase in economic influences over time suggests that long-term political stability could be subtly shaped by economic conditions.
 - These insights can be crucial for policymakers and economic planners in Latin America, emphasizing the importance of considering the broader economic impacts when designing policies related to remittances and the informal sector, as well as the potential for these economic factors to influence political stability over time.
-

Table 37: Forecast-error variance decomposition (FEVD), OECD region

		Impulse variable			
		LogInformal	LogRem	PS	
Response variable and Forecast horizon	LogInformal	0	0	0	0
		1	1	0	0
		2	0.9763146	0.0191097	0.0045757
		3	0.928192	0.0557916	0.0160164
		4	0.8653089	0.1008749	0.0338162
		5	0.7967162	0.1468299	0.056454
		6	0.7290688	0.1888359	0.0820954
		7	0.6663591	0.2245626	0.1090783
		8	0.6104619	0.253419	0.136119
		9	0.5618644	0.2758067	0.1623289
	10	0.5202729	0.2925794	0.1871477	
	LogRem	0	0	0	0
		1	0.0082166	0.9917834	0
		2	0.005863	0.9841817	0.0099553
		3	0.0043723	0.9670662	0.0285615
		4	0.0034959	0.9446308	0.0518733
		5	0.0030338	0.9199247	0.0770414
		6	0.0028363	0.8950301	0.1021337
		7	0.0027962	0.8712844	0.1259193
		8	0.0028404	0.8494837	0.147676
		9	0.0029209	0.8300407	0.1670384
	10	0.0030086	0.8131056	0.1838858	
	PS	0	0	0	0
		1	0.0104699	0.0006255	0.9889045
		2	0.0091488	0.001594	0.9892572
		3	0.0080325	0.0054318	0.9865357
		4	0.0071697	0.0113083	0.981522
		5	0.0065861	0.0183945	0.9750194
		6	0.0062836	0.0259389	0.9677775
		7	0.0062426	0.0333255	0.9604319
8		0.0064275	0.0401048	0.9534677	
9		0.0067932	0.045998	0.9472088	
10	0.0072908	0.0508788	0.9418305		

Interpretation of FEVD

- **Loginf (Logarithm of the Informal Sector Size):**
 - Initially, the forecast error variance of loginf is solely due to its own shocks (1.0 or 100% at horizon 1).
 - Over time, the influence of its own shocks decreases, while the contributions from logrem (Logarithm of Remittances) and ps (Political Stability) gradually increase. By horizon 10, loginf's variance due to its own shocks has decreased to about 54.53%, with logrem and ps explaining around 12.29% and 33.18% of the variance, respectively.
- **Logrem (Logarithm of Remittances):**
 - For logrem, the variance is predominantly explained by its own shocks across all horizons, starting at 98.76% at horizon 1 and slightly decreasing to about 96.94% by horizon 10.
 - The impact of shocks to loginf and ps on logrem is minimal but slightly increases over the horizons, indicating a small but growing interconnectedness with these variables.
- **PS (Political Stability):**
 - The variance of ps is almost entirely due to its own shocks at horizon 1 (99.36%). However, this dominance gradually decreases over time.
 - By horizon 10, shocks to ps still explain a significant majority (about 84.83%) of its forecast error variance, but the influence of shocks to loginf and logrem increases, indicating that both the informal sector size and remittances begin to play a role in explaining the forecast variance of political stability.

Implications for Economic Policy and Analysis

- **Sectorial Interdependence:** These results highlight the interdependence between the informal sector, remittances, and political stability. Policies aimed at one area (e.g., increasing formalization of the informal sector or stabilizing political environments) will likely have spillover effects on the other variables.
- **Importance of Remittances:** The strong influence of remittances on its own variance suggests that remittances are a critical economic factor in OECD countries, with a relatively independent path that is less affected by the informal sector and political stability initially.
- **Stability and Response to Shocks:** The results indicate that political stability is mostly influenced by its own innovations but is increasingly affected by economic factors over time. This suggests that efforts to enhance political stability might benefit from considering economic factors such as the size of the informal sector and remittance flows.

Table 38: Forecast-error variance decomposition (FEVD), OECD region, Remittances Paid

		Impulse variable			
		LogRem	LogInformal	PS	
Response variable and Forecast horizon	LogRem	0	0	0	0
		1	1	0	0
		2	0.9810145	0.0180724	0.0009132
		3	0.9517386	0.0470208	0.0012407
		4	0.9207377	0.0781188	0.0011435
		5	0.8904969	0.108538	0.0009652
		6	0.8615031	0.1375027	0.0009942
		7	0.8337334	0.1647959	0.0014707
		8	0.8070793	0.1903287	0.002592
		9	0.7814491	0.2140384	0.0045125
		10	0.7567851	0.235873	0.0073419
	LogInformal	0	0	0	0
		1	0.0484798	0.9515203	0
		2	0.0407632	0.9539642	0.0052726
		3	0.0354473	0.9486228	0.01593
		4	0.0308437	0.938464	0.0306923
		5	0.0266723	0.9246339	0.0486938
		6	0.0229862	0.9078984	0.0691154
		7	0.0199007	0.8889199	0.0911794
		8	0.017514	0.8682984	0.1141875
		9	0.0158854	0.8465678	0.1375468
		10	0.0150334	0.8241898	0.1607768
	PS	0	0	0	0
		1	0.0033905	0.0000673	0.9965422
		2	0.0043232	0.0108132	0.9848637
		3	0.0087608	0.0173275	0.9739118
		4	0.0157239	0.0193287	0.9649474
		5	0.0242151	0.0190254	0.9567595
		6	0.0335221	0.0178606	0.9486174
		7	0.0431603	0.0165384	0.9403012
8		0.0527972	0.0153463	0.9318566	
9		0.0622063	0.0143693	0.9234244	
10		0.0712388	0.0136052	0.9151561	

Interpretation of FEVD

- **loginf (Log of the size of the informal sector)**

- At horizon 0, **loginf** is solely responsible for its own forecast error variance, as expected.
- Over time, while **loginf** continues to explain the majority of its forecast error variance (over 81.8% at horizon 10), the impact of **ps** (political stability) on the forecast error variance of **loginf** increases from nearly 0% to about 16.1% by the 10th period. This suggests that shocks to political stability increasingly affect the forecast error variance of the informal sector size as time progresses.
- The impact of **logrempaid** (log of remittances paid) is relatively minor but grows to about 2% by the 10th period, indicating a small but increasing influence of migration-related financial flows on the informal sector.

- **logrempaid (Log of remittances paid)**

- Initially, **logrempaid** mainly explains its own variance (95.2%) at horizon 1.
- As the horizon extends, the influence of **loginf** on the forecast error variance of **logrempaid** grows significantly, accounting for 41.3% by the 10th period. This illustrates a substantial interdependence between the size of the informal sector and remittance flows, potentially indicating that changes in the informal sector significantly affect remittance behaviors over time.
- **ps** has a very modest influence, increasing slightly to just over 0.8% by the 10th period.

- **ps (Political stability)**

- Political stability is overwhelmingly determined by its own past values, with nearly 99.6% at horizon 1 and about 91.7% by the 10th period.
- **loginf** and **logrempaid** together increase their explanatory power over the variance in **ps**, totaling approximately 8.1% by the 10th period. This indicates that economic factors, encapsulated by the informal sector size and remittances, gradually exert a growing influence on political stability.

Implications and Policy Insights

The FEVD results suggest that while each variable is primarily influenced by its own shocks in the short term, there is significant interplay among them as the forecast horizon extends. In particular:

- **Economic and Political Interactions:** The increasing influence of **loginf** and **logrempaid** on the variance of **ps** suggests that economic conditions and financial flows have a growing impact on political stability over time. This can be crucial for policy planning, indicating that economic interventions could have long-term political implications.
- **Migration and Informal Sector:** The strong impact of the informal sector on remittances over time implies that policies targeting economic formalization need to consider the potential impacts on migration patterns and remittance flows.
- **Policy Stability:** The dominant influence of past values of political stability on its own variance emphasizes the inherent inertia in political systems, suggesting that changes in political stability are gradual and heavily influenced by past conditions.

These findings are critical for policymakers, economists, and researchers focusing on the dynamics within OECD countries, providing a foundation for developing strategies that consider the temporal interdependencies among informal economic size, migration, and political stability.

Table 39: Forecast-error variance decomposition (FEVD), High Remittance-to-GDP Ratio
 Countries ($\frac{Rem}{GDP} > 0.84\%$)

		Impulse variable			
		LogInformal	LogRem	PS	
Response variable and Forecast horizon	LogInformal	0	0	0	0
		1	1	0	0
		2	0.9631816	0.0353342	0.0014841
		3	0.9226218	0.0733567	0.0040215
		4	0.8898038	0.1031277	0.0070685
		5	0.8647301	0.1249165	0.0103534
		6	0.8455073	0.1407699	0.0137229
		7	0.8304608	0.1524606	0.0170786
		8	0.8184013	0.1612452	0.0203535
		9	0.8085266	0.1679726	0.0235008
		10	0.800297	0.1732141	0.026489
	LogRem	0	0	0	0
		1	0.0318104	0.9681897	0
		2	0.0640698	0.9359244	5.90e-06
		3	0.0974688	0.9025193	0.0000119
		4	0.1276555	0.8722493	0.0000952
		5	0.1533246	0.846348	0.0003275
		6	0.1746026	0.8246585	0.000739
		7	0.1920813	0.8065951	0.0013236
		8	0.206417	0.7915286	0.0020544
		9	0.2181963	0.7789078	0.0028958
		10	0.2279059	0.7682825	0.0038116
	PS	0	0	0	0
		1	6.51e-06	0.0004577	0.9995358
		2	0.0002461	0.0017234	0.9980305
		3	0.000654	0.0035646	0.9957814
		4	0.0011294	0.0049552	0.9939154
		5	0.0016341	0.005835	0.9926309
		6	0.0021507	0.0063368	0.9915124
		7	0.0026695	0.0065931	0.9907373
8		0.003183	0.0067007	0.9901164	
9		0.0036849	0.0067239	0.9895912	
10		0.0041701	0.0067032	0.9891267	

Interpretation of FEVD

loginf Forecast Error Variance

- **Immediate term (Horizon 0):** No variance explained as the initial condition.
- **Short term (Horizon 1):** 100% of the forecast error variance in **loginf** is explained by itself.
- **Medium to long term:** The contribution of **loginf** to its own forecast error variance decreases gradually, indicating increasing influence from the other variables, particularly **logrem**. By horizon 10, **loginf** explains about 80.03% of its own forecast variance, **logrem** contributes about 17.32%, and **ps** about 2.65%.

LogRem Forecast Error Variance

- **Immediate term (Horizon 0):** Similarly, no variance explained at the outset.
- **Short term (Horizon 1):** Nearly 97% of the variance in **logrem** is explained by itself, with a small contribution from **loginf**.
- **Medium to long term:** **logrem**'s own contribution to its forecast error variance decreases, though it remains predominant. By horizon 10, **logrem** accounts for about 76.83% of its own forecast error variance, **loginf** contributes about 22.79%, and **ps** about 0.38%.

Ps Forecast Error Variance

- **Immediate term (Horizon 0):** Almost entirely explained by **ps** itself.
- **Short term to long term:** The variance in **ps** remains overwhelmingly explained by itself across all horizons, maintaining above 98.91% by horizon 10. The contributions from **loginf** and **logrem** remain marginal, indicating that **ps** is largely influenced by its own past values rather than by the other variables in the model.

Insights and implications

- **Dynamics and interdependencies:** The FEVD shows significant interdependencies between **loginf** and **logrem**, reflecting a substantial reciprocal influence. However, **ps** appears relatively isolated in terms of its error variance being influenced by the other variables, suggesting it might be driven by different factors not captured by **loginf** and **logrem**.

- **Policy and analysis considerations:** Understanding these dynamics can be crucial for policy formulation, especially in contexts where the informal sector and remittances play significant roles. It suggests that policies affecting one may have significant spillover effects on the other.

Recommendations for multicollinearity consideration

Despite the presence of multicollinearity between **loginf** and **logrem**, the FEVD analysis suggests meaningful dynamic interactions worth considering. However, it's important to acknowledge that multicollinearity could still affect the precision of the estimates. In terms of policy analysis and forecasting, it would be prudent to include robustness checks, possibly exploring scenarios with reduced multicollinearity to confirm the consistency of these interactions.

Appendix 7: Impulse response factor (IRF) analysis

Figure 10 : Impulse response factor (IRF), Sub-Saharan Africa and MENA region

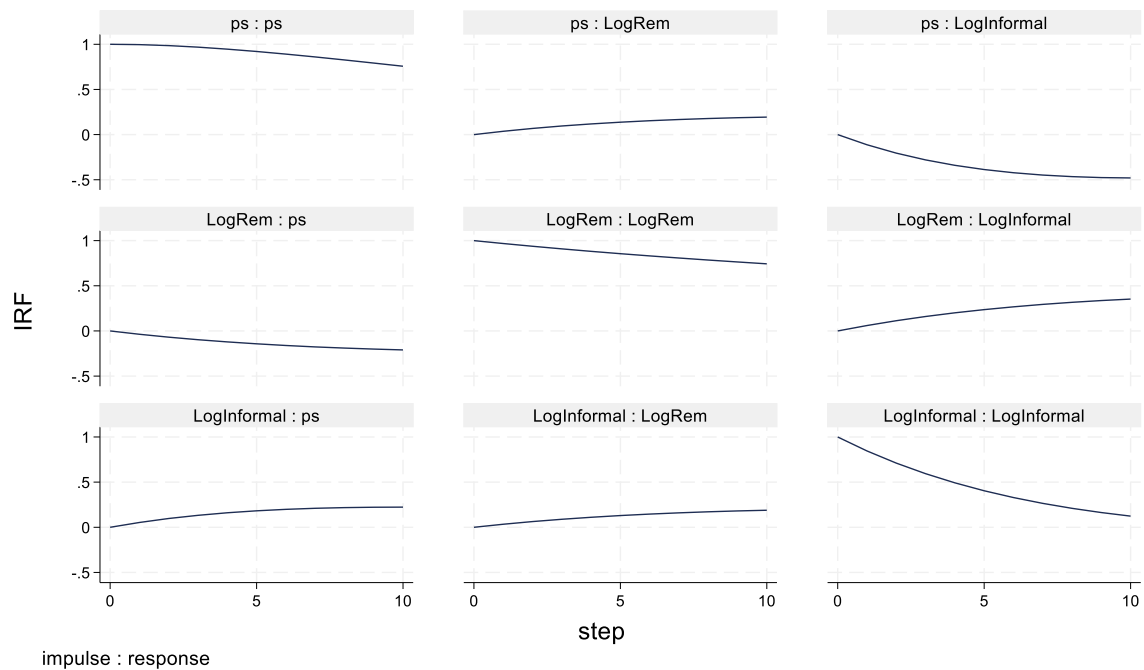


Figure 10 shows Impulse Response Function (IRF) graphs for the Sub-Saharan Africa and MENA region. Impulse Response Functions (IRFs) describe how one variable in a system responds to a shock or impulse in another variable over time. This is crucial in time-series analysis, particularly in Vector Autoregression (VAR) or Panel Vector Autoregression (PVAR) models, as it helps understand the dynamic effects of shocks across variables.

Given the dimensions and brief description, the IRFs seem to plot the response of each variable to shocks in each of the other variables across different time steps (0 to 10). Each row and column in the IRF plots likely represents:

- Columns (Impulse Variables): The source of the shock (e.g., PS, LogRem, LogInformal).
- Rows (Response Variables): The variables whose responses to the shocks are being measured (e.g., PS, LogRem, LogInformal).

Steps to Analyze the IRFs:

- Identify the Nature of Shocks: Determine what a positive or negative shock in each impulse variable represents (e.g., increase in political stability, increase in remittances).

- Observe the Response Patterns: Look at how each response variable's graph changes over time following a shock:
 - Immediate vs. Delayed Responses: Does the variable respond immediately, or is there a lag?
 - Direction of Response: Does the variable increase or decrease in response to a shock?
 - Duration and Decay: How long does the response last, and how quickly does it return to baseline or stabilize?
 - Inter-variable Dynamics: Understand the interactions between variables. For example, how does an increase in remittances affect political stability and the informal sector?

Panel Descriptions and Interpretations

- **PS Impulse Responses:**
 - **PS → PS:** Shows a decline in response over time, starting from 1, which suggests that the effect of a shock to political stability on itself diminishes gradually.
 - **LogRem → PS:** A negative response that diminishes over time, indicating that a positive shock in remittances initially decreases political stability, but the effect lessens as time progresses.
 - **LogInformal → PS:** A small, initially flat response that begins to increase slightly, suggesting a delayed and modest positive effect of shocks in the informal sector on political stability.
- **LogRem Impulse Responses:**
 - **PS → LogRem:** A negative response that gradually diminishes, indicating that a shock to political stability tends to reduce remittances initially, but this effect decreases over time.
 - **LogRem → LogRem:** Starts high and diminishes slightly, showing the persistence of shocks in remittances on themselves, though the impact slightly weakens.
 - **LogInformal → LogRem:** A slight increase over time, suggesting that a shock to the informal sector has a progressively positive influence on remittances.
- **LogInformal Impulse Responses:**
 - **PS → LogInformal:** A negative and somewhat constant response, indicating a consistent negative effect of shocks in political stability on the informal sector.
 - **LogRem → LogInformal:** A generally increasing response, suggesting that shocks in remittances have a growing positive effect on the informal sector size over time.

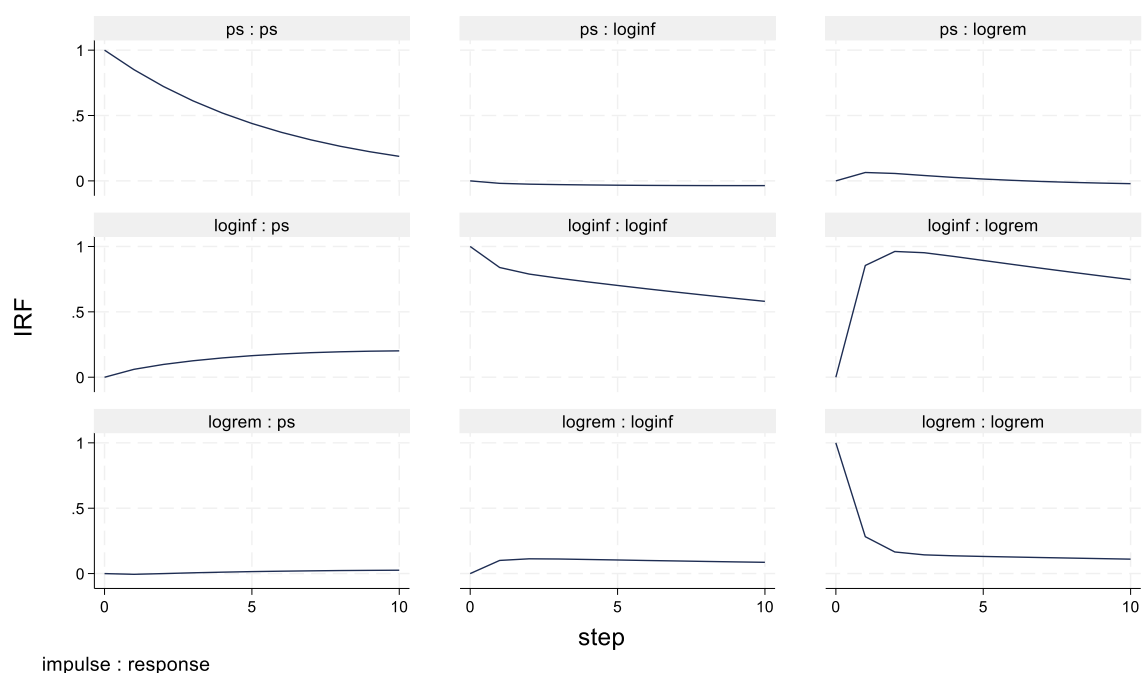
- **LogInformal → LogInformal:** Starts at zero and decreases, showing that a shock to the informal sector size tends to reduce its size over time, possibly indicating self-correcting mechanisms within the sector.

Insights for SSA and MENA Regions

- **Political Stability:** The negative initial responses of remittances and the informal sector to shocks in political stability highlight how instability might disrupt economic activities, though these effects diminish over time.
- **Remittances:** The increasing influence of the informal sector on remittances suggests potential feedback loops where growth in informal activities could encourage more remittances, possibly as remittances are used to support or expand these activities.
- **Informal Sector:** The different dynamics shown in response to shocks in PS and LogRem indicate the sector's sensitivity to changes in political and economic environments. A stable political climate might discourage reliance on the informal sector, while increased remittances might bolster it.

These IRF plots provide valuable insights into the interconnectedness of political, economic, and informal sector dynamics in the SSA and MENA regions. Policymakers could use this information to craft strategies that consider the implications of changes in one area on the others. For instance, stabilizing political conditions or facilitating remittance flows could have broader effects on economic stability and the size of the informal sector.

Figure 11 : Impulse response factor (IRF), Latin America region



Graph Analysis: loginf to a Shock in logrem

- **Immediate response (Step 0 to Step 1):** The graph shows a significant initial rise in the response of the informal sector size (**loginf**) to a shock in remittances (**logrem**). This implies that remittances have a strong, immediate stimulative effect on the informal sector.
- **Short-term response (Step 1 to around Step 5):** After the initial sharp increase, the response slightly plateaus or slightly declines but remains substantially above the baseline. This pattern indicates that while the most substantial impact is immediate, the effect of the shock persists over time, maintaining a higher level than the initial state.
- **Long-term response (Step 5 to Step 10):** As the forecast horizon extends, the response gradually begins to taper but remains elevated relative to the baseline throughout the observed period. This suggests a lasting impact of the initial remittance shock on the informal sector, albeit with a decreasing influence as time progresses.

Economic interpretation

- **Immediate economic boost :**

The significant initial rise could be interpreted as an influx of remittances quickly being absorbed into the informal sector, possibly because these funds are used to support or expand small-scale, informal businesses or compensate for a lack of formal employment opportunities. This is particularly plausible in Latin American contexts where formal job markets may not be sufficient to absorb all labor force participants.

- **Sustained higher activity in the Informal Sector:**

- The sustained, albeit slowly decreasing, higher level of the informal sector size after a remittance shock might indicate that these financial inflows contribute to a medium-term expansion or support of informal economic activities. This could involve informal businesses scaling up or more individuals entering the informal economy as a reaction to increased availability of capital through remittances.

- **Long-term economic adjustments:**

The gradual decrease in the level of response over time, though still above the baseline, suggests that the informal sector gradually adjusts to the new economic conditions brought about by the remittance inflow. This adjustment might be due to the normalization of remittance flows or increased economic integration and formalization stimulated by initial remittance-driven growth.

Policy implications

- **Support for formalization efforts:** Policymakers might consider how to channel remittance inflows into more formal economic sectors or use them to stimulate formal employment creation, given their evident potential to boost economic activity.
- **Economic development strategies:** Understanding the strong link between remittances and the informal sector can guide the development of tailored economic development strategies that leverage remittances for broader economic benefits, such as through microfinance initiatives or small business support programs that encourage formalization.
- **Social protection and economic stability:** Ensuring that the informal sector, buoyed by remittances, can contribute to stable economic growth and development might

require integrated policy approaches that address both remittance management and informal sector regulation.

This interpretation helps underline the significant role remittances play in influencing the size and scope of the informal sector in economies heavily reliant on these financial inflows, particularly in regions like Latin America where both remittances and informal economic activities are pivotal to the livelihoods of many.

Graph analysis: logrem to a Shock in loginf

- **Immediate response (Step 0 to Step 1):** The graph shows an abrupt and substantial increase in the response of remittances (**logrem**) to an initial shock in the informal sector size (**loginf**). This suggests a strong immediate sensitivity of remittance flows to changes in the informal sector.
- **Short-term response (Step 1 to around Step 5):** Following the initial sharp rise, the response of remittances quickly stabilizes and begins a gradual decline, though it remains considerably elevated above the baseline. This pattern indicates that while the initial reaction is strong, the impact of the shock begins to dissipate over time, yet it has a lasting effect that extends through the short-term period.
- **Long-term response (Step 5 to Step 10):** Over the longer term, the graph shows that the response of remittances slowly continues to decline, approaching but not completely returning to the baseline. This indicates a prolonged impact of the initial shock, although its influence diminishes progressively.

Economic interpretation

- **Immediate and strong reaction:**
 - The significant initial rise in remittances following a shock to the informal sector size could be interpreted as a compensatory mechanism. For instance, an increase in the informal sector might reflect economic distress or inadequate formal employment opportunities, prompting the diaspora to increase remittances to support family members involved in or affected by the informal economy.
- **Gradual normalization with sustained effects:**

- The gradual decline in the response over time suggests that the need for elevated remittance levels decreases as the situation stabilizes or as the initial shock's effects become fully absorbed and managed within the local economy. However, the fact that remittances do not completely revert to baseline levels within the observed period indicates a lasting change in remittance behavior.
- **Long-term adjustments :**
 - The sustained, though decreasing, level of response over the long term suggests that changes in the informal sector have a durable impact on remittance behaviors. This could be due to structural changes in the economy, lasting economic challenges, or a reevaluation by the diaspora of the economic needs of their families back home.

Policy implications

- **Economic policy and planning:** Understanding that remittances are responsive to the size of the informal sector can help policymakers develop strategies that either support the formalization of the economy or provide better support mechanisms for those who rely on the informal sector. Such strategies could potentially stabilize remittance flows.
- **Support for migrant families:** Policies aimed at supporting families that rely heavily on remittances could consider the implications of the informal sector's dynamics. Enhancing economic opportunities within the formal sector might reduce the dependence on remittances, leading to more sustainable economic development.

This analysis highlights the interconnectedness of remittances with the informal sector, reflecting how economic conditions directly influence financial support behaviors among migrant communities. This insight is particularly valuable for Latin American countries where both remittances and the informal sector play significant roles in the national economy.

Graph Analysis: logrem to a shock in ps

- **Immediate response (Step 0 to Step 1):** There appears to be a small immediate increase in the response of remittances to a shock in political stability. This suggests that any immediate reaction to changes in political stability is relatively quick, with remittances slightly increasing.

- **Short-term response (Step 1 to Step 5):** The response appears stable and maintains a slight elevation compared to the baseline. This implies that remittances consistently respond to an initial shock in political stability but do not continue to increase or decrease sharply; rather, they stabilize at a slightly higher level.
- **Long-term response (Step 5 to Step 10):** Over the longer term, the response continues to remain slightly above the baseline, suggesting a prolonged effect of the initial shock on remittances, although the effect size is modest.

Economic Interpretation

- **Immediate reaction and adjustment:**
 - The initial slight increase in remittances following a shock in political stability could indicate that migrants or the diaspora respond quickly to perceived threats or improvements in their home country’s political landscape. This might be seen as a protective or supportive measure, sending more funds home either to help their families weather uncertainty or to take advantage of stabilizing conditions.
- **Sustained moderate response:**
 - The sustained yet moderate level of response suggests that while remittances are sensitive to changes in political stability, they do not fluctuate wildly in response to these changes. This could be because while political stability is an important factor influencing remittance flows, other factors such as economic conditions, exchange rates, and personal circumstances of the migrants also play crucial roles.
- **Long-term implications:**
 - The fact that the response levels off but remains above the baseline throughout the 10 steps might indicate a long-term adjustment in the remittance behavior of individuals influenced by the initial political shock. This could reflect a new equilibrium in remittance behavior—possibly a new, slightly higher level of remittances as a regular occurrence, influenced by the continuing perceptions of political stability or instability.

Policy implications

- **Remittance dependence:** Given that remittances show a response to political stability, policymakers should consider the implications of political decisions and stability on economic inflows from abroad, which can be significant for many families and even national economies in Latin America.
- **Support mechanisms:** Enhancing political stability might be used as a strategy not just for improving domestic conditions but also as a way to stabilize and possibly increase economic support from abroad through remittances.

This interpretation relies on the assumption that the shocks are unidirectional (from **ps** to **logrem**) and that other external factors are held constant. This analysis helps in understanding the dynamics of how political changes can affect economic behaviors such as remittance flows within the Latin American context.

Graph analysis: loginf to a shock in ps

From the IRF graph:

- **Immediate response (Step 0 to Step 1):** The graph shows a slight initial increase in the informal sector size in response to a shock in political stability. This suggests that political stability has a positive, though modest, immediate impact on the informal sector.
- **Short-Term response (Step 1 to around Step 5):** The response flattens somewhat after the initial increase, indicating that the immediate effects stabilize quickly. The informal sector size remains slightly above the baseline, suggesting a sustained, though not strong, effect of the initial shock.
- **Long-Term response (Step 5 to Step 10):** The response continues to plateau at this slightly elevated level without significant further changes. This stability indicates that the effects of the initial shock have a durable but steady impact on the informal sector over the observed period.

Economic Interpretation

- **Subtle positive influence:**
 - The slight initial rise in the informal sector size following a positive shock in political stability could suggest that greater stability makes informal sector activities either more viable or necessary. This might occur if, for instance, improved political stability

leads to better overall economic conditions or if a stable political environment enables more predictable informal transactions.

- **Stabilization of the Informal Sector:**

- The fact that the increase stabilizes quickly and does not continue to rise or fall dramatically could imply that the informal sector quickly adjusts to the new level of political stability. This could be due to the sector reaching a new equilibrium where the benefits of increased stability, such as reduced uncertainty and possibly improved law enforcement, have been fully realized.

- **Long-Term steady impact:**

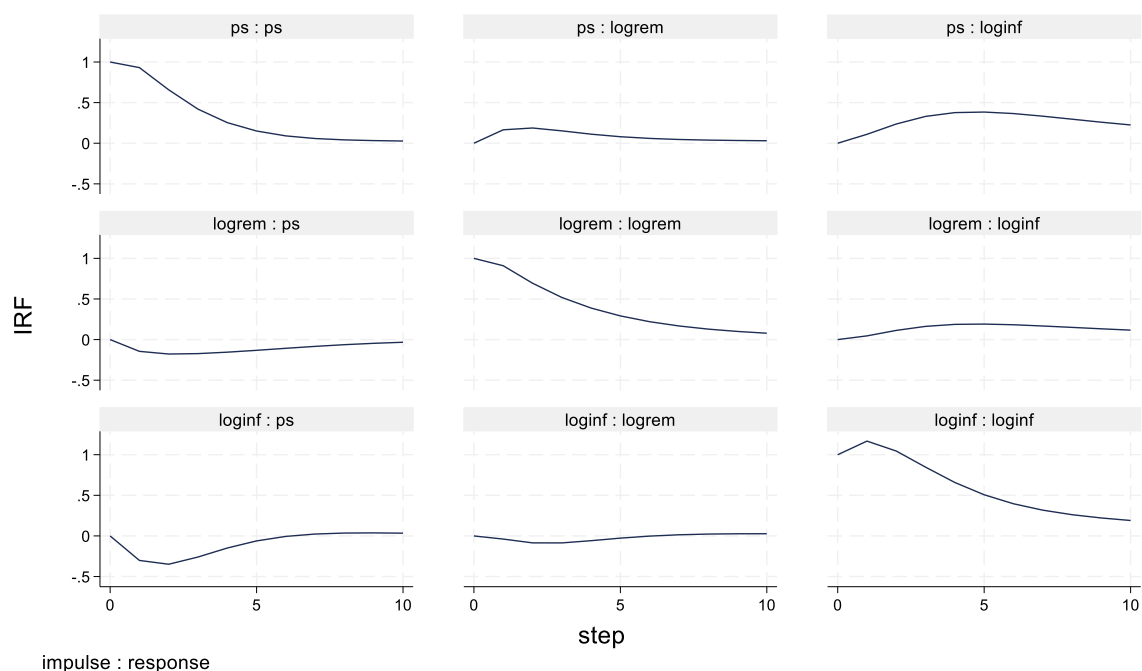
- The prolonged steady state of the informal sector size above the baseline suggests that the effects of improved political stability are enduring but do not progressively transform the sector. This could reflect a scenario where political stability has a foundational but limited role in influencing informal sector dynamics, possibly due to the resilience or inherent characteristics of the informal economy that make it less responsive to political changes beyond initial adjustments.

Policy Implications

- **Policy Design and implementation:** The modest impact of political stability on the informal sector suggests that while efforts to improve political stability are certainly beneficial, they might need to be complemented with specific policies targeting the informal sector to significantly alter its size. This might include measures to encourage formalization, provide legal and financial support to informal businesses, or improve the regulatory environment to reduce barriers to formal sector entry.
- **Monitoring and evaluation:** Policymakers should continue to monitor the relationship between political stability and the informal sector, considering that stability alone does not drastically change the sector's size. Understanding this dynamic can help in designing more targeted interventions that address specific needs and opportunities within the informal economy.
- **Supportive infrastructure:** Improvements in political stability should be leveraged to build infrastructure and support systems that help integrate the informal sector more effectively into the formal economy. This can lead to more sustainable economic growth and reduced vulnerability of those working within the informal sector.

This analysis highlights that while political stability has a positive impact on the informal sector, the effect is moderate and stabilizes quickly, suggesting that other factors also play significant roles in shaping the sector's dynamics.

Figure 12: Impulse response factor (IRF), OECD region

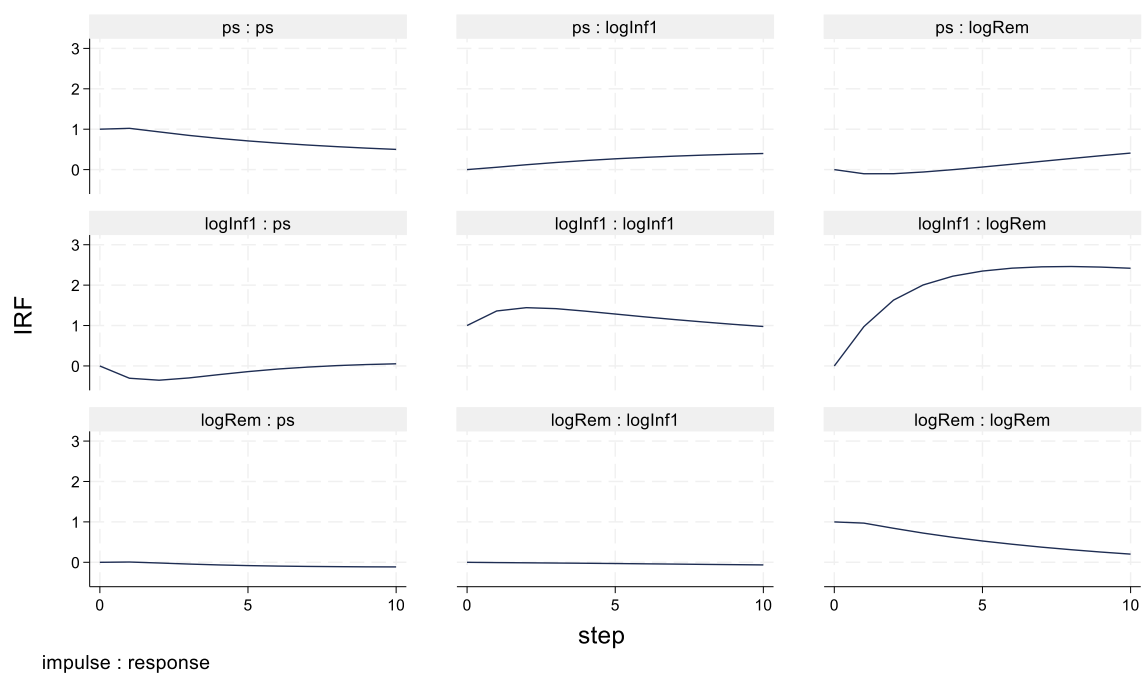


Impulse Response Analysis

- **PS Response to various shocks:**
 - **PS to PS shock:** The response is initially positive and decays towards zero, indicating that political stability tends to gradually return to its equilibrium after a shock.
 - **PS to Logrem shock:** Shows a flat response close to zero, suggesting that shocks in remittances have minimal immediate or long-term impact on political stability.
 - **PS to Loginf shock:** Also near zero across the horizon, implying that shocks in the informal sector size similarly have little impact on political stability.
- **Logrem Response to various shocks:**
 - **Logrem to PS shock:** Indicates a slight negative response, turning neutral over time. This suggests a weak inverse relationship where increases in political stability may slightly depress remittances initially.

- **Logrem to Logrem shock:** The response is negative and diminishes over time, indicating that a shock in remittances leads to an initial reduction but stabilizes over time.
 - **Logrem to Loginf shock:** Shows minimal response, implying that changes in the informal sector size do not significantly affect remittances.
 - **Loginf response to various shocks:**
 - **Loginf to PS shock:** Displays a very slight negative response before stabilizing, suggesting a negligible impact of political stability shocks on the informal sector size.
 - **Loginf to Logrem shock:** The response is almost neutral throughout, indicating that remittances do not significantly affect the informal sector size.
 - **Loginf to Loginf shock:** Begins with a negative response and gradually approaches a less negative value, suggesting a damping effect where the informal sector may initially contract after a shock but recovers slightly thereafter.
 - **Limited interdependence:** The overall minimal cross-variable responses suggest that each of these economic and political variables is somewhat insulated from shocks in the others within the time frame analyzed. This could imply either a strong internal equilibrium mechanism within each variable or that other external factors not included in this model are playing a significant role.
 - **Economic stability:** The stability observed in responses, particularly for political stability and remittances, could reflect underlying resilience or robustness in these systems. This might be due to strong institutional frameworks in OECD countries that buffer against internal shocks.
-

Figure 13: Impulse response factor (IRF), OECD region, Remittances Paid



Analysis of Impulse Response Functions (IRFs)

- **ps : ps:**
 - A shock to political stability (**ps**) results in an immediate and relatively strong response in itself, which decays gradually over time. This suggests that political stability is primarily self-driven but does stabilize back to equilibrium slowly.
- **ps : logrempaid:**
 - A shock to remittances (**logrempaid**) has a minimal initial impact on political stability, which appears to increase slightly over time. This indicates a delayed and growing effect of remittance flows on political stability.
- **ps : loginf:**
 - A shock to the informal sector size (**loginf**) has almost no immediate or long-term impact on political stability. This suggests that changes in the informal sector do not significantly affect political stability.
- **logrempaid : ps:**

- Political stability shocks have negligible impacts on remittances, as shown by the flat IRF. This suggests that political stability does not significantly influence remittance behaviors.
- **logrempaid : logrempaid:**
 - Remittances are highly responsive to their own shocks, demonstrating an immediate strong response that decays slightly but remains quite influential over time. This indicates that remittance flows are self-sustaining and persistently influenced by their own past values.
- **logrempaid : loginf:**
 - A shock to the informal sector size has a very minor influence on remittances, which seems to remain consistent over the forecast horizon.
- **loginf : ps:**
 - Shocks to political stability have a very slight impact on the informal sector, which remains fairly constant throughout the periods. This implies limited influence of political conditions on the informal sector.
- **loginf : logrempaid:**
 - The response of the informal sector to shocks in remittances starts minimal and grows considerably over time, peaking at around period 10. This suggests a cumulative and increasing impact of remittance flows on the informal sector, possibly as migrant are absorbed into the economy and contribute mostly to informal activities.
- **loginf : loginf:**
 - The informal sector shows a strong response to its own shocks, which stabilizes slightly but remains fairly constant. This reflects the self-driven nature of the informal sector and its persistence over time.

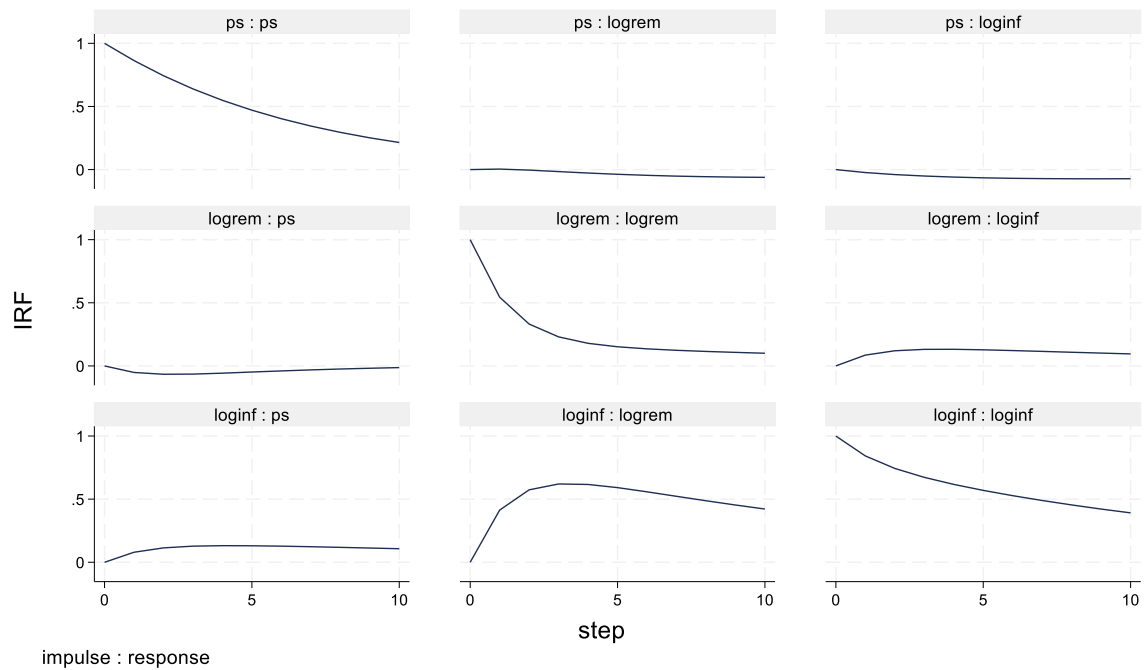
Summary and implications

- **Self-driven dynamics:** Each variable primarily responds to its own shocks, indicating that each is driven by internal dynamics.

- **Cross-variable influence:** There is a noticeable impact of remittances on the informal sector, suggesting economic ties between migration-related financial flows and informal economic activities.
- **Policy considerations:** The minimal cross-impact of political stability on economic variables suggests that policy measures aimed at political stability might not directly influence economic variables like the informal sector and remittances in the short term.

This detailed analysis of the dynamic responses can help policymakers and researchers understand the complex interrelationships between economic activities and political conditions within OECD countries, guiding targeted interventions and policy formulation.

Figure 14: Impulse response factor (IRF), High Remittance-to-GDP Ratio Countries ($\frac{Rem}{GDP} > 0.84\%$)



Plot Analysis

Row 1: Responses to shocks in ps

- **ps to ps (ps : ps):** A shock in **ps** shows a decreasing impact on itself over time, indicating that its influence diminishes gradually.
- **ps to logrem (ps : logrem):** A shock in **ps** appears to have a negligible and stable effect on **logrem**, suggesting little to no dynamic influence.
- **ps to loginf (ps : loginf):** Similarly, a shock in **ps** has minimal impact on **loginf**, reinforcing the notion of political stability being largely independent of changes in the informal sector size.

Row 2: Responses to shocks in logrem

- **logrem to ps (logrem : ps):** The response of **ps** to a shock in **logrem** is minimal, consistent with the FEVD results showing that **ps** is primarily influenced by its own shocks.
- **logrem to logrem (logrem : logrem):** A shock in **logrem** has a significant and decaying impact on itself, indicating persistence but diminishing over time.

- **logrem to loginf (logrem : loginf):** The effect of a shock in **logrem** on **loginf** is noticeable and also decreases over time, reflecting a transfer of economic impacts from remittances to the informal sector.

Row 3: Responses to Shocks in loginf

- **loginf to ps (loginf : ps):** A shock in **loginf** has a very slight impact on **ps**, consistent with the earlier observations of political stability's independence.
- **loginf to logrem (loginf : logrem):** The response of **logrem** to a shock in **loginf** decreases slightly over time, suggesting some economic interactions but relatively moderate.
- **loginf to loginf (loginf : loginf):** Shocks in **loginf** show strong self-persistence with a decaying impact, indicating that changes in the informal sector can sustain themselves over time but diminish.

Key Insights

- **Independence of Political Stability:** **ps** is largely unaffected by shocks in economic variables (**loginf** and **logrem**), highlighting its stability and perhaps different driving factors not captured by the other two variables.
- **Economic interdependence:** There's a significant interaction between **loginf** and **logrem**. Shocks in remittances (**logrem**) have visible impacts on the informal sector size (**loginf**), and vice versa. This suggests that policies affecting one may have ramifications for the other.
- **Time decay in responses:** Most IRF plots show a decay in impact over time, typical in economic systems where initial shocks are absorbed or mitigated through various economic or institutional adjustments.

Considerations for multicollinearity

Although the IRFs provide useful insights, the underlying multicollinearity between **loginf** and **logrem** suggests caution in interpretation. The precision of these estimates could be compromised, meaning that while the trends and directions of influence might be clear, the exact magnitudes should be interpreted with some skepticism.

Overall, these IRFs are valuable for understanding the dynamic interplay among the variables in our model, especially for policy-making and economic forecasting in contexts heavily influenced by remittances and the informal sector.
